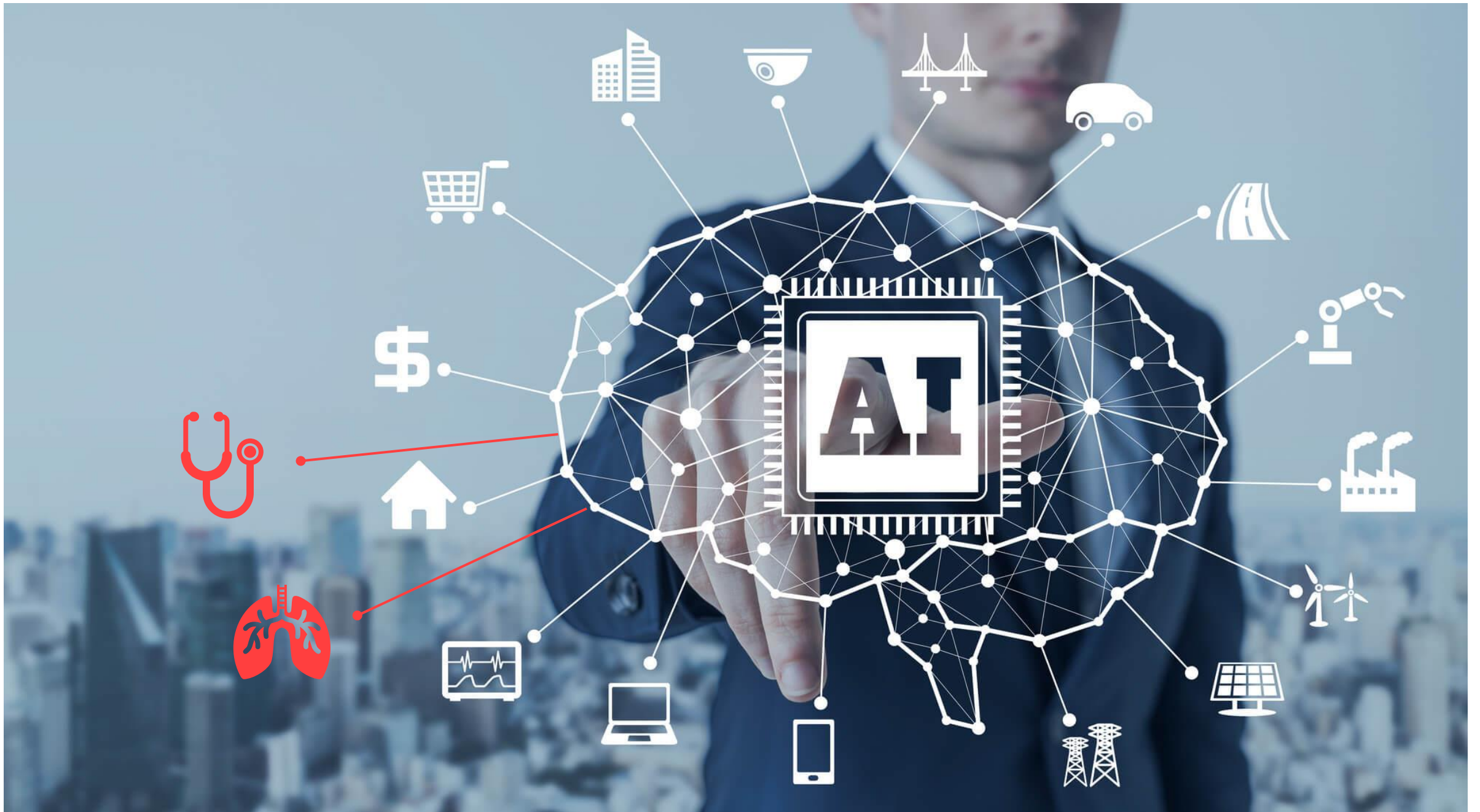


# Tüdőrák diagnosztikai mesterséges intelligencia mellkas CT felvétel alapján

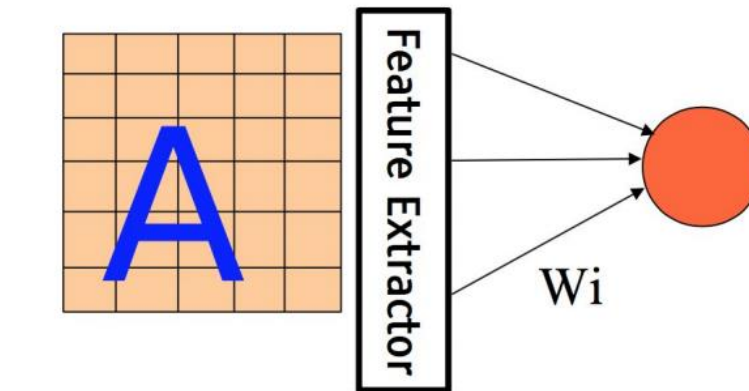
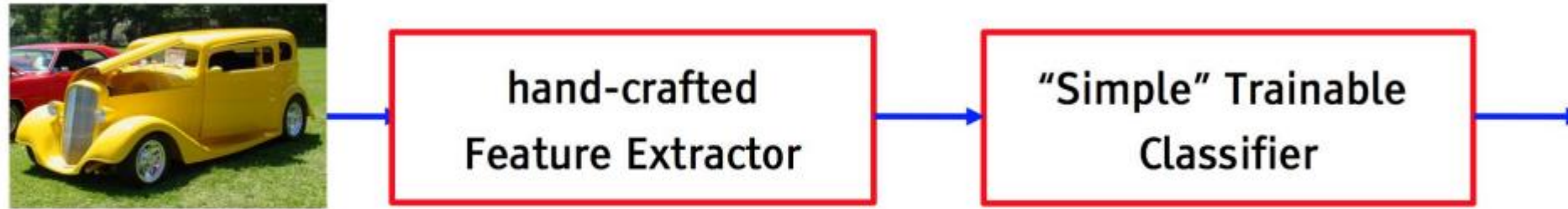


Radványi Mihály

*AI kutató*



# Traditional methods



Linear Regression  
SVM  
Decision Trees  
Random Forest

...

$$y = \text{sign} \left( \sum_{i=1}^N W_i F_i(X) + b \right)$$

Article | [Open Access](#) | [Published: 21 March 2019](#)

## Effective and Reliable Framework for Lung Nodules Detection from CT Scan Images

[Sajid Ali Khan](#), [Shariq Hussain](#), [Shunkun Yang](#) & [Khalid Iqbal](#)

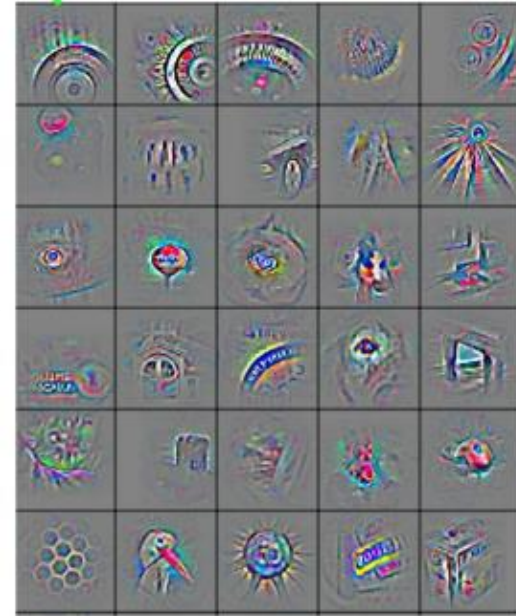
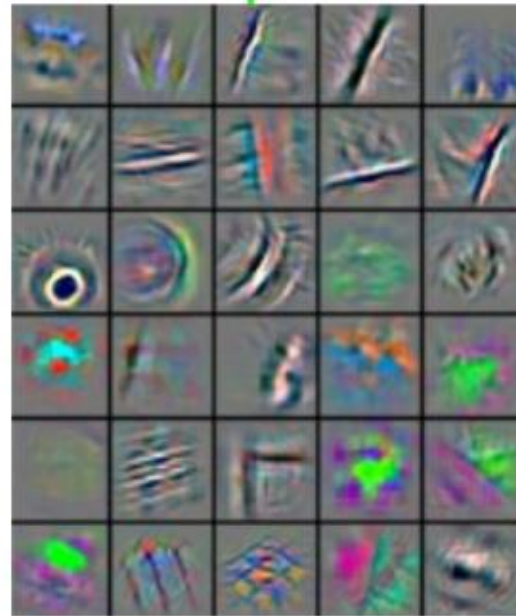
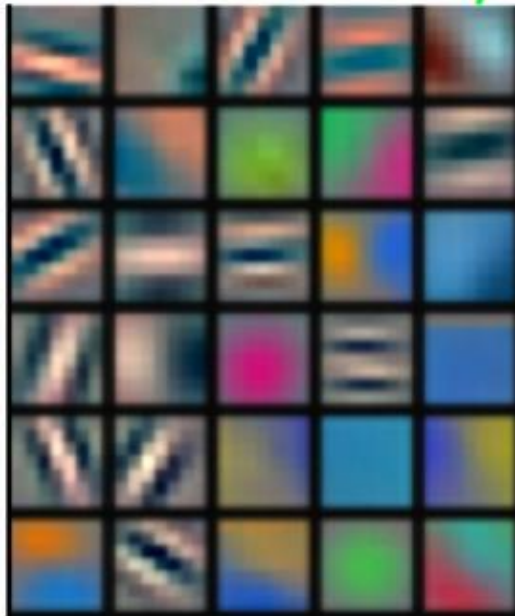
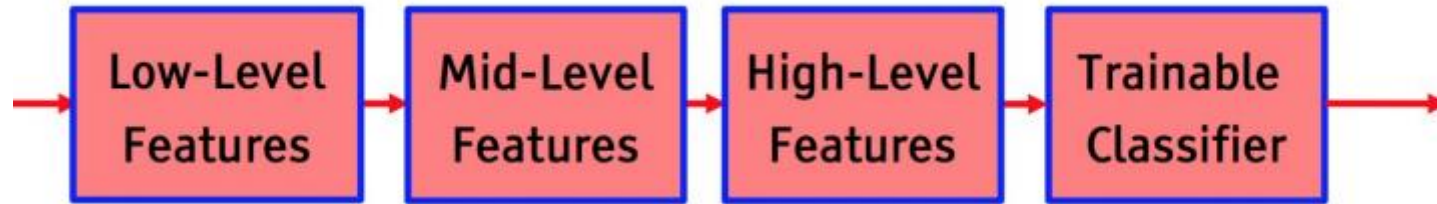
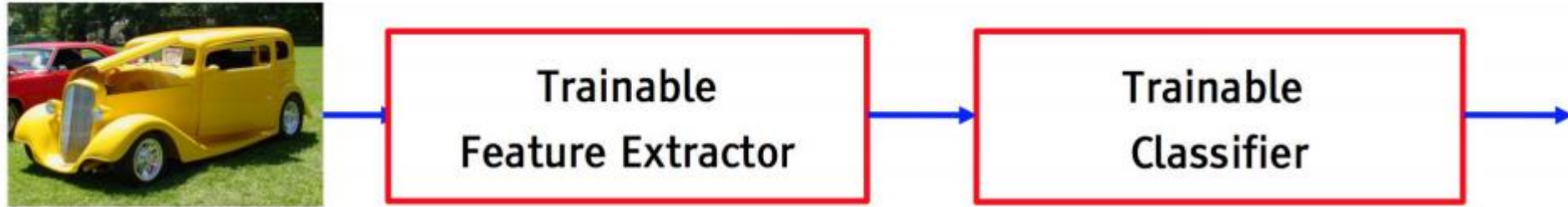
[Scientific Reports](#) 9, Article number: 4989 (2019) | [Cite this article](#)

6935 Accesses | 5 Citations | 1 Altmetric | [Metrics](#)

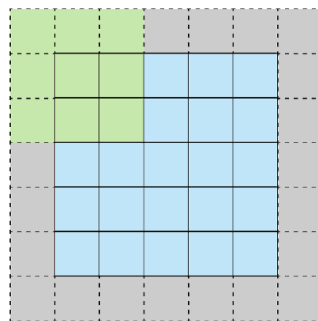
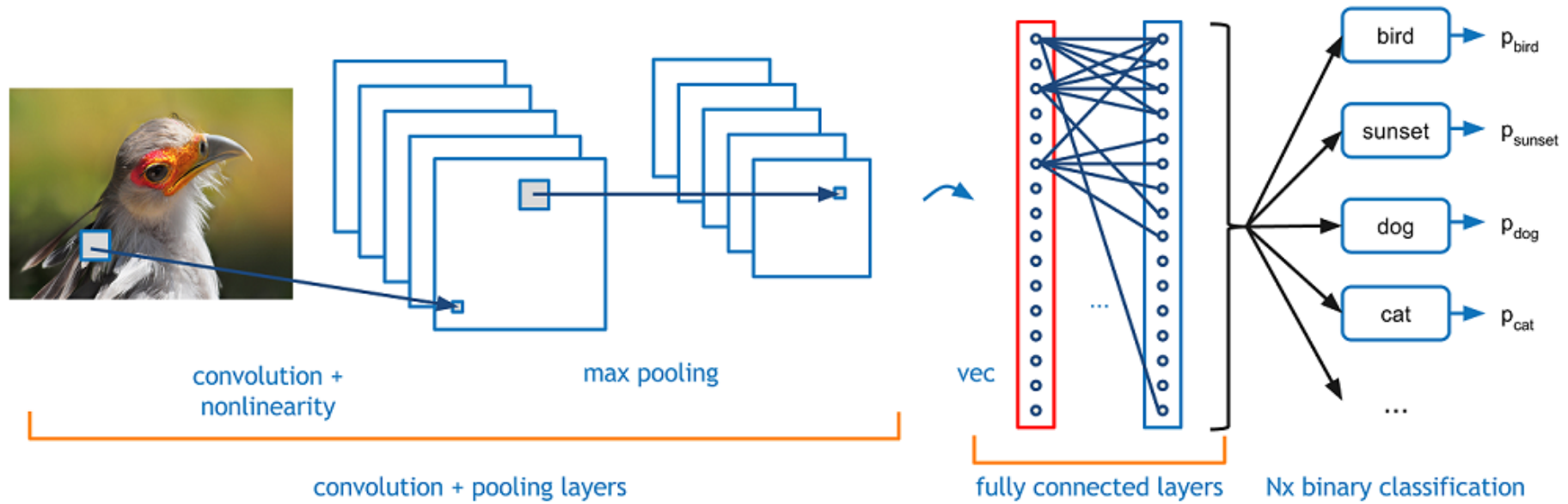
### Abstract

Lung cancer is considered more serious among other prevailing cancer types. One of the reasons for it is that it is usually not diagnosed until it has spread and by that time it becomes

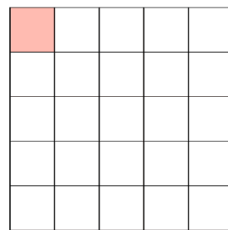
# Feature learning



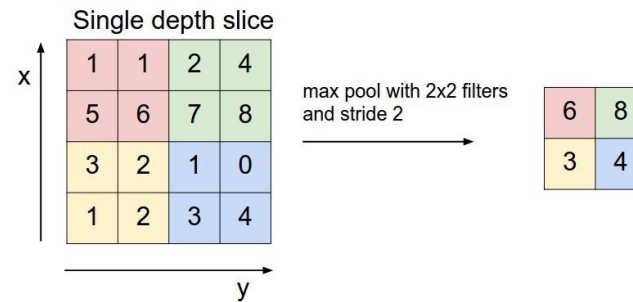
# Convolutional Neural Networks



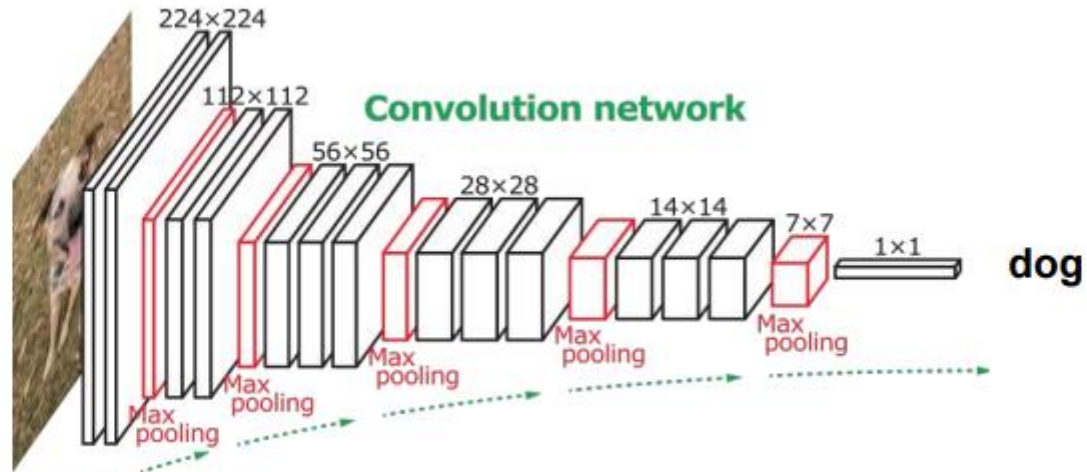
Stride 1 with Padding



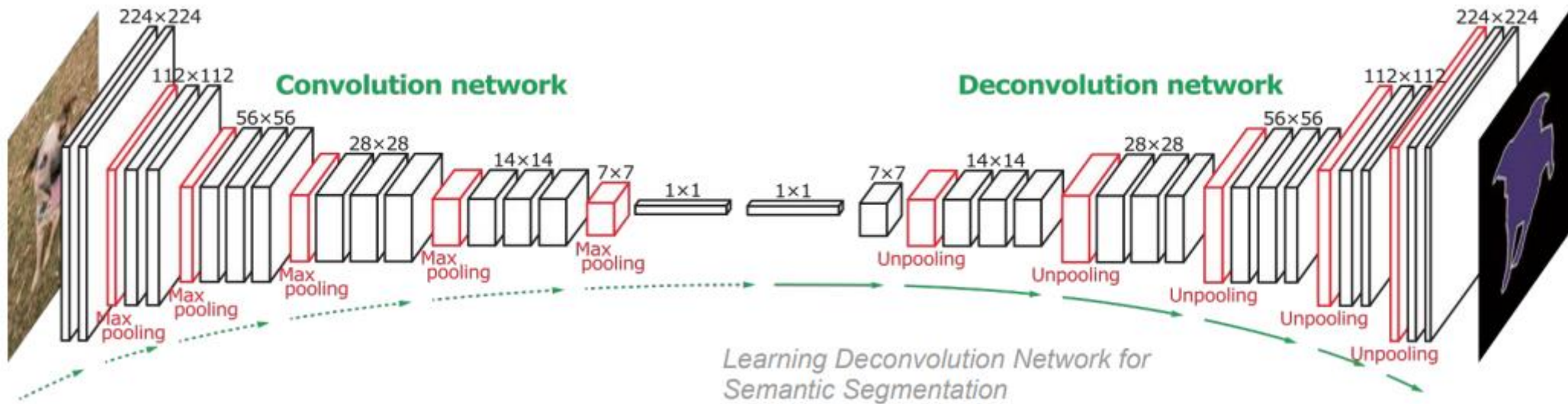
Feature Map



### Classification:



### Segmentation:



# A mostly complete chart of Neural Networks

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- Input Cell
- Backfed Input Cell
- △ Noisy Input Cell
- Hidden Cell
- Probabilistic Hidden Cell
- △ Spiking Hidden Cell
- Capsule Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- △ Gated Memory Cell
- Kernel
- Convolution or Pool

Perceptron (P)



Feed Forward (FF)



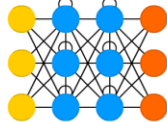
Radial Basis Network (RBF)



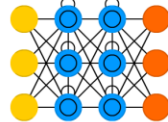
Deep Feed Forward (DFF)



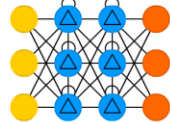
Recurrent Neural Network (RNN)



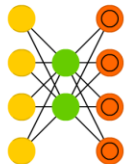
Long / Short Term Memory (LSTM)



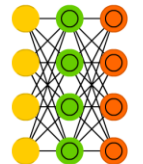
Gated Recurrent Unit (GRU)



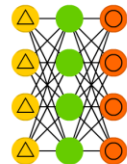
Auto Encoder (AE)



Variational AE (VAE)



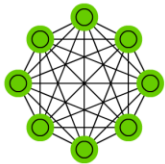
Denosing AE (DAE)



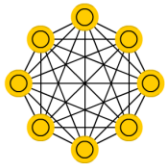
Sparse AE (SAE)



Markov Chain (MC)



Hopfield Network (HN)



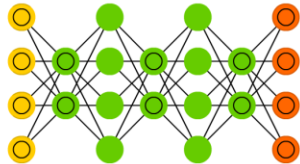
Boltzmann Machine (BM)



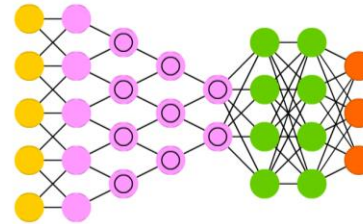
Restricted BM (RBM)



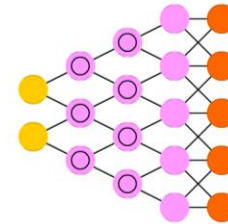
Deep Belief Network (DBN)



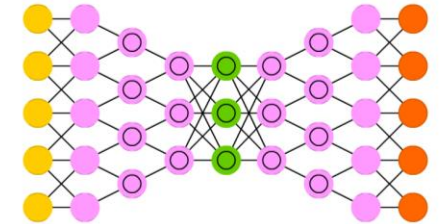
Deep Convolutional Network (DCN)



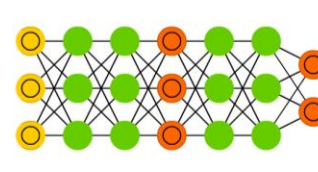
Deconvolutional Network (DN)



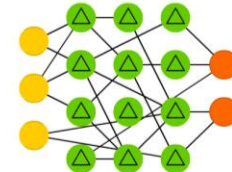
Deep Convolutional Inverse Graphics Network (DCIGN)



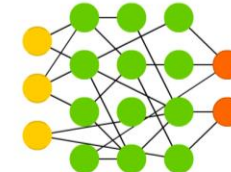
Generative Adversarial Network (GAN)



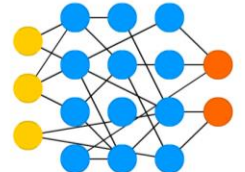
Liquid State Machine (LSM)



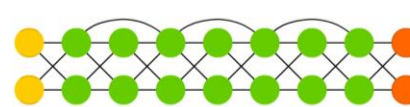
Extreme Learning Machine (ELM)



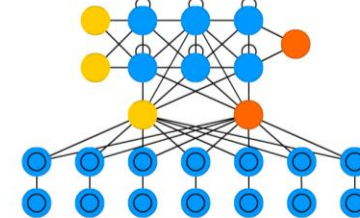
Echo State Network (ESN)



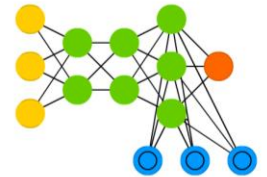
Deep Residual Network (DRN)



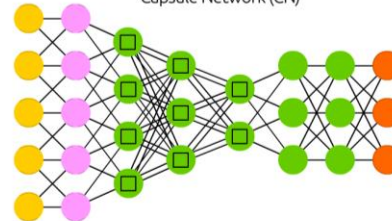
Differentiable Neural Computer (DNC)



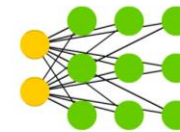
Neural Turing Machine (NTM)



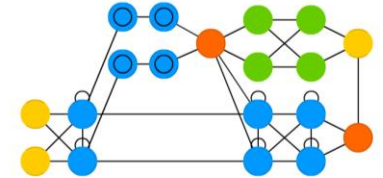
Capsule Network (CN)



Kohonen Network (KN)

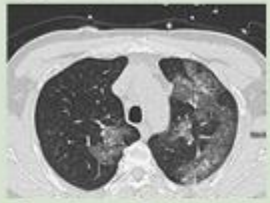
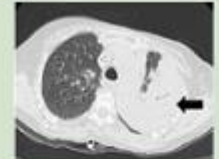



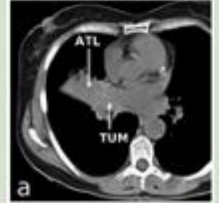


Attention Network (AN)









# Feladattípusok

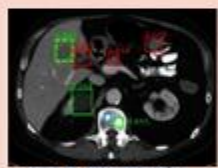
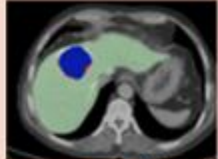
### Clinical Goal

<b>ground glass</b>  <small>Ground glass source: <a href="#">Radiology Assistant</a></small>	<b>pneumonia</b>  <small>Pneumonia source: <a href="#">Kalpana Barua</a></small>
<b>nodule</b>  <small>Nodules source: <a href="#">pulmonarychronicles</a></small>	<b>honeycombing</b>  <small>Honeycombing: <a href="#">radiopedis.org</a></small>
<b>emphysema</b>  <small>emphysema source: <a href="#">TFS.com</a></small>	<b>atelectasis</b>  <small>atelectasis source: <a href="#">ResearchGate</a></small>

### Data

<b>3D</b>  <b>CT volume</b>	<b>3D patch</b> 
<b>2.5D</b>  <b>2.5D slice</b>	<b>2.5D patch</b> 
<p>"2.5D" is axial + coronal + sagittal slices to make 3-channel image</p>	
<b>2D</b>  <b>CT slice</b>	<b>2D patch</b> 

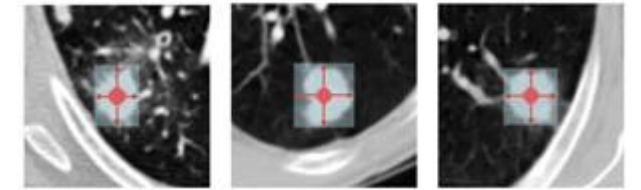
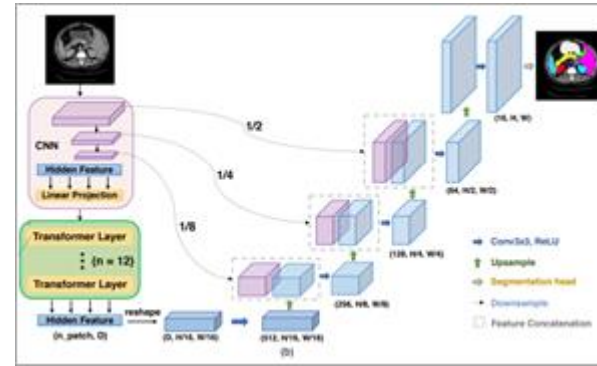
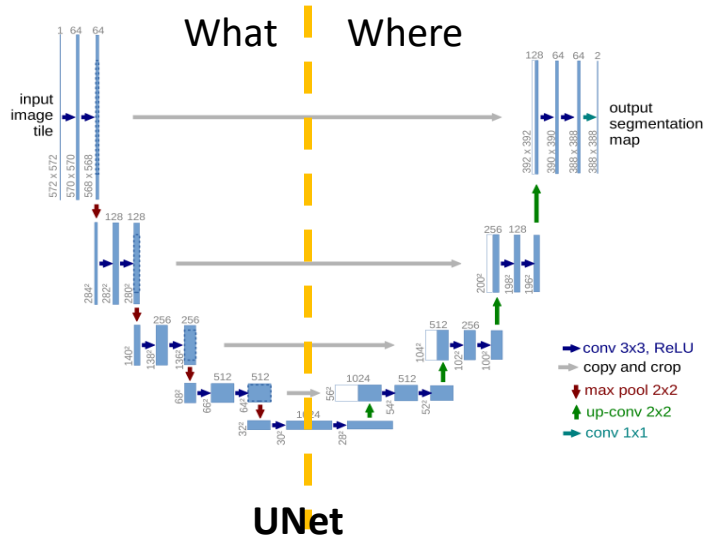
### Task

<b>binary classification</b> <i>e.g. emphysema or not</i>	$0 \text{ or } 1$
<b>multi-class classification</b> <i>for mutually exclusive categories</i>	$\begin{bmatrix} \text{IPF} & 0 \\ \text{iNSIP} & 0 \\ \text{CHP} & 1 \end{bmatrix}$
<b>multi-label classification</b> <i>for non-mutually-exclusive categories</i>	$\begin{bmatrix} \text{atelectasis} & 1 \\ \text{cardiomegaly} & 0 \\ \text{mass} & 1 \end{bmatrix}$
<b>object detection</b> <i>predict bounding boxes around findings of interest</i>	 <small>Van et al. 2018 DeepLusion</small>
<b>segmentation</b> <i>label every pixel, i.e. trace the outlines of all findings of interest</i>	 <small>Liang et al. 2018</small>

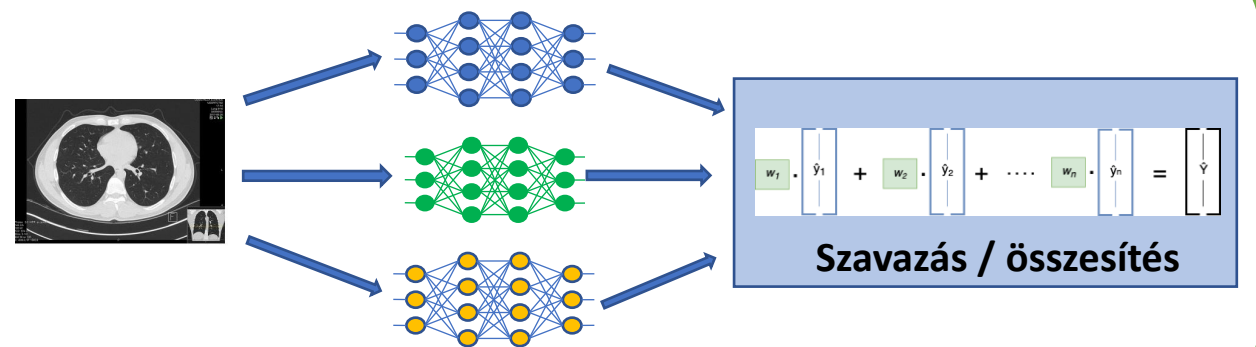
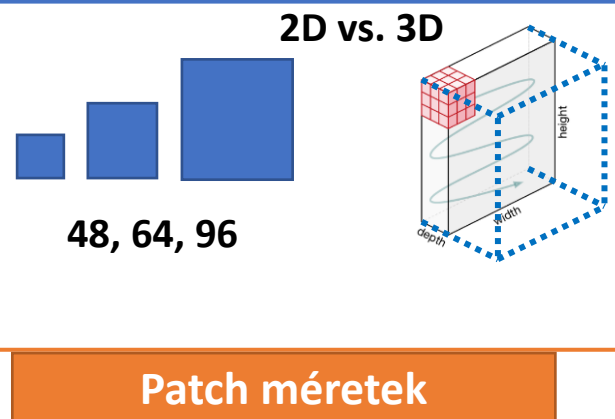
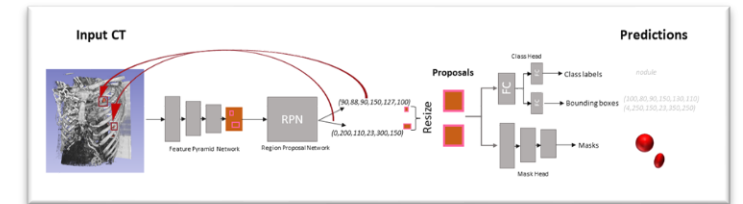


# Alkalmazott modellek

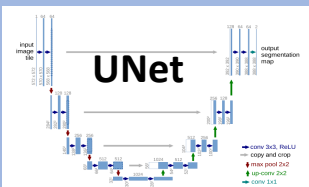
## Architektúrák



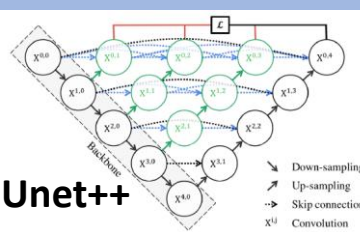
**CenterNet**



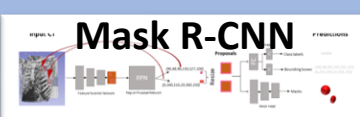
# Összemérhetőség - Adat, Architektúra, Publikált eredmények




**UNET**



**Unet++**

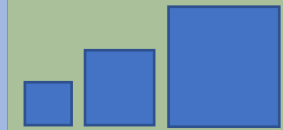


**Mask R-CNN**




**CenterNet**

**Architektúrák**



**Patch Méret**



**Dimenziók**

**Optimizer**  
**Loss**  
**BatchSize**  
**Epoch**

**Tanítási Paraméterek**

LIDC-IDRI

Luna16

NLST

Saját

**Adathalmazok**

Train

Val

Test

Transfer learning

Iteration 1	Test	Train	Train	Train	Train
Iteration 2	Train	Test	Train	Train	Train
Iteration 3	Train	Train	Test	Train	Train
Iteration 4	Train	Train	Train	Test	Train
Iteration 5	Train	Train	Train	Train	Test

**Adat elosztás – Train / Val / Test split**

NoduleNet

NoduleNet – Luna16 – 4.fold

# Architektúrák kiértékelése: SE-ULY model vs. NoduleNet

## Publikus tanítóadaton – LUNA 16

2019

NoduleNet: Decoupled False Positive Reduction for Pulmonary Nodule Detection and Segmentation

Hao Tang<sup>1,2</sup>, Chupeng Zhang<sup>2</sup>, and Xiaohui Xie<sup>1</sup>

<sup>1</sup> Department of Computer Science, University of California Irvine

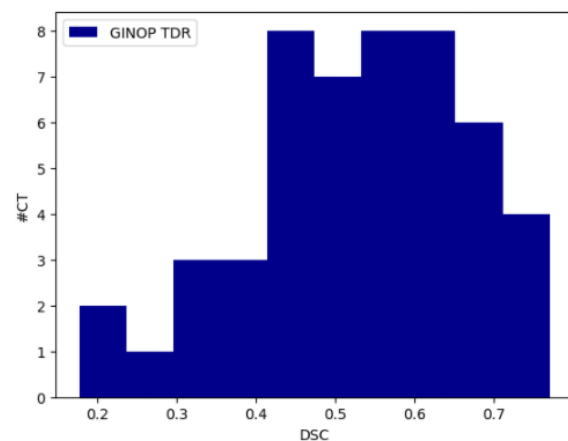
{htang6, xhx}@uci.edu

<sup>2</sup> Deep Voxel Inc.

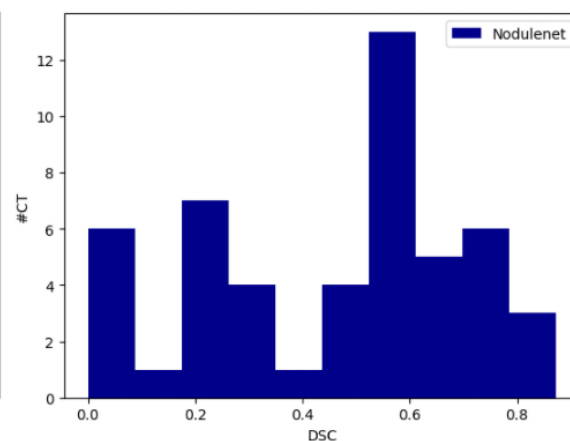
{chupengz}@deep-voxel.com



SE-ULY TDR

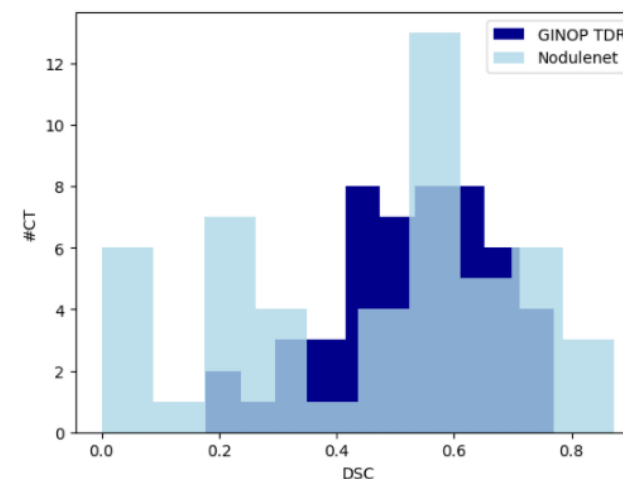


NoduleNet



DSC

Mean	0.527	0.460
Std	0.139	0.244
Max	0.770	0.873



SE-ULY TDR NoduleNet

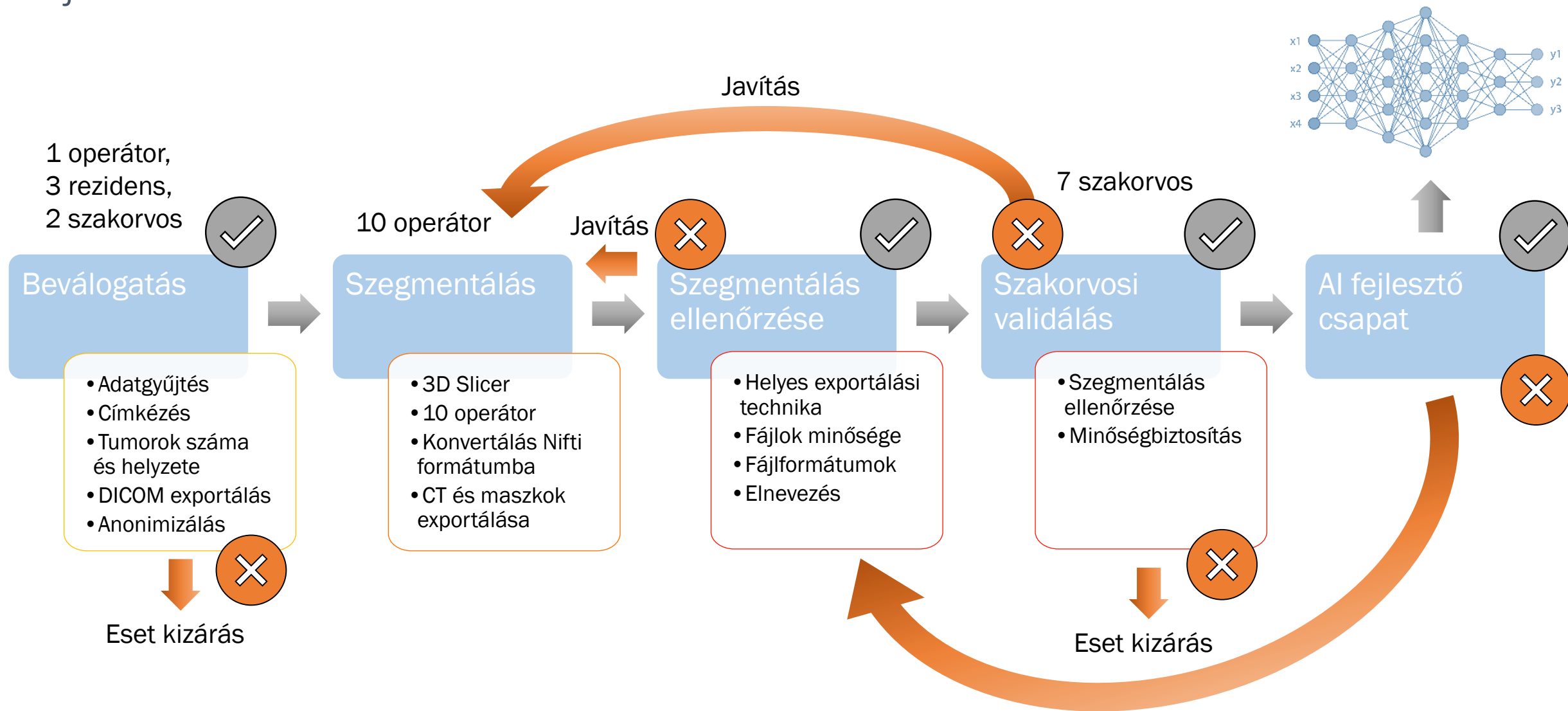
TP	71	69
FP	227	654
FN	8	10

Nodusok kiértékelése

SE-ULY TDR 50 elemén DSC alapján kiértékelve. A kiválasztott 50 CT-vel egyik háló sem találkozott a tanítás során.

# Saját adatok - SE

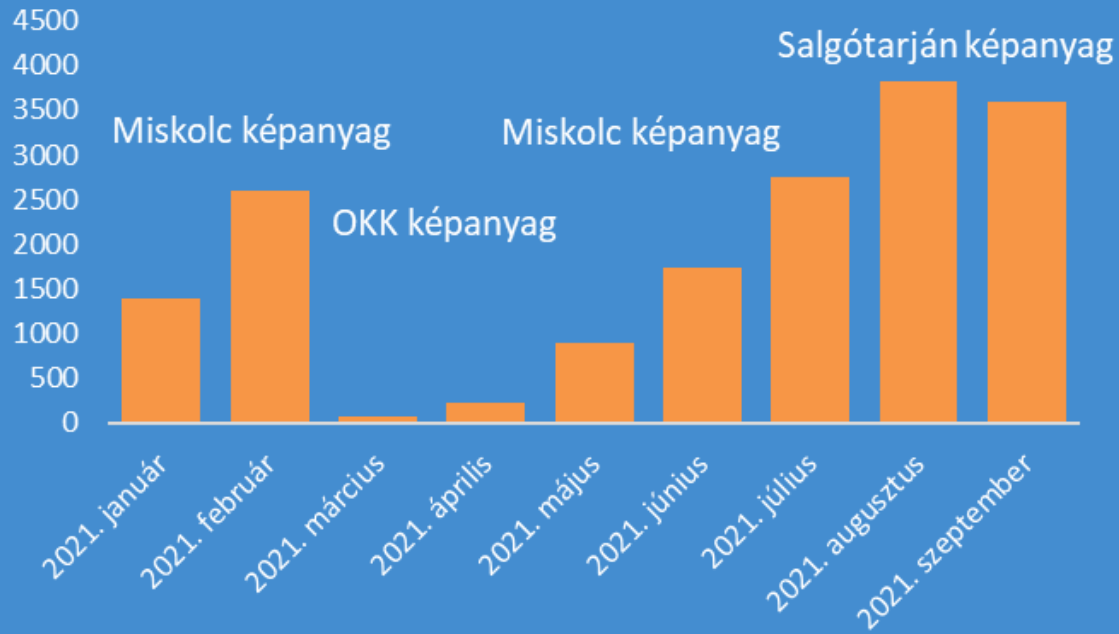
## Mesterséges Intelligencia



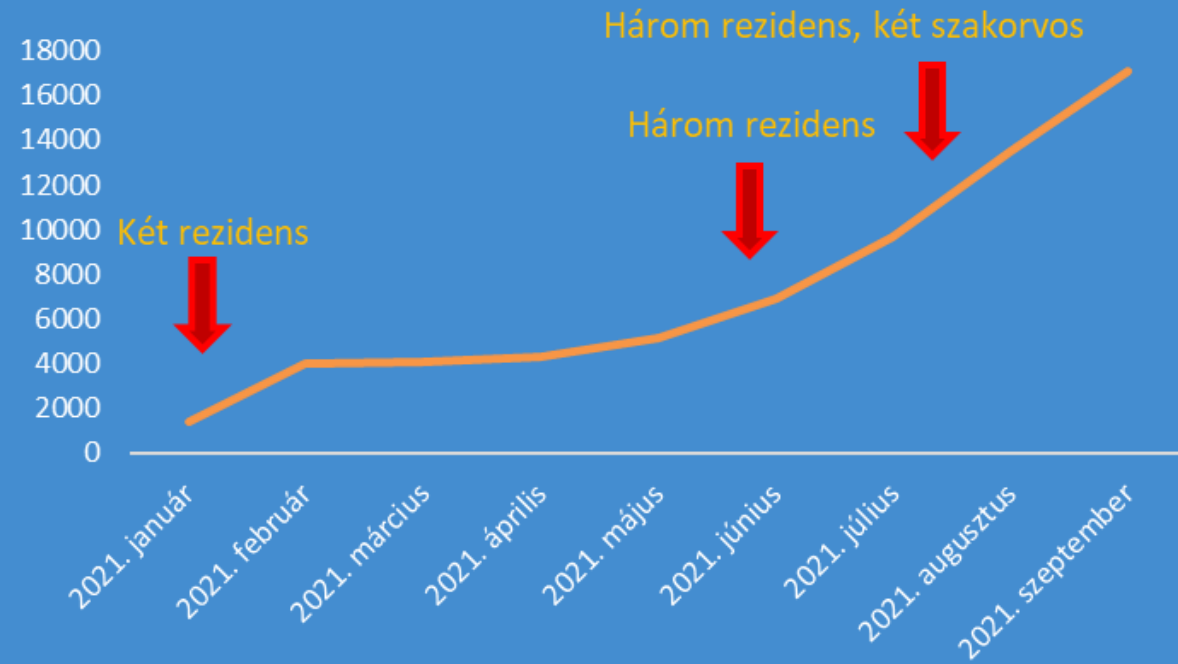
# Előválogatott felvételek száma

Több, mint 20 ezer felvétel előválogatása

## Előválogatott felvételek száma havonta

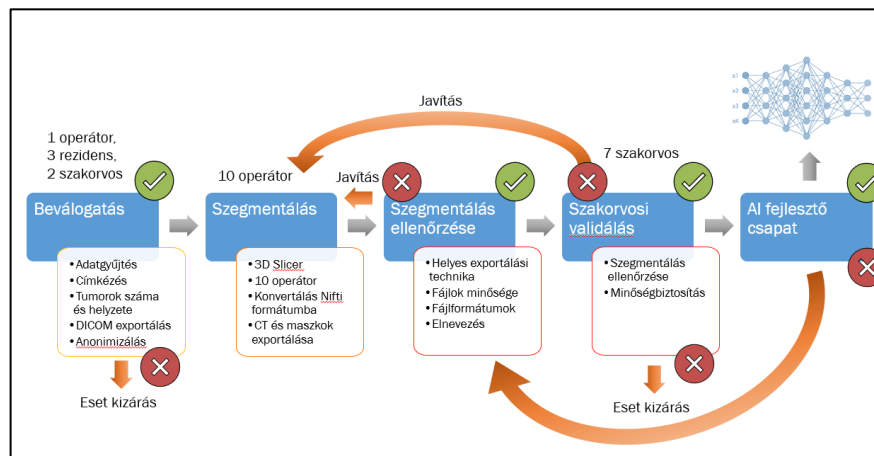


## Előválogatott felvételek számának növekedése

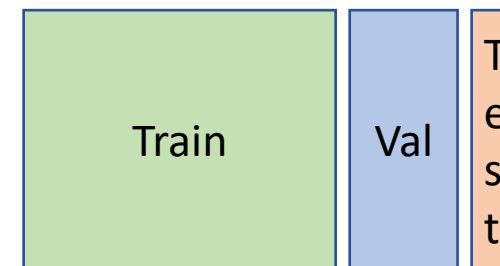


# Saját adathalmaz

- Több, mint 8000 db
    - Válogatott
    - Szegmentált
    - Validált
    - Pozitív felvétel
  - Ebből 7300 db került a tanító halmazba
  - Maradékból teszt adat + köztes kiértékelés
- 
- Iteratív kiértékelés és tanítás



8'000 +



7'300 +

Reprezentatív  
teszthalmaz

100 pozitív  
100 negatív

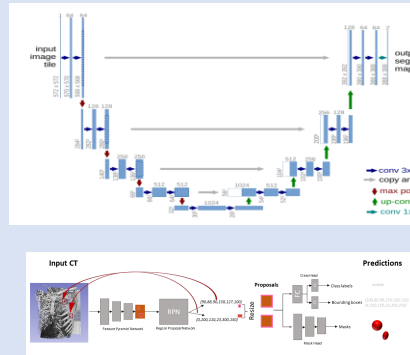
# Tanítóadat folyamatos javítása - Iteratív tanítás



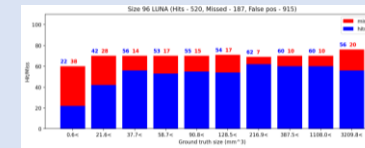
CT felvétel



Szegmentálás

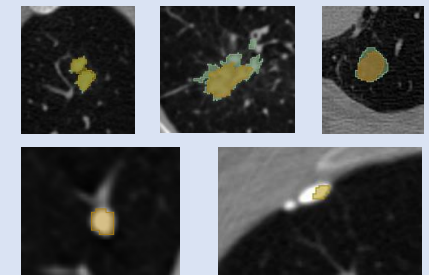


Tanítás

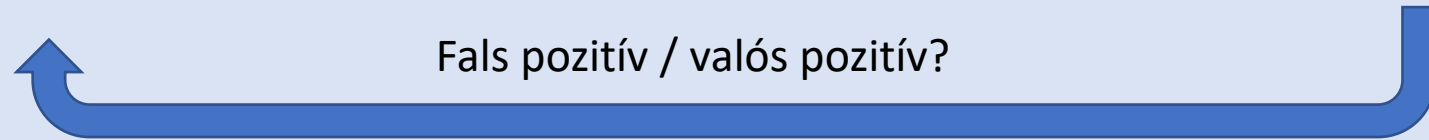


Kiértékelés

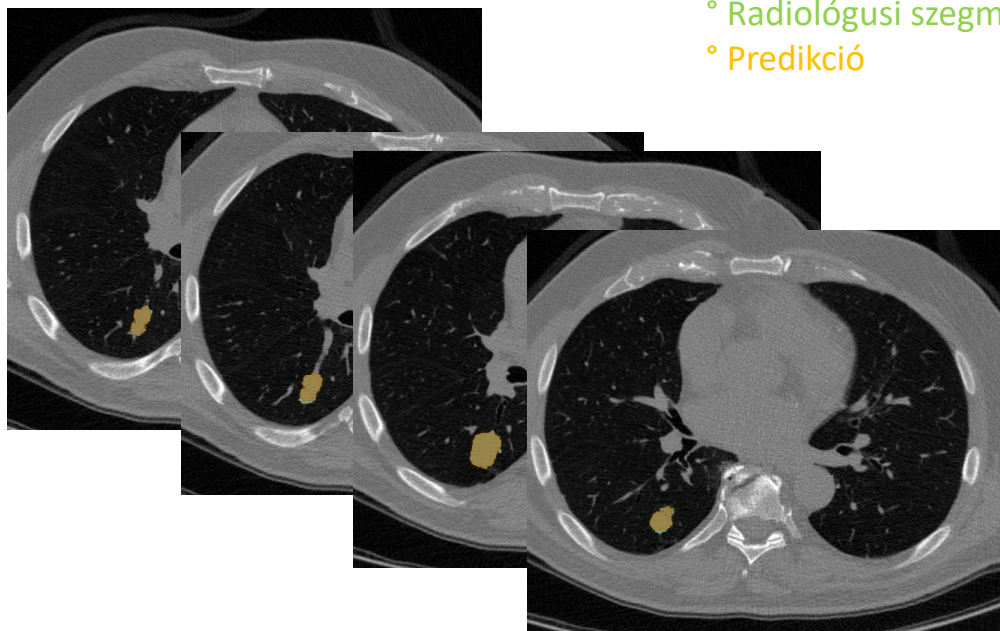
	A	B	C
1	Szegmentáció fajneve	Kiértékelés	Nodus axiális indexe
2	PROPOS_06_1604X2_2_AxialFast_43.nii.gz	Negatív	43
3	PROPOS_06_1604X2_2_AxialFast_57.nii.gz	Negatív	57
4	PROPOS_06_1604X2_2_AxialFast_67.nii.gz	Posztív	67
5	PROPOS_06_1604X2_2_AxialFast_68.nii.gz	Követendő	68
6			85
7	PROPOS_06_1604X2_2_AxialFast_86.nii.gz	Követendő	86
8			
9			
10			



Fals pozitív / valós pozitív?

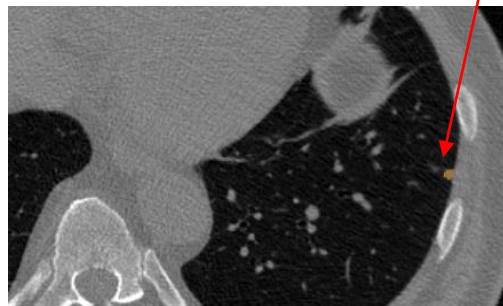


# Iteratív tanítás – predikciók elemzése



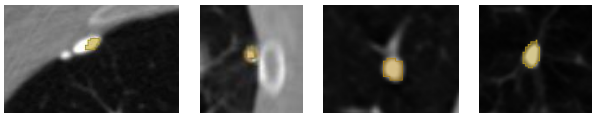
- Radiológusi szegmentáció
- Predikció

	A	B	
	Szegmentáció fájlneve	Kiértékelés	Nodusus
1			
2	PREDPOS_006_SEOKK2.2_Kontraszt_43.nii.gz	Negatív	43
3	PREDPOS_001_SEOKK2.2_Kontraszt_57.nii.gz	Negatív	57
4	PREDPOS_003_SEOKK2.2_Kontraszt_67.nii.gz	Pozitív	67
5	PREDPOS_002_SEOKK2.2_Kontraszt_68.nii.gz	Követendő	68
6	TRUEPOS_005_SEOKK2.2_Kontraszt_85.nii.gz		85
7	PREDPOS_004_SEOKK2.2_Kontraszt_86.nii.gz	Követendő	86
8			
9			

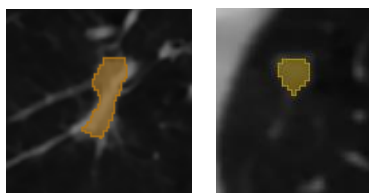


## Típushibák azonosítása

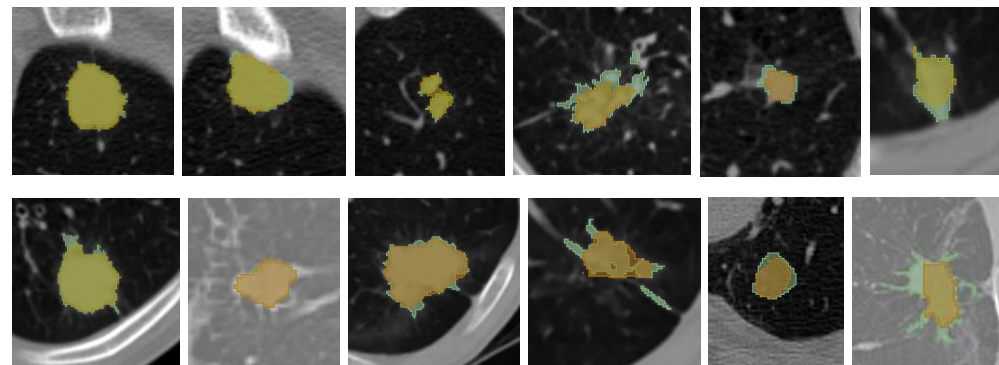
- Meszes területek



- Gyulladásból visszamaradt



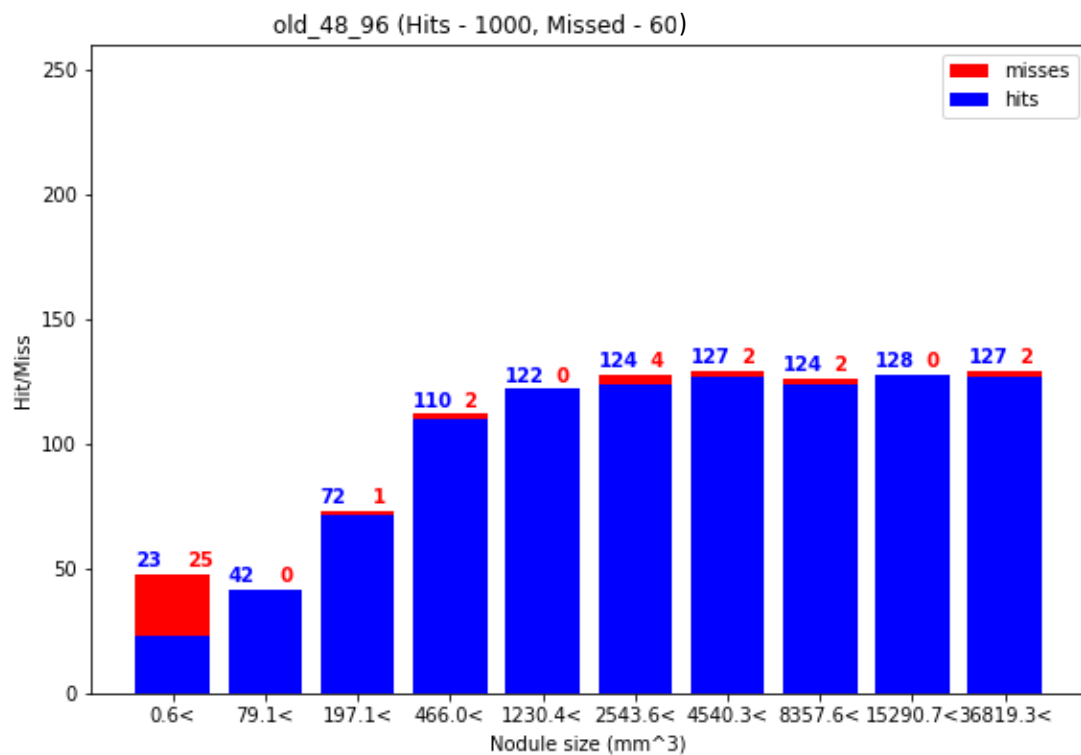
## Helyes predikciók



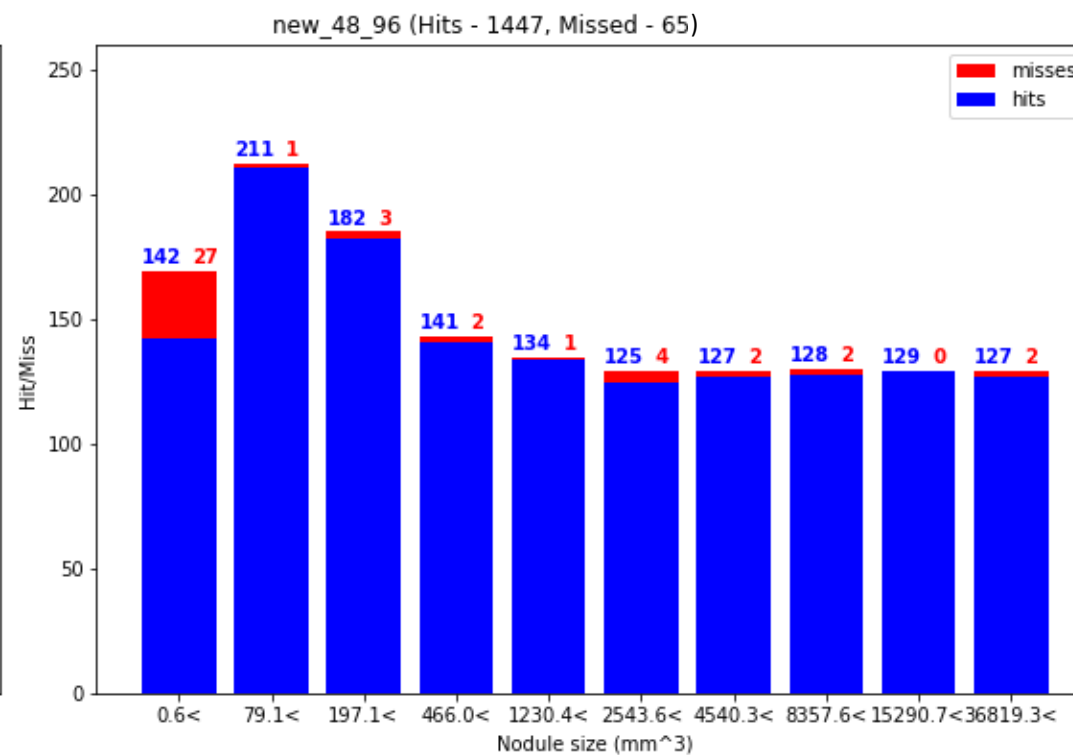


# Iteratív tanítás hatása

48-96 union modell on all SEOKK dataset

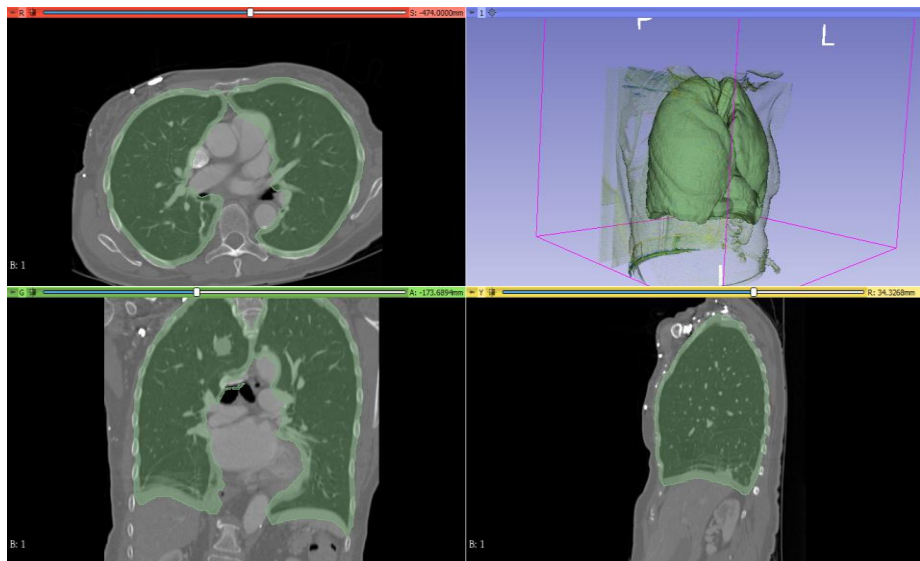


Predikciók elemzése előtt



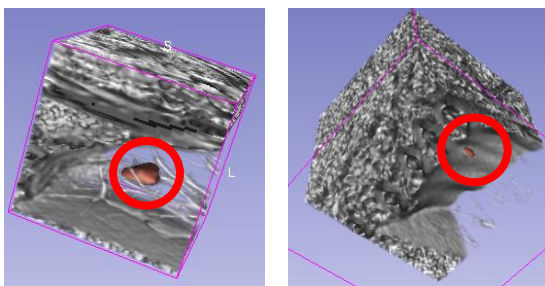
Predikciók elemzése után

# Tanítási adatok - paraméterek

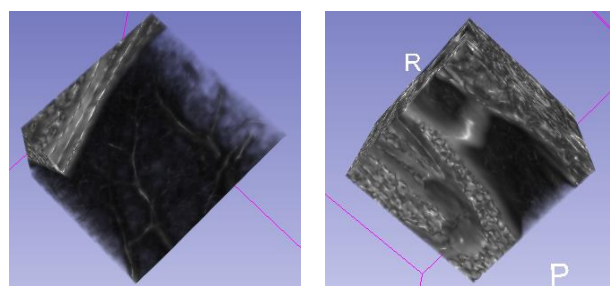


Tüdő szegmentálása

NODULUST TARTALMAZÓ PATCHEK



NODULUST **NEM** TARTALMAZÓ PATCHEK

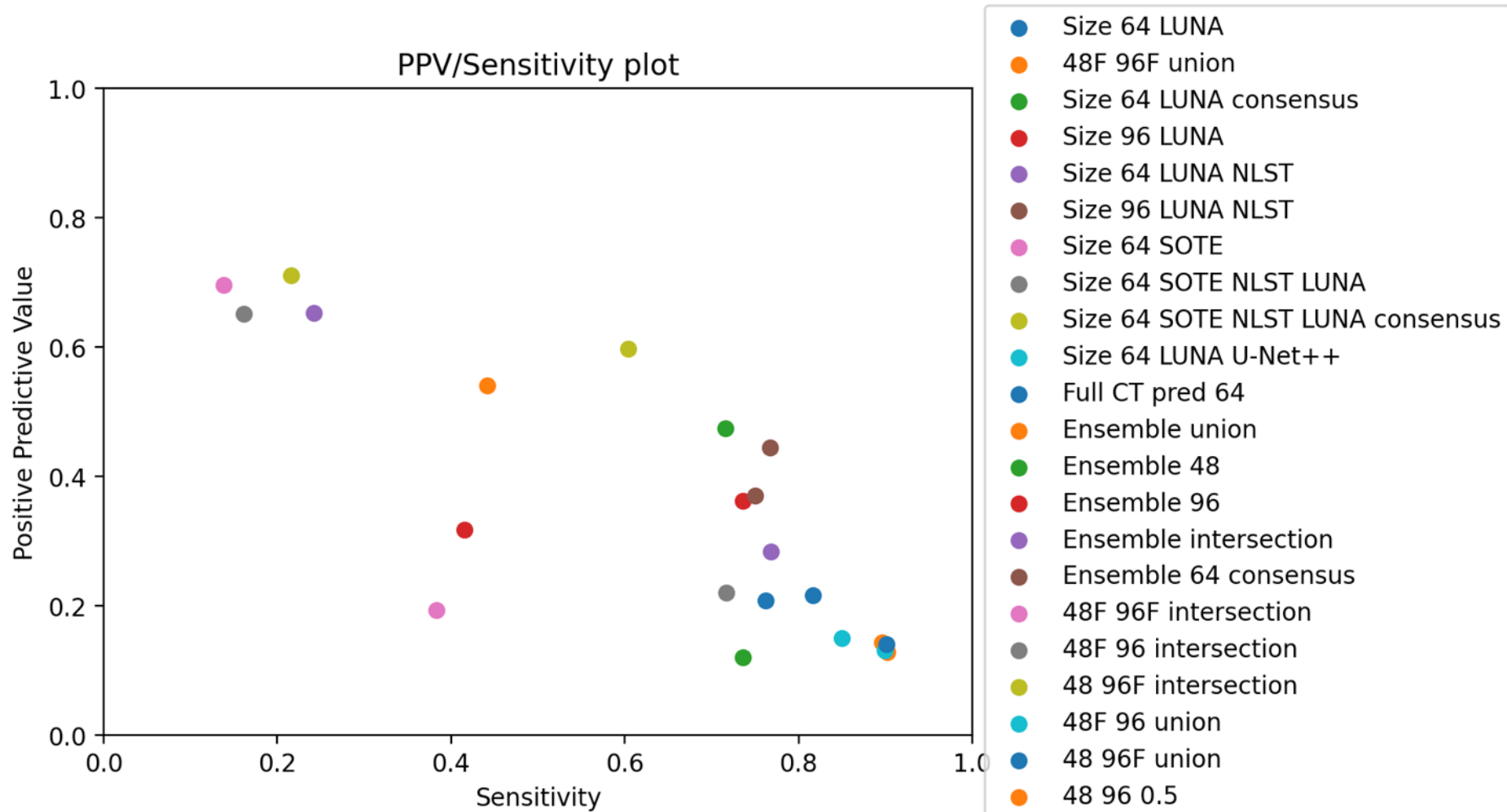


Tetszés szerint állítható tanító paraméterek*	Általában használt értékek
Egy felvételtől hány patchet vágunk	30
Hány CT patcheit keverjük össze a tanítás előtt	10
A patchek milyen arányban legyenek pozitívok/negatívok	7:3
Patchek mérete	[64,64,64]
Egy patchnek minimum mekkora részét foglalja el nodulus ahhoz, hogy azt pozitívnak osztályozzuk	10%**
Egy patchre maximum hány nodulust prediktálhatunk	10
Milyen predikciót engedünk tovább	>0.85 score <10 pixel outline >0.45 prediktált maszk érték

\*Ezen kívül is rengeteg konfigurációban állítható paraméter van, ezek csak a legtriviálisabbak

\*\* az is elég ha egy vagy több teljes nodulus rajta van, amennyiben nem éri el a 10%-ot

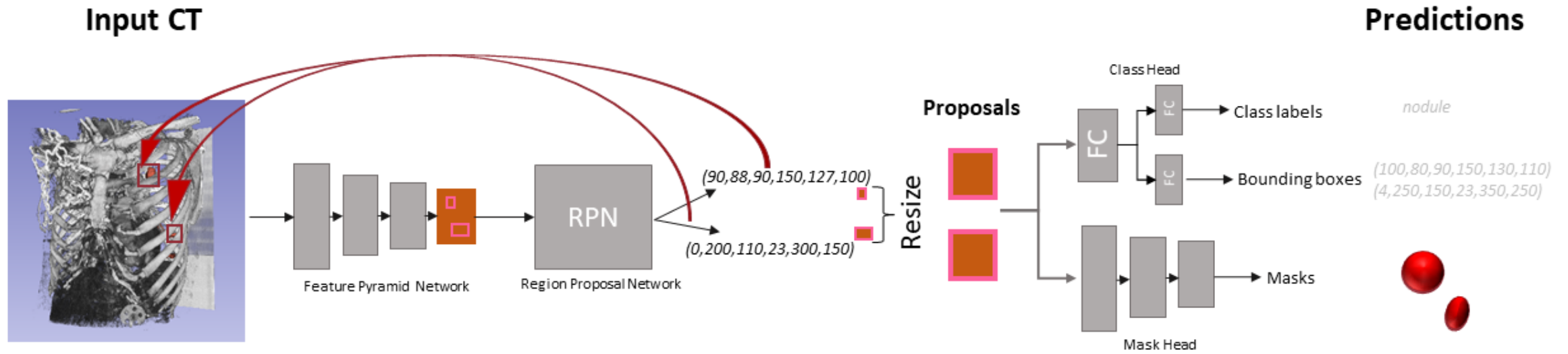
# Eredmények – 3D Attention Unet -ek



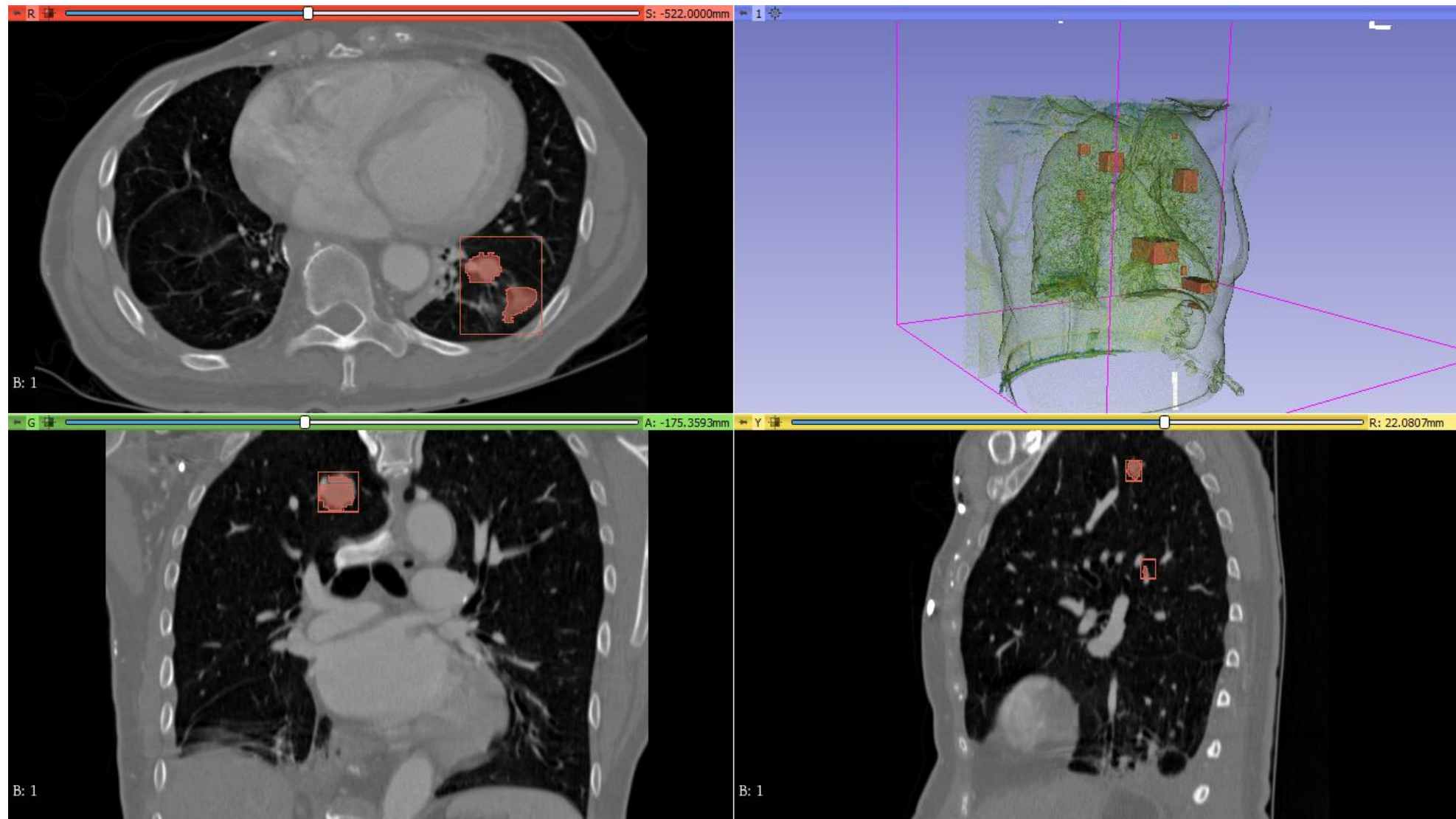
$$\text{Sensitivity} = \frac{TP}{GT \text{ nodule count}}$$

$$\text{Positive Predictive Value} = \frac{TP}{TP + FP}$$

# 3D Mask R-CNN

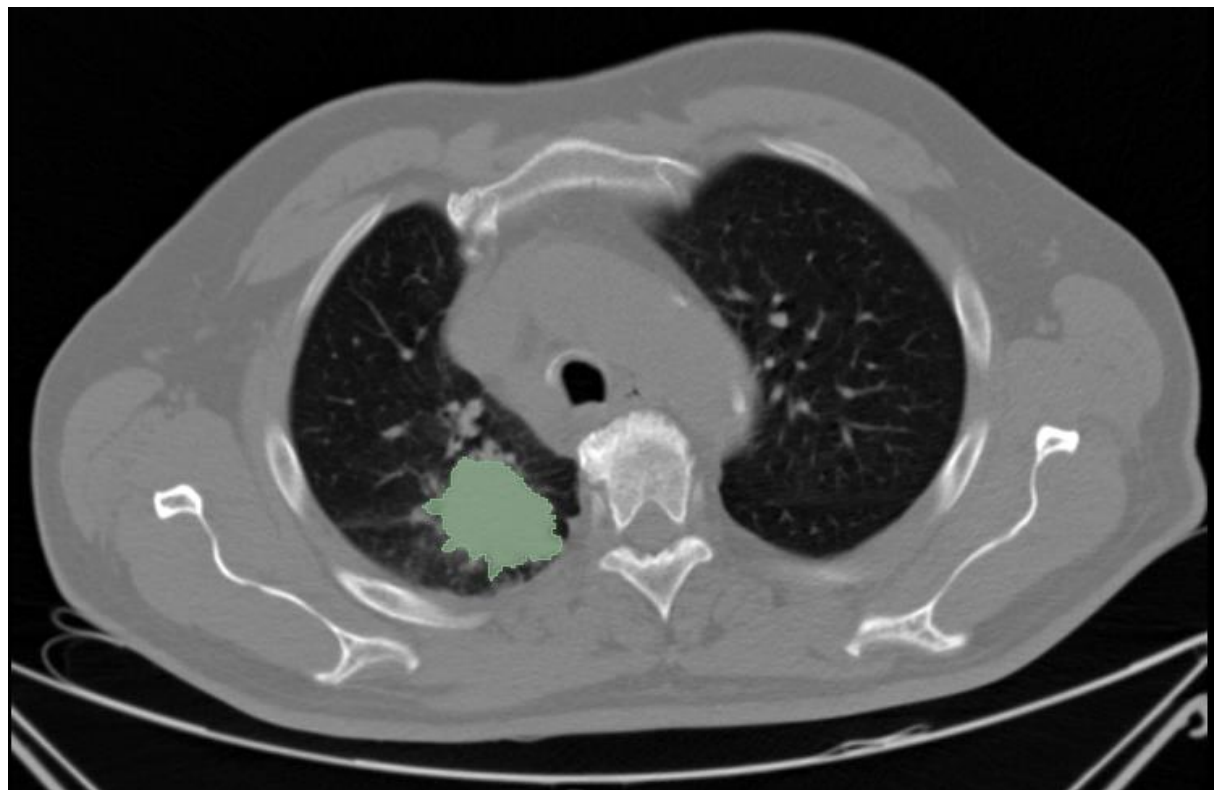


# Mask R-CNN predikció



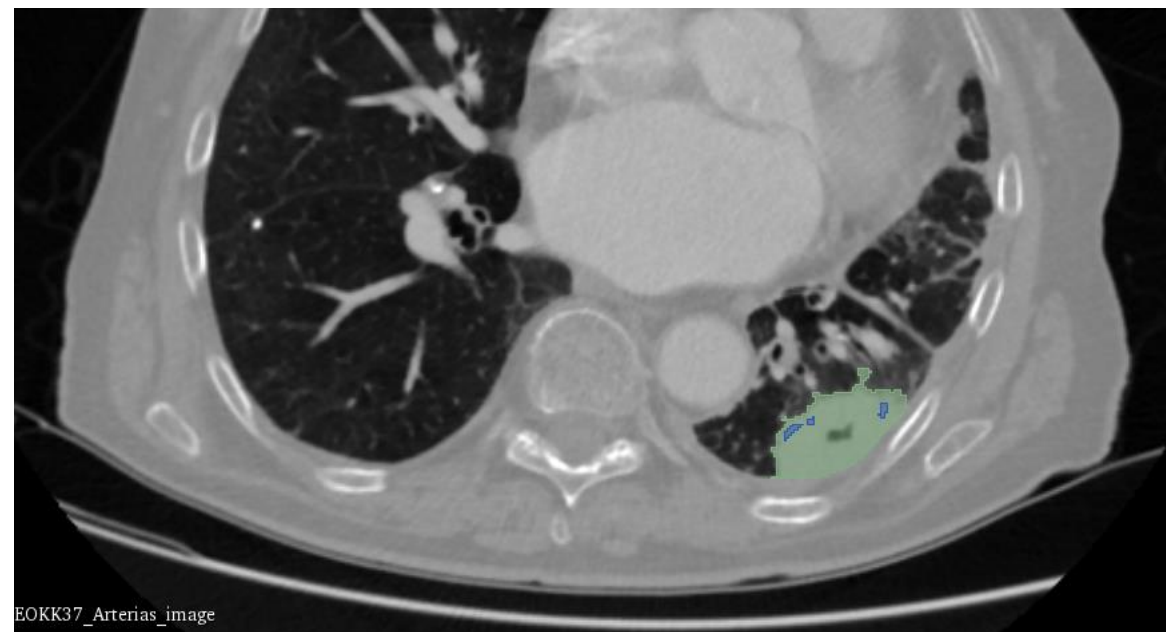
# Nagy nodulusok

Volume  $\geq 10'000\text{vx}$

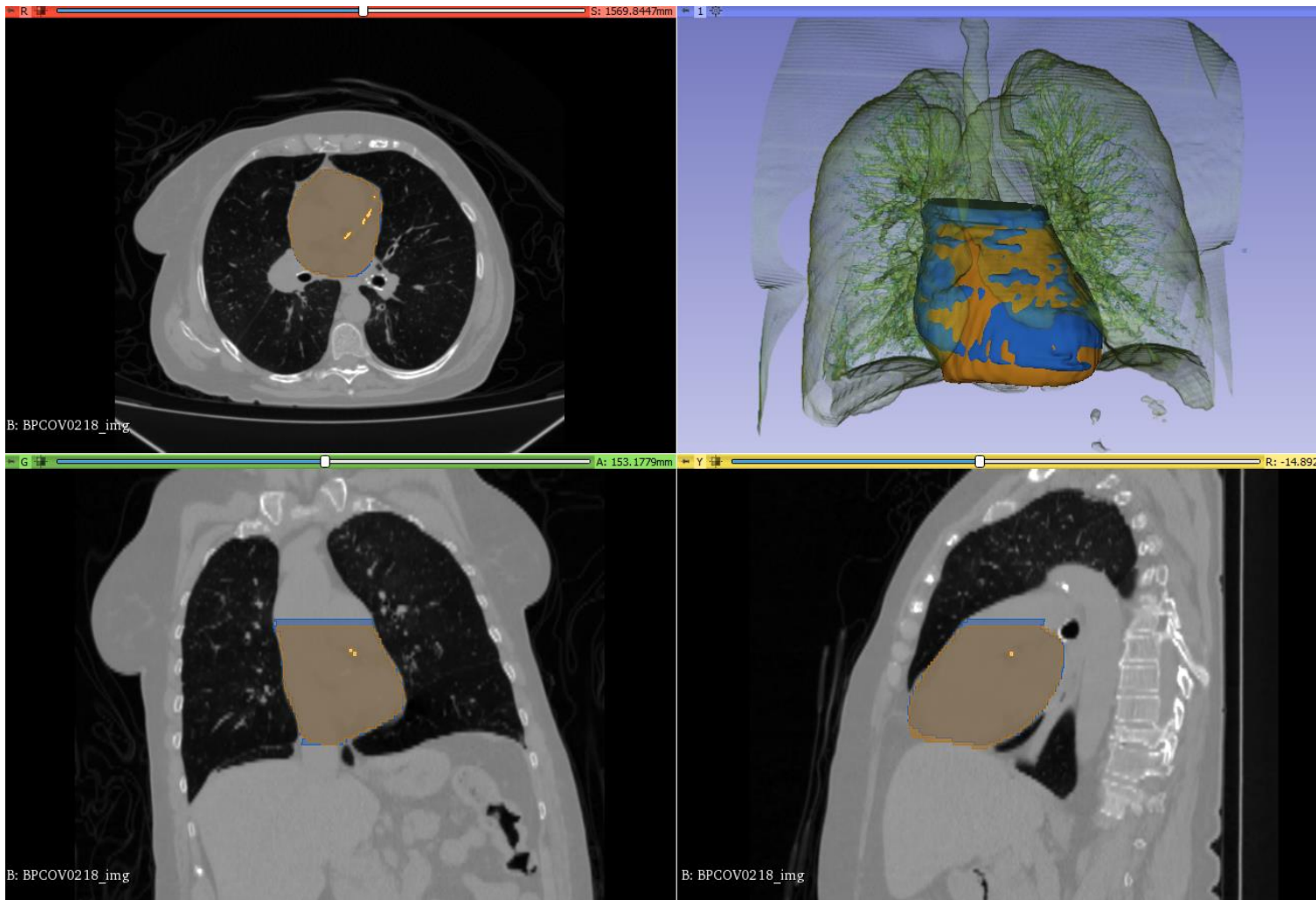
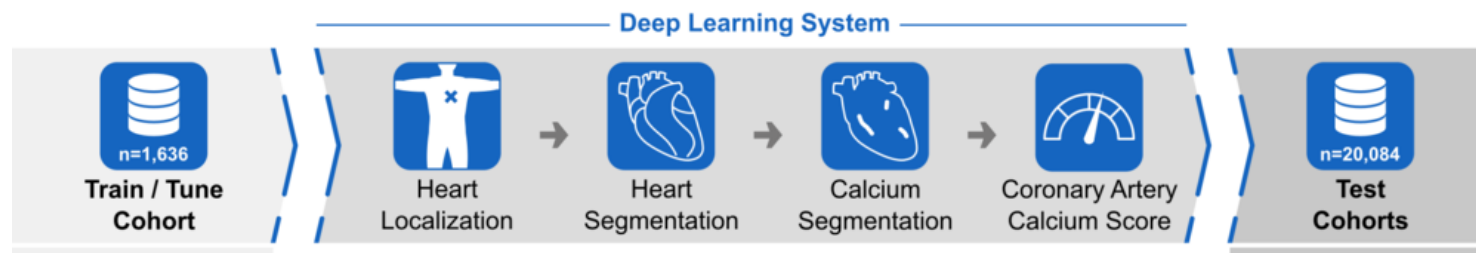


° Radiológusi szegmentáció

° 48-96 Predikció



# DeepCAC - kitérő



Heart localization: 3D Unet

- 112 x 112 x 112 px

Heart segmentation: 3D Unet

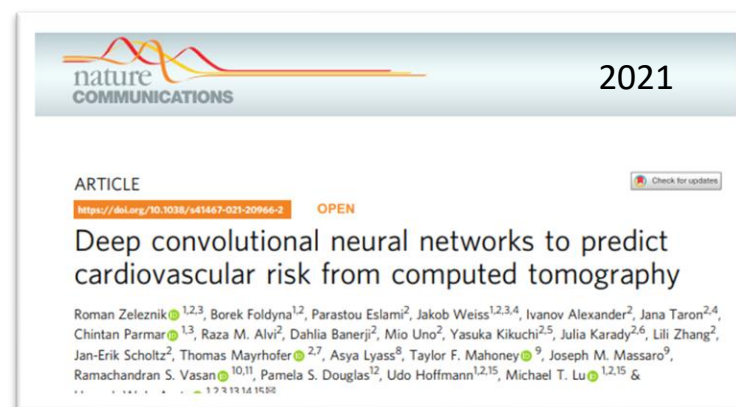
- 128 x 128 x 80 px

CAC segmentation: 3D Unet

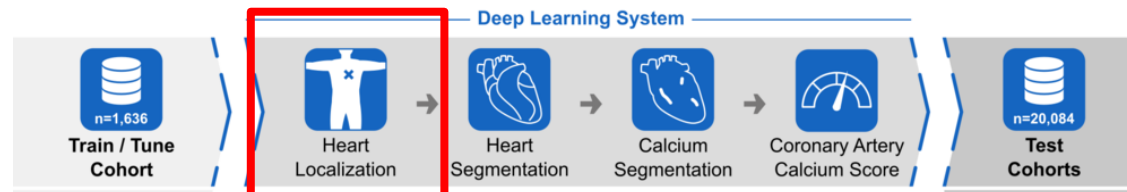
- 48 x 48 x 32 px

Resize  
Crop  
Resize

Resize  
Cut cubes



# DeepCAC – transfer learning



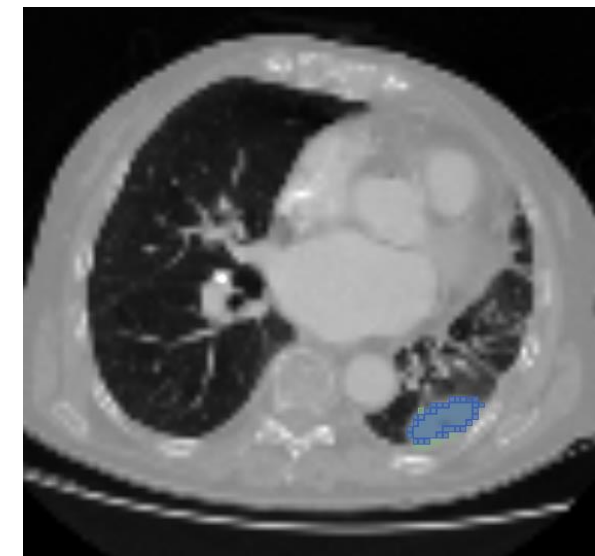
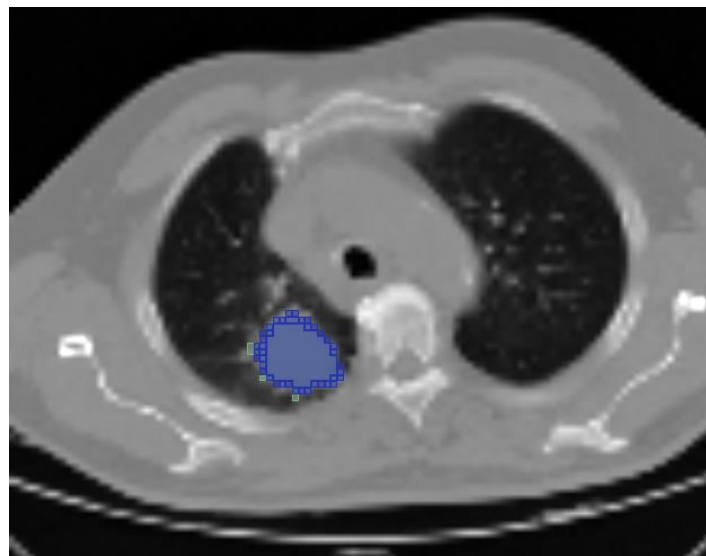
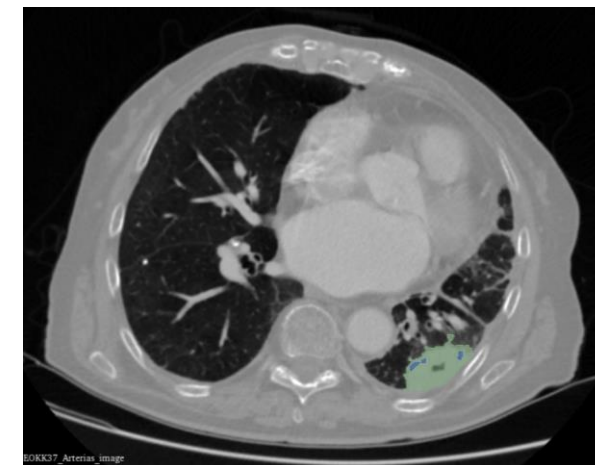
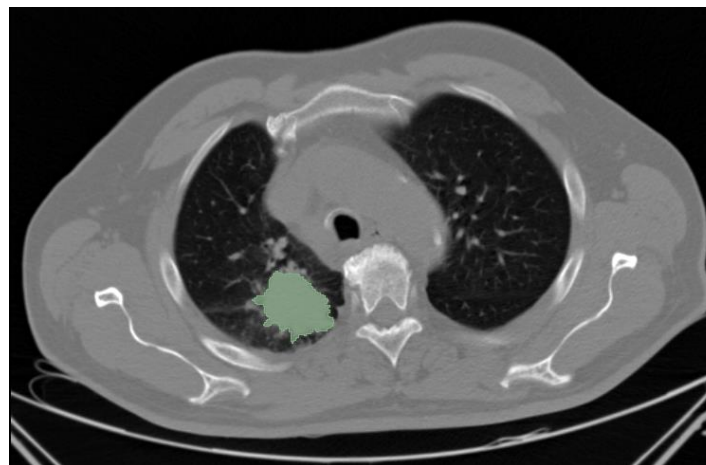
## Heart localization: 3D Unet

- 112 x 112 x 112 px
- Training data: 1636 CT, 1200 epoch



## Transfer Learning

- Large nodules  $\geq 10'000$  vx
  - Train data: 285 SE CT
  - Epoch: 54 epoch

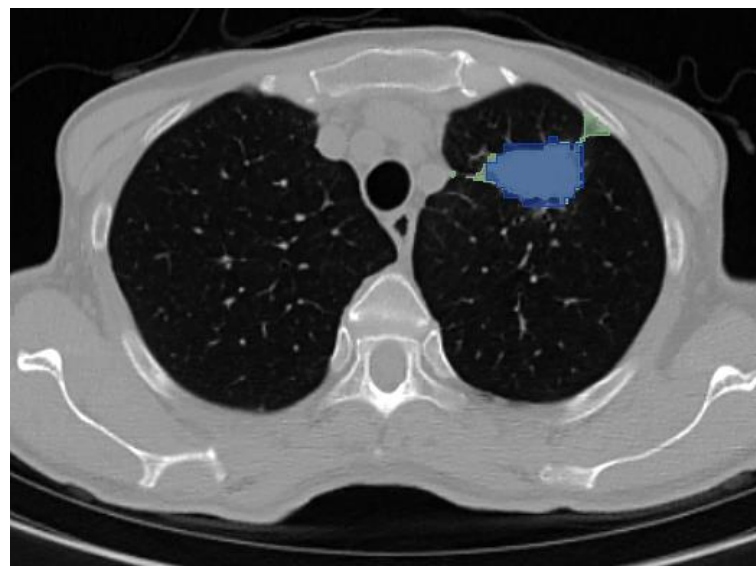
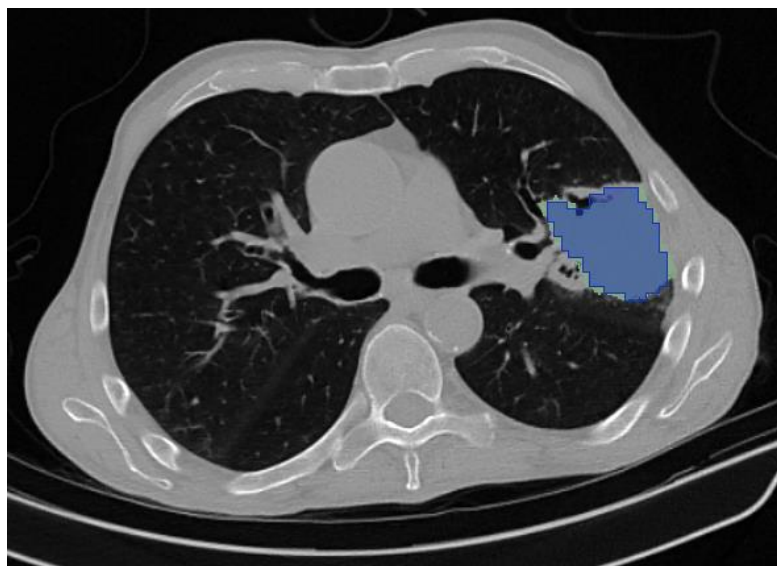
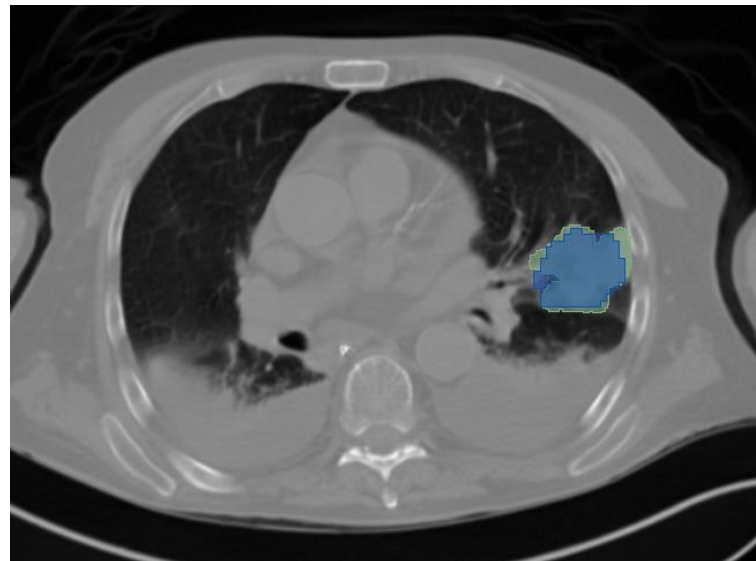
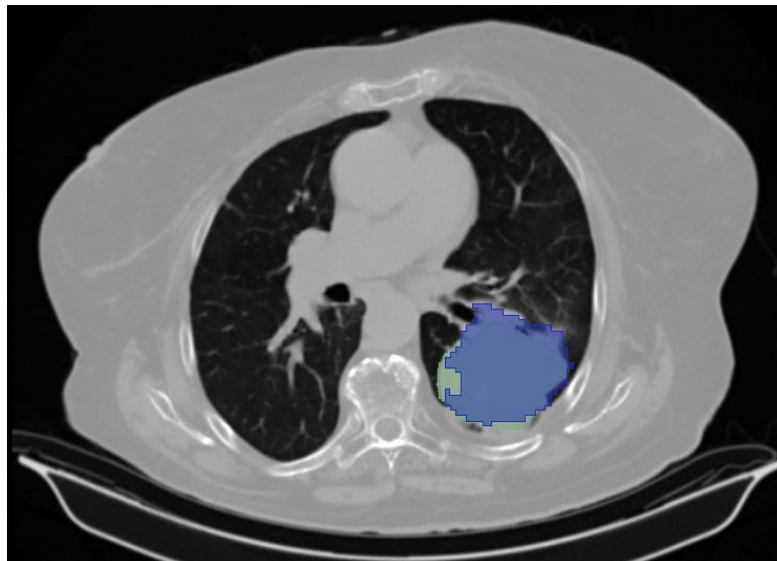




# DeepCAC – transfer learning

Test data: 58 SE CT

Proof-of-Concept

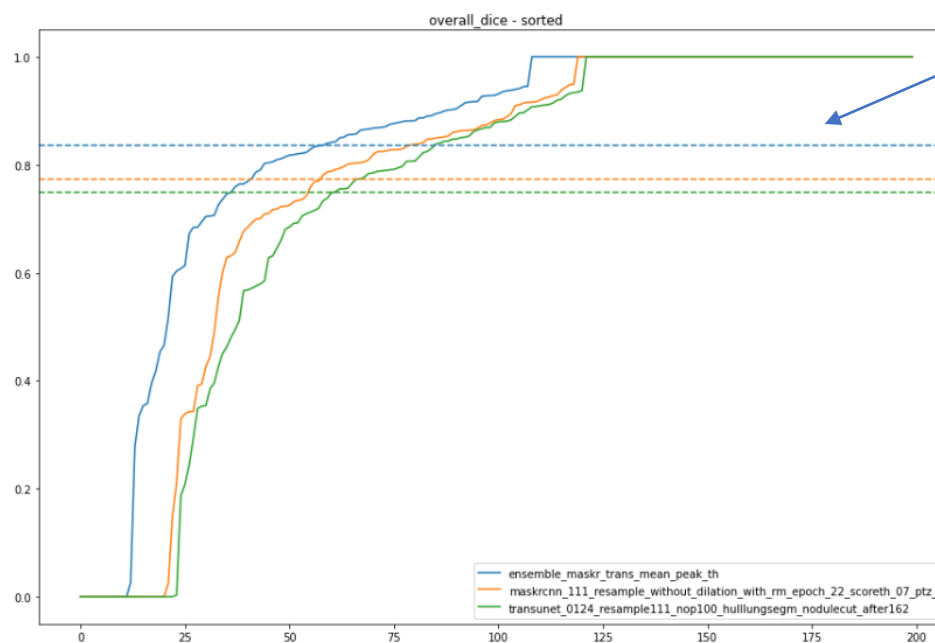
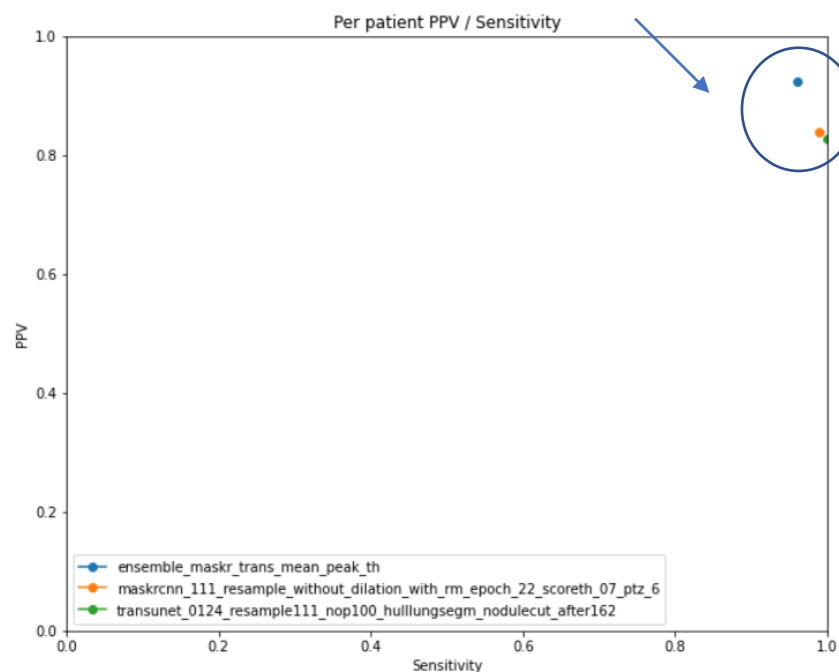


# Eredmények

Teszt

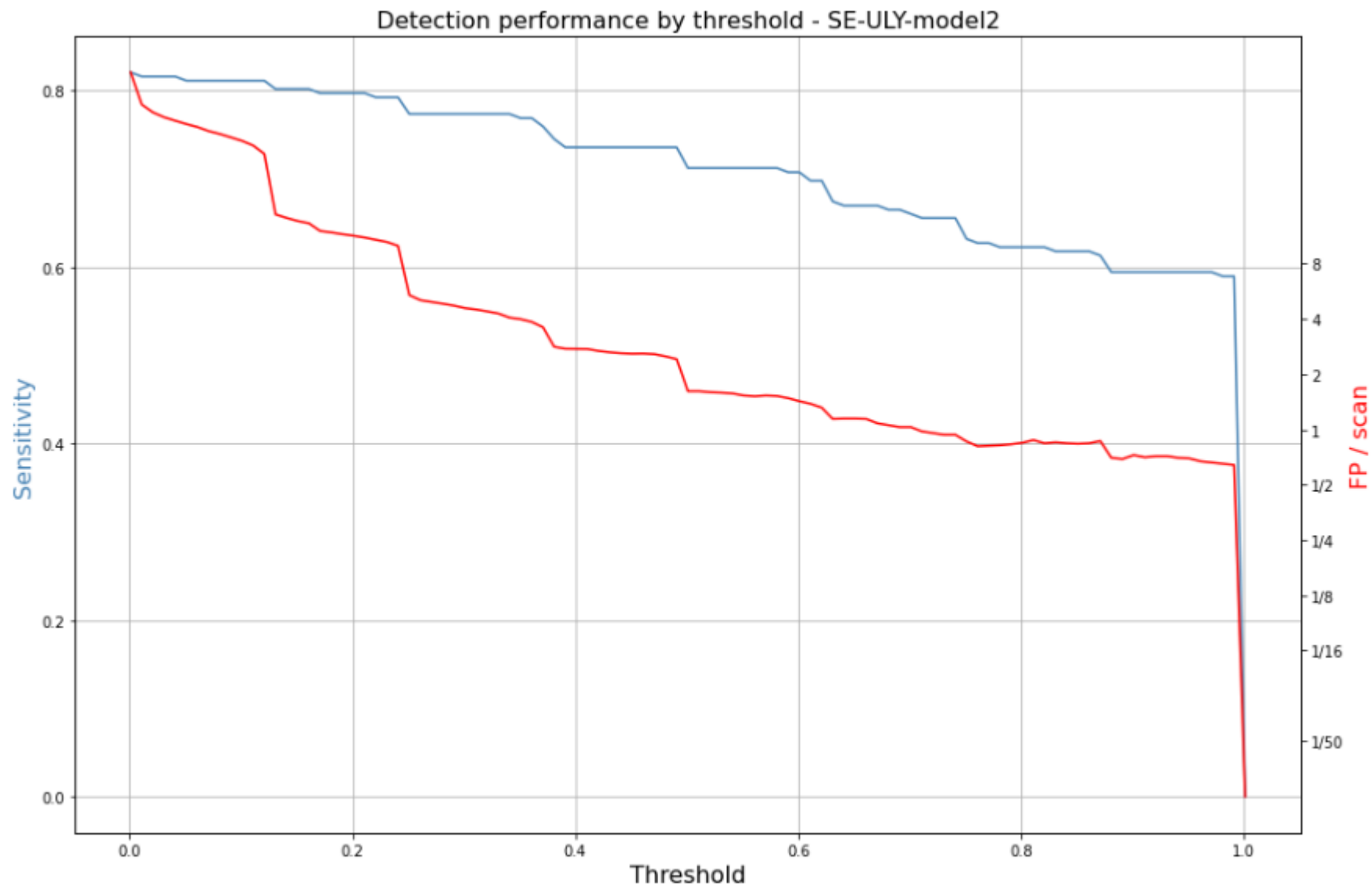
100 pozitív  
100 negatív

model	Páciens szintű metrikák								Nodus szintű metrikák		
	Szenzitivitás	Specifitás	PPV	NPV	TN	FN	TP	FP	Szenzitivitás	PPV	Mean Dice
SE-ULY-model1	0.99	0.81	0.839	0.988	81	1	99	19	0.675	0.633	0.774
SE-ULY-model2	1.00	0.79	0.826	1.000	79	0	100	21	0.660	0.406	0.750
<b>ensemble (model1 + model2)</b>	0.96	<b>0.92</b>	<b>0.923</b>	<b>0.958</b>	92	4	96	8	0.585	<b>0.780</b>	<b>0.836</b>

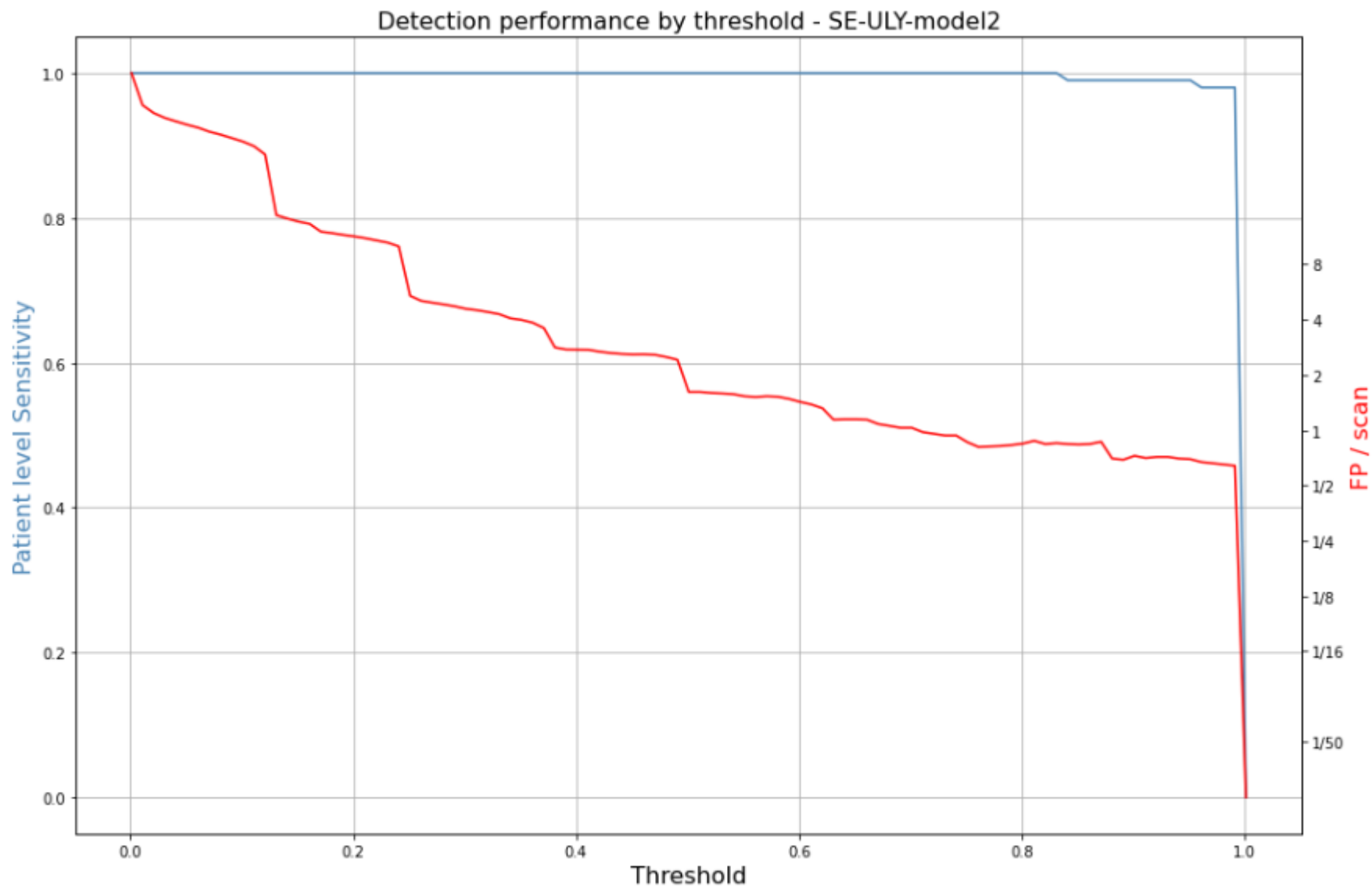


Szenzitivitás =  $TP / (TP + FN)$   
 Specifitás =  $TN / (FP + TN)$   
 PPV =  $TP / (TP + FP)$   
 NPV =  $TN / (TN + FN)$

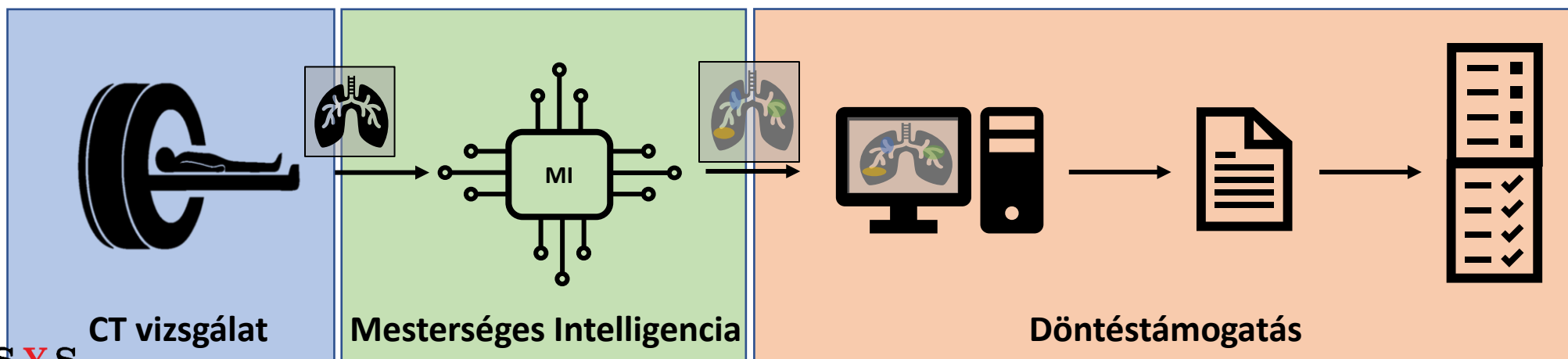
# Predikció érzékenységeinek hangolása – nodulus szinten



# Predikció érzékenységének hangolása – páciens szinten




# Radiológusi döntés / diagnózis támogatása



## Predikciók prioritizálása

Azonosító	Térfogat (mm <sup>3</sup> ) (max)	Valószínűség (max)	Nodulusok száma	Dátum	Predikációs riport
ULY_001810	13619	1	3	2022.09.19 9:07	<a href="#">ULY_001810_prediction_report.pdf</a>
ULY_001775	61262	0,899	4	2022.09.19 8:29	<a href="#">ULY_001775_prediction_report.pdf</a>
ULY_001882	164846	0,897	8	2022.09.19 10:22	<a href="#">ULY_001882_prediction_report.pdf</a>
ULY_001869	107479	0,863	4	2022.09.19 9:50	<a href="#">ULY_001869_prediction_report.pdf</a>
ULY_001790	424	0,854	2	2022.09.19 8:48	<a href="#">ULY_001790_prediction_report.pdf</a>
NEG_000170	52	0,846	1	2022.09.19 4:53	<a href="#">NEG_000170_prediction_report.pdf</a>
NEG_000124	2294	0,835	2	2022.09.19 0:39	<a href="#">NEG_000124_prediction_report.pdf</a>
ULY_001880	4549	0,823	7	2022.09.19 10:15	<a href="#">ULY_001880_prediction_report.pdf</a>
NEG_000109	297	0,805	4	2022.09.18 23:18	<a href="#">NEG_000109_prediction_report.pdf</a>
NEG_000108	198	0,801	1	2022.09.18 23:12	<a href="#">NEG_000108_prediction_report.pdf</a>
NEG_000165	1583	0,782	1	2022.09.19 4:27	<a href="#">NEG_000165_prediction_report.pdf</a>
NEG_000182	3203	0,745	1	2022.09.19 6:00	<a href="#">NEG_000182_prediction_report.pdf</a>
NEG_000121	92	0,686	1	2022.09.19 0:23	<a href="#">NEG_000121_prediction_report.pdf</a>
NEG_000151	2301	0,608	1	2022.09.19 3:10	<a href="#">NEG_000151_prediction_report.pdf</a>
NEG_000176	0	0,47	0	2022.09.19 5:26	<a href="#">NEG_000176_prediction_report.pdf</a>
NEG_000186	0	0,374	0	2022.09.19 6:21	<a href="#">NEG_000186_prediction_report.pdf</a>
NEG_000101	0	0,373	0	2022.09.18 22:36	<a href="#">NEG_000101_prediction_report.pdf</a>
NEG_000115	0	0,243	0	2022.09.18 23:49	<a href="#">NEG_000115_prediction_report.pdf</a>
NEG_000131	0	0,124	0	2022.09.19 1:20	<a href="#">NEG_000131_prediction_report.pdf</a>
NEG_000136	0	0,124	0	2022.09.19 1:46	<a href="#">NEG_000136_prediction_report.pdf</a>

# Predikciós riport - Lelet


**ULYSSYS**  **Prediction report**

### Prediction summary


Patient id: ULY\_001810  
Date: 2022-03-07 14:22:03

Nodules found:

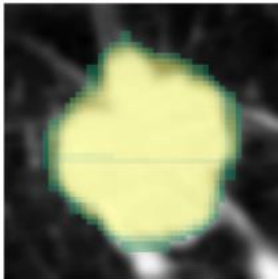
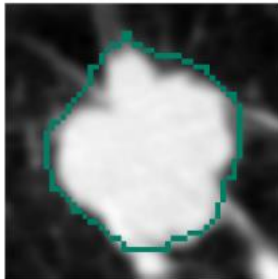
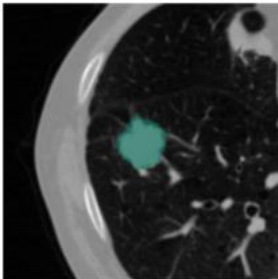
id	slice	volume [mm <sup>3</sup> ]	max probability	mean probability
1	112	13619	1.00	0.81
2	143	7203	1.00	0.70
3	152	38	0.56	0.45





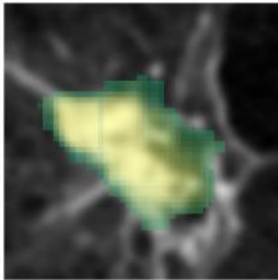
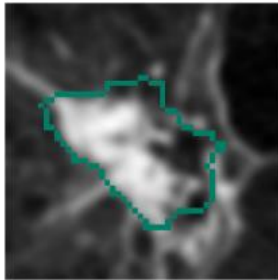
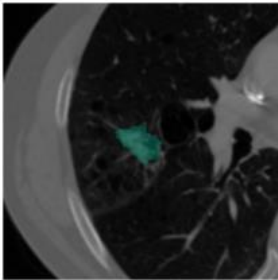
**ULYSSYS**  **Prediction report**

id	slice	volume [mm <sup>3</sup> ]	max probability	mean probability
1	112	13619	1.00	0.81



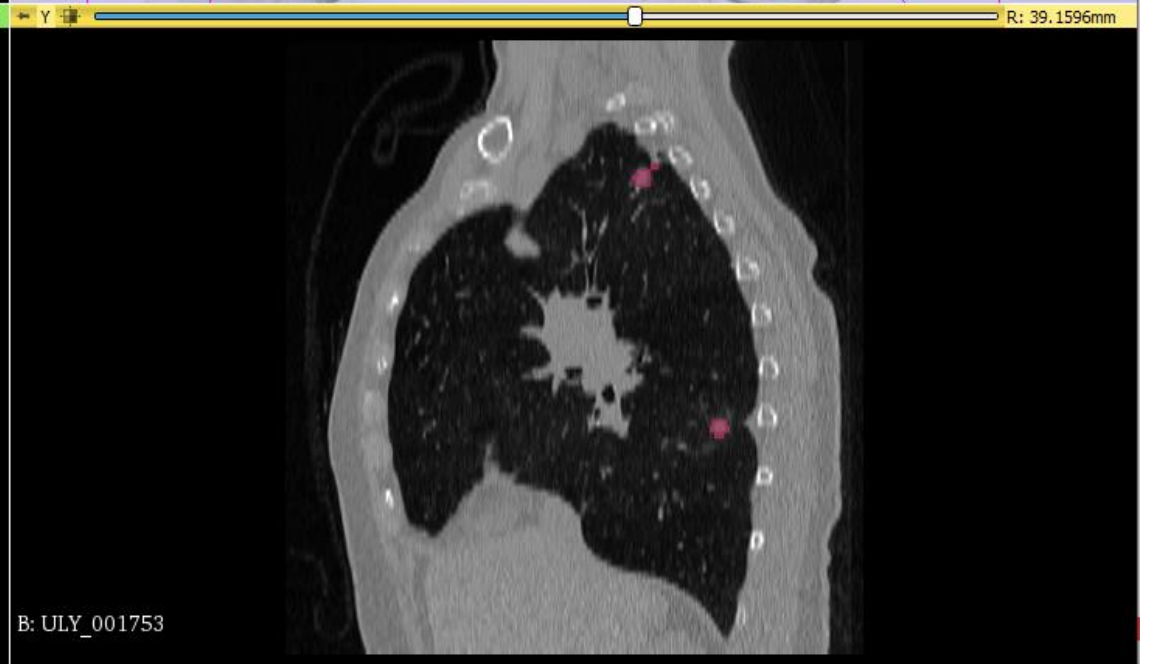
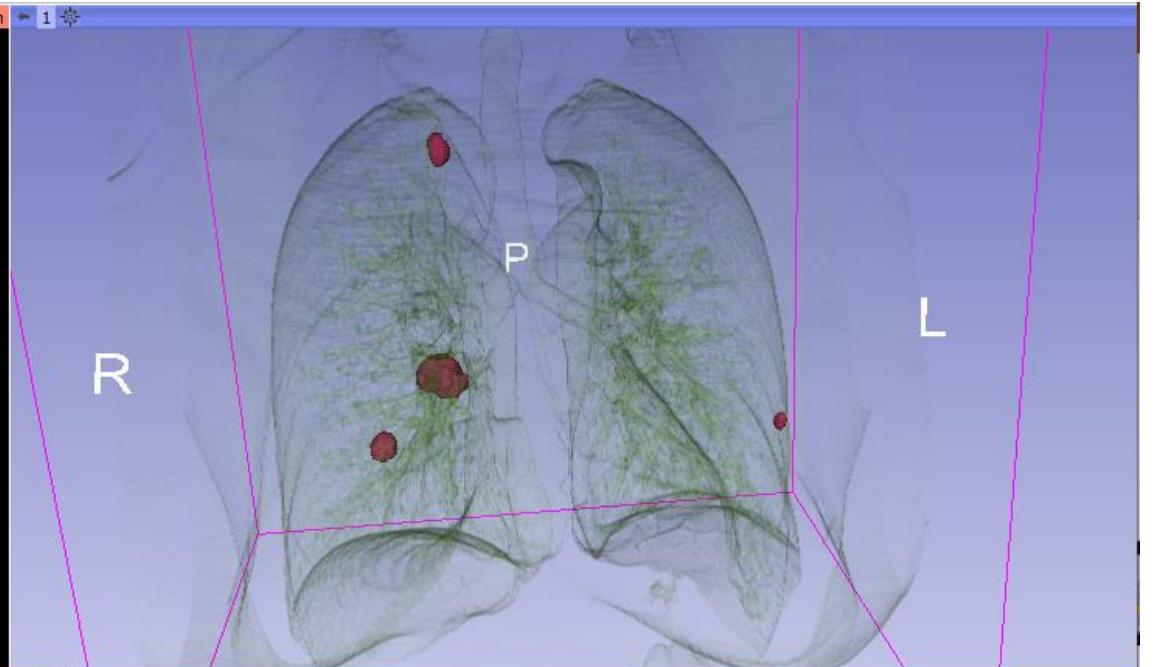
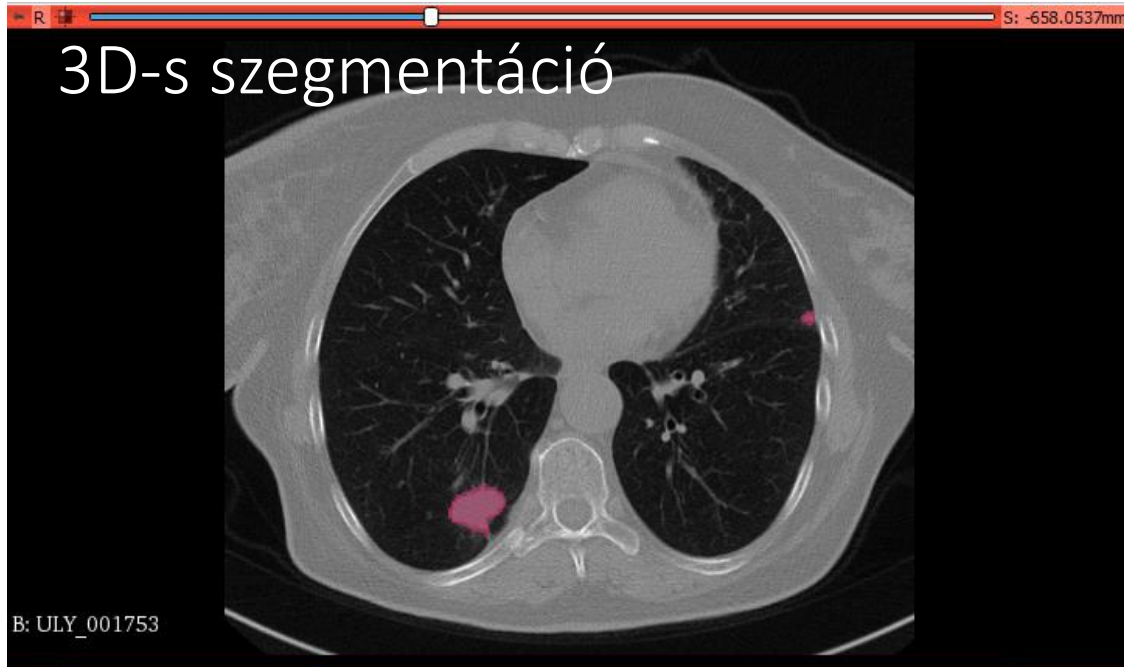
Location Predicted contour Probability map

id	slice	volume [mm <sup>3</sup> ]	max probability	mean probability
2	143	7203	1.00	0.70



Location Predicted contour Probability map

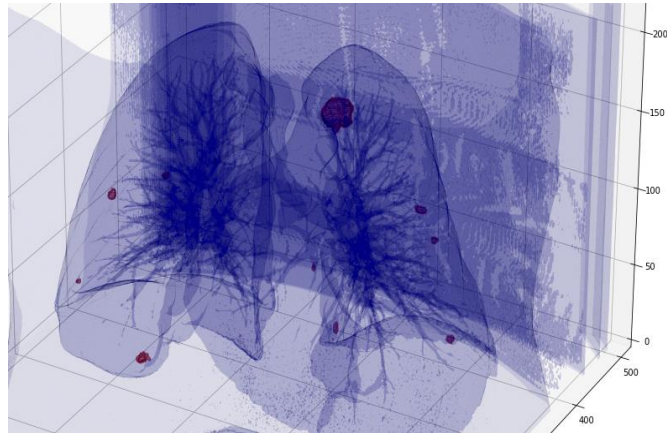
# 3D-s szegmentáció



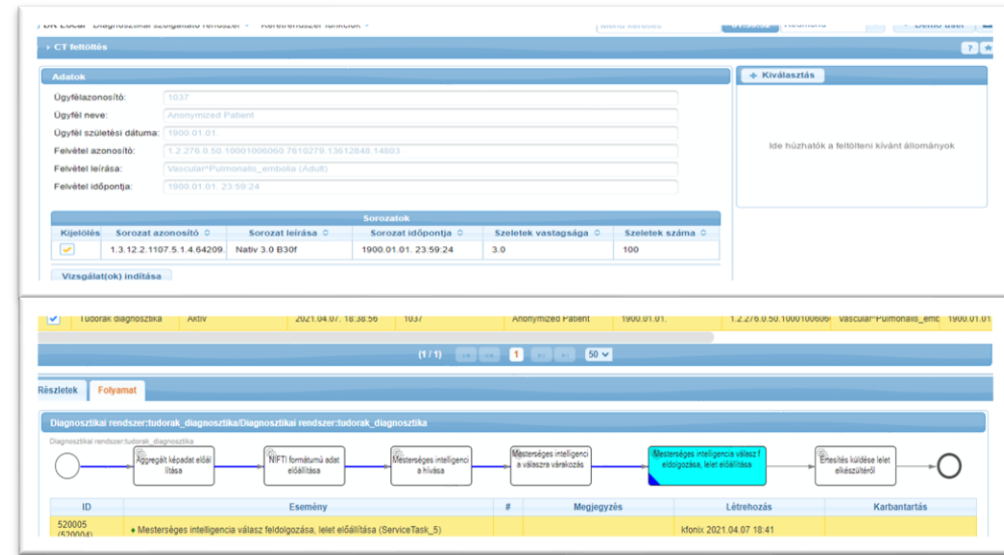


# Tüdőrák diagnosztika mesterséges intelligenciával

Cél: automatikus nodulus detekció

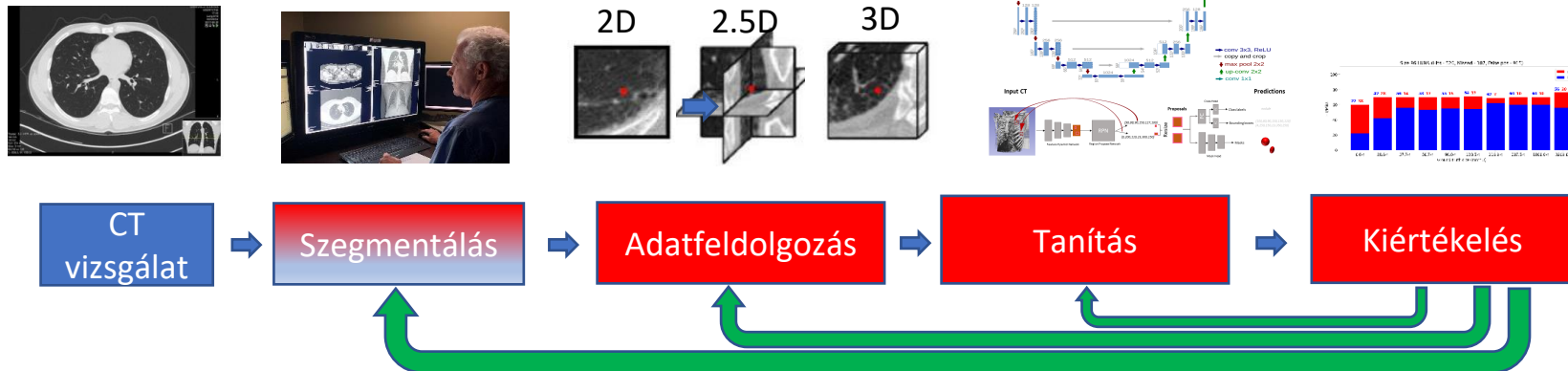


Eredmény: diagnosztikai szolgáltató rendszer



The screenshot shows a web-based interface for CT scan analysis. It includes a patient information section with fields for patient ID, name, date of birth, and scan details. Below this is a table of scan series with columns for 'Kijelölés', 'Sorozat azonosító', 'Sorozat leírása', 'Sorozat időpontja', 'Szeletek vastagsága', and 'Szeletek száma'. A workflow diagram at the bottom illustrates the process from 'Diagnosztikai rendszer: tüdőrák diagnosztika' through various steps like 'Röntgenképek előkészítése', 'NIFTI formátumú adat előkészítés', 'Választott intelligens a hívás', 'Mesterséges intelligens a válaszra várakozás', 'Mesterséges intelligens válasz feldolgozása, lelet előkészítése', and 'Értesítés küldése lelet elkészültől'.

Eszköz: iteratív kutatás és tanítás



## A jelen és a folytatás

- Klinikai validáció folyamatban
  - Országos Korányi Pulmonológiai Intézetben
  - HUNCHEST felvételein és eredményein
  - Közel 2000 felvételen
- ISO 13485 (Medical Device) tanúsítvány és CE minősítés folyamatban
- Cél: országos szűrőprogramban alkalmazhatóság
- További kutatási lehetőség
  - Mellkasi CT felvételeken egyéb szűrővizsgálatok (pl. kardiovaszkuláris betegségek)