Segmentation of lungs on CT

tools to aid Radiotherapy Planning







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Contextualization

2

Segmentation algorithms

2.1

Region Growing

2.2

U-Net CNN

3

Comparison of approaches

4

Conclusions

5

Future directions



Contextualization

Cancer and Radiotherapy Planning



Cancer

1,762,450 new cancer cases and 606,880 cancer deaths

Projected to occur in the United States in 2019

2nd largest cause of death in Europe

21.4% of cumulative risk of developing cancer before the age of 75 years. For dying, 17.7%, globally



Radiotherapy Planning

At least half of the cancer patients require radiotherapy

Radiotherapy alone is responsible for $\frac{78\%}{}$ of non-surgical cancer cures

Some normal tissue will be inevitable irradiated

Such radiation may lead to sequelae





Sensitivity to toxicities of the lungs and heart limits the radiation dose escalation in some tumours

Risk of severe pneumonitis (fibroses)

No guideline or atlas is available, the delineation of the normal lung used for dose computation was not yet standardized

Underestimation of this volume may have two outcomes:

- the participation exclusion of a patient from a clinical trial
- unnecessary limitation of the dose prescribed



Objectives:

Evaluate the efficiency of traditional approaches on lung segmentation for Radiotherapy Planning

Use of a Deep Learning architecture for this task

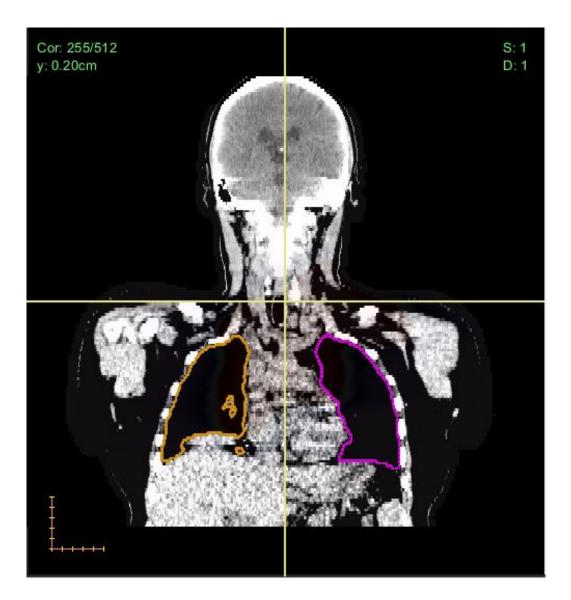
Compare both approaches in this particular problem

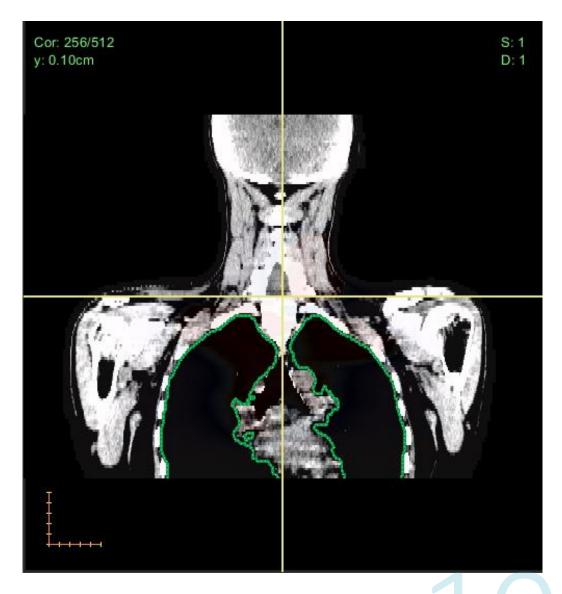


Dataset preparation



Name	Quantity
Patients	145
CTV	198
PTV	248
GTV	42
Lungs	93
Esophagus	121
Heart	97
Liver	20



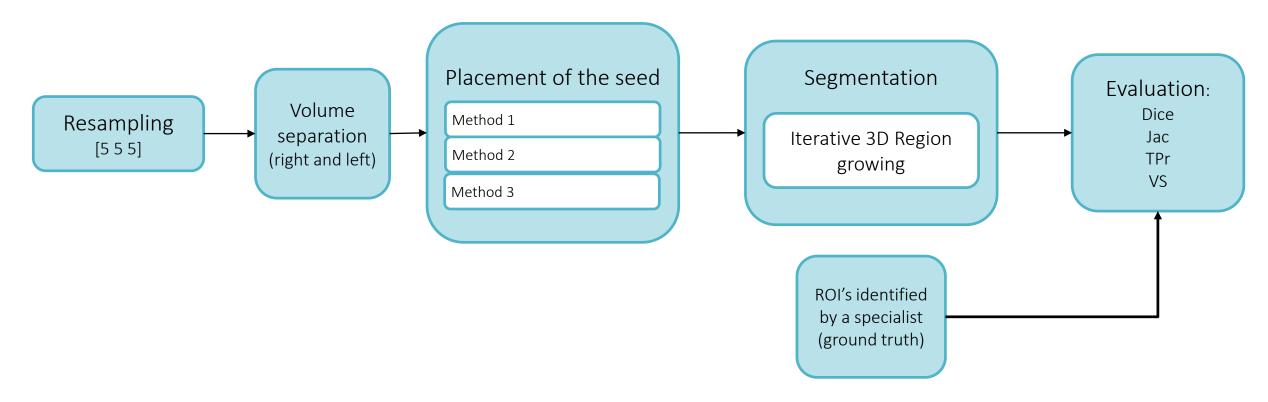


Group A Group B



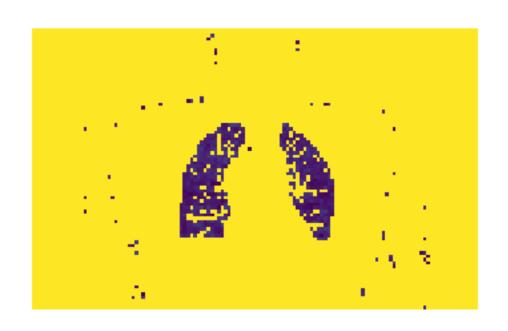
Region Growing

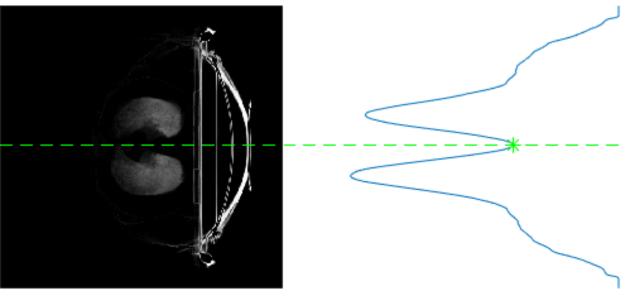




Volume Separation

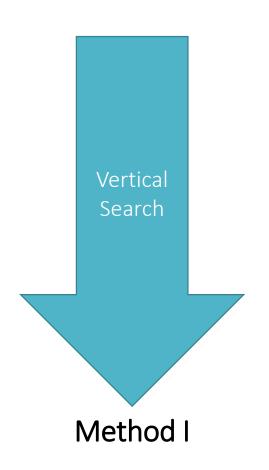


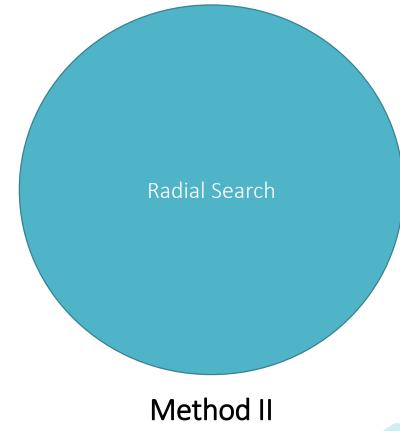




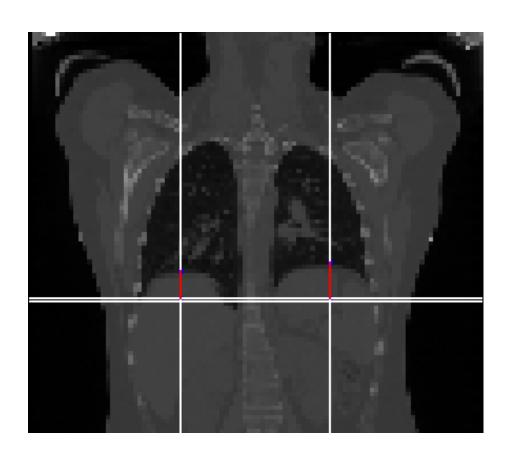


Placement of the seed



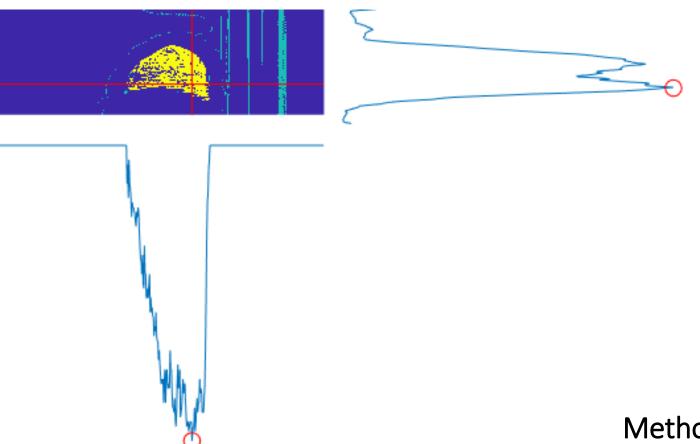






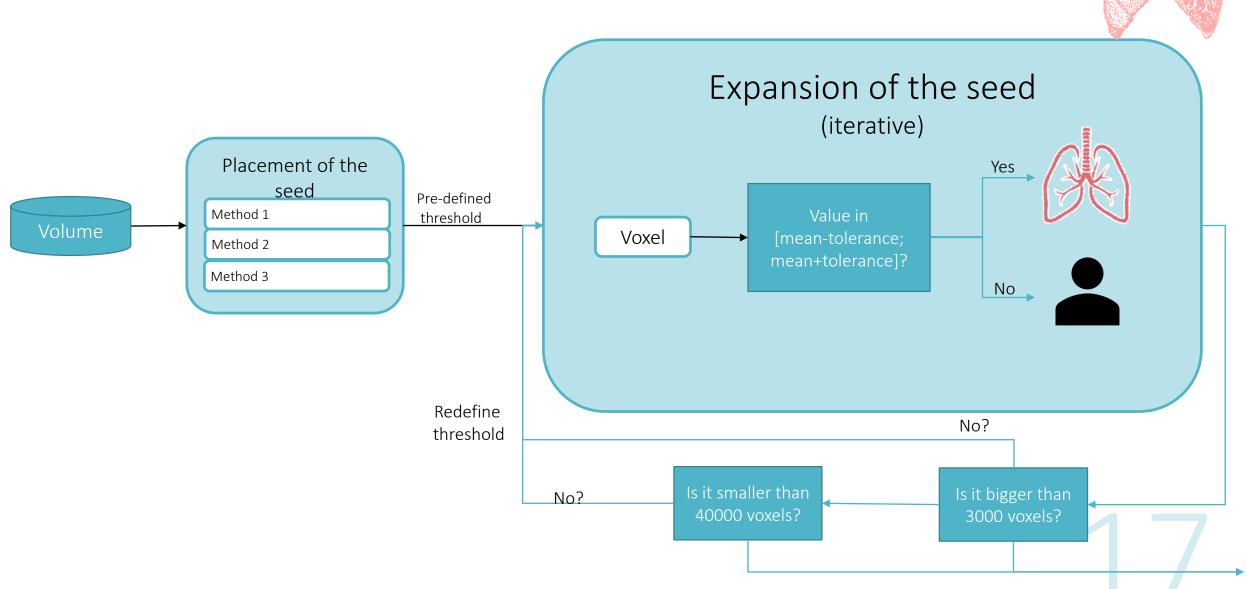






Method III

Iterative Region Growing

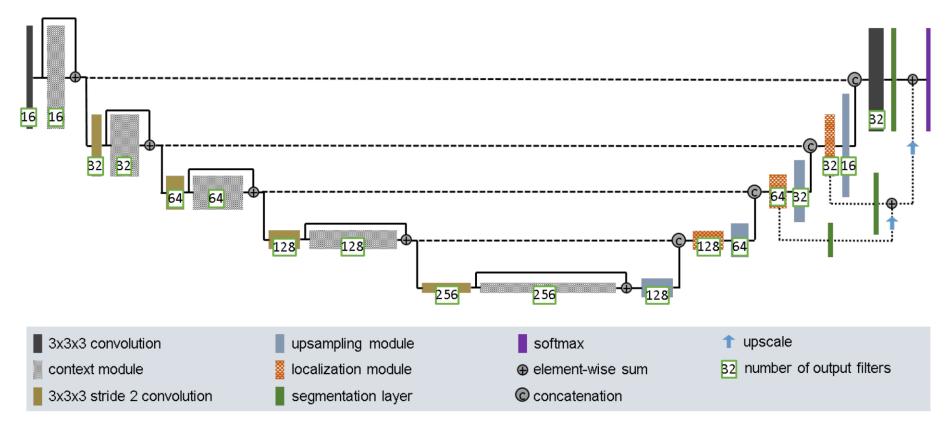


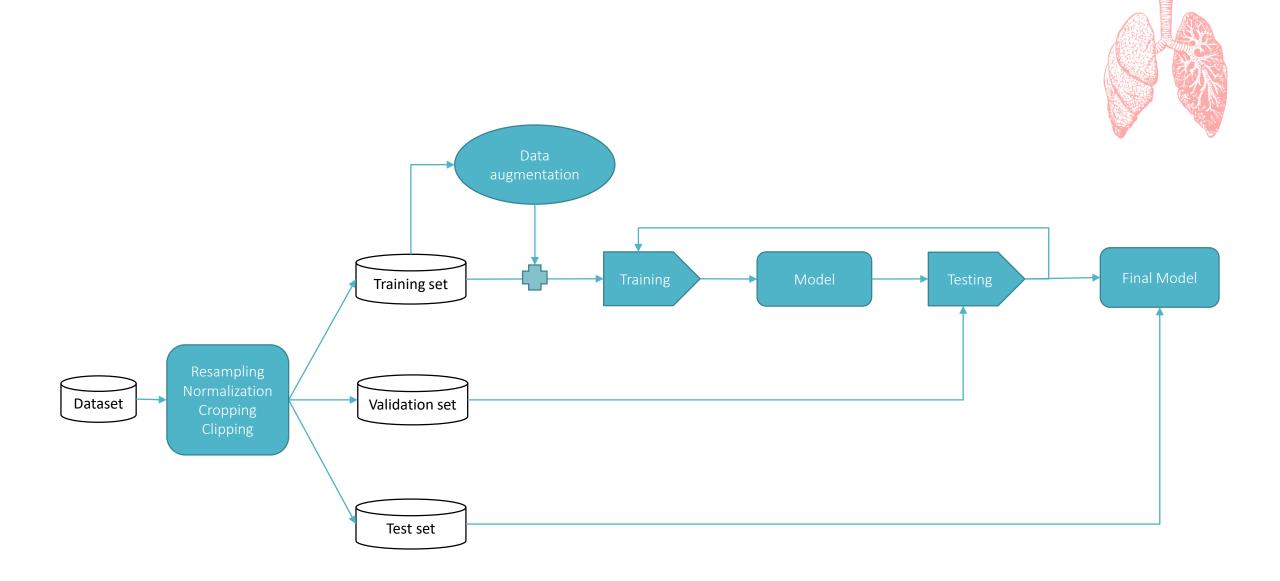


U-Net CNN



U-Net architecture

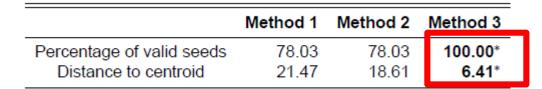




14 models, parameters:

Parameter	Experimented Values
Volume Size	$64^3,112^3$
Up-convolution operation	Deconvolution, Upsampling
Batch Size	1,5
Validation Size	2,5
Number of Epochs	250,300
Patience	6,70,107
Early Stop	30,129,150
Flip	False, True
Permute	False, True
Distort	False, True

Results





Iterative Region Growing

Segmentation	Seed	DICE	Jac	TPr	VS
HU threshold	Method 1	0.661	0.576	0.605	0.703
HU threshold	Method 2	0.656	0.571	0.600	0.691
HU threshold	Method 3	0.812	0.707	0.740	0.858
HU threshold	GT centroid	0.812	0.707	0.740	0.861
Standard Region Growing	Method 1	0.736	0.703	0.716	0.779
Standard Region Growing	Method 2	0.720	0.687	0.700	0.752
Standard Region Growing	Method 3	0.894	0.853	0.871	0.926
Standard Region Growing	GT centroid	0.872	0.833	0.850	0.916
Iterative Region Growing	Method 1	0.736	0.703	0.716	0.836
Iterative Region Growing	Method 2	0.741	0.707	0.721	0.841
Iterative Region Growing	Method 3	0.923	0.882	0.900	0.956
Iterative Region Growing	GT centroid	0.886	0.846	0.863	0.930

Results

Percentage of valid seeds

Distance to centroid

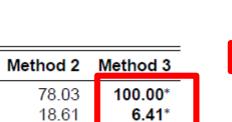
Method 1

78.03

21.47

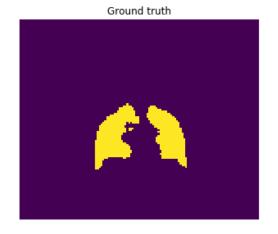
78.03

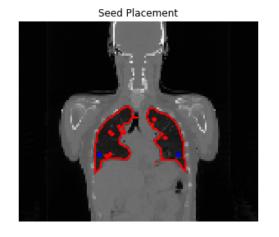
18.61

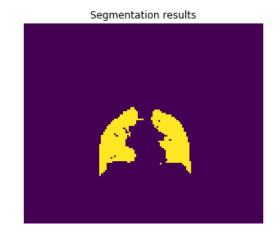


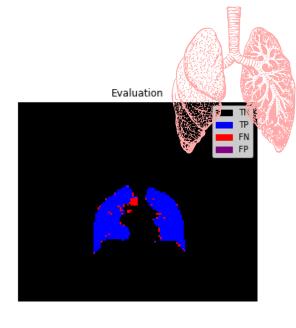


First method

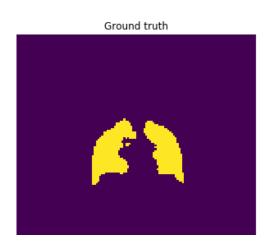


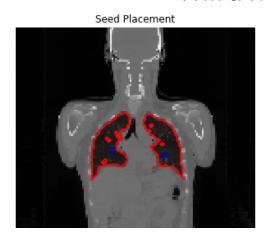


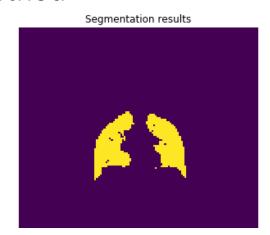


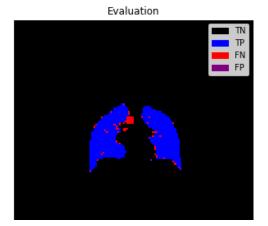


Third method



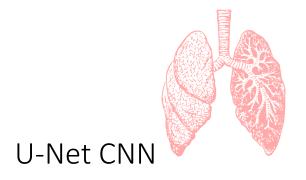






Results

Model	Multiclass Dice mean	Metrics mean	Multiclass Dice median	Metrics median
1	96.6 ± 0.6	96.5 ± 0.7	96.8 ± 0.6	96.7 ± 0.7
2	96.3 ± 1.9	96.1 ± 1.9	96.6 ± 1.9	96.6 ± 1.9
3	96.5 ± 0.6	96.4 ± 0.8	96.6 ± 0.6	96.6 ± 0.8
4	96.4 ± 0.6	96.2 ± 0.9	96.5 ± 0.6	96.3 ± 0.9
5	96.2 ± 0.8	96.1 ± 1.0	96.2 ± 0.8	96.0 ± 1.0
6	96.2 ± 0.9	95.9 ± 1.2	96.5 ± 0.9	96.2 ± 1.2
7	88.0 ± 17	88.5 ± 13.2	93.0 ± 17	91.3 ± 13.2
8	96.3 ± 0.6	96.2 ± 0.7	96.5 ± 0.6	96.5 ± 0.7
9	95.8 ± 1.3	95.3 ± 1.5	96.0 ± 1.3	95.2 ± 1.5
10	96.9 ± 0.7	96.7 ± 0.9	97.1 ± 0.9	97.0 ± 0.9
11	97.3 ± 0.5	97.1 ± 0.7	97.4 ± 0.5	97.2 ± 0.7
12	97.4 ± 0.7	97.3 ± 0.9	97.7 ± 0.7	97.6 ± 0.9
13	97.4 ± 0.6	97.2 ± 0.9	97.8 ± 0.6	97.4 ± 0.9
14	97.5±0.7	97.3±0.9	97.7±0.7	97.7±0.9





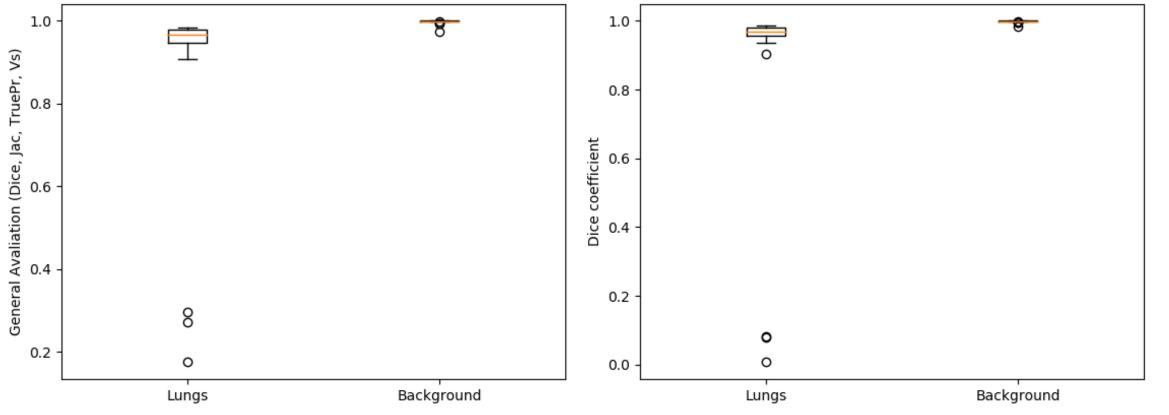
No data augmentation Upsampling



Group B

Model	Multiclass Dice mean	Metrics mean	Multiclass Dice median	Metrics median
1	91.0±22.1	91.8±17.4	96.9±22.1	96.5±17.4

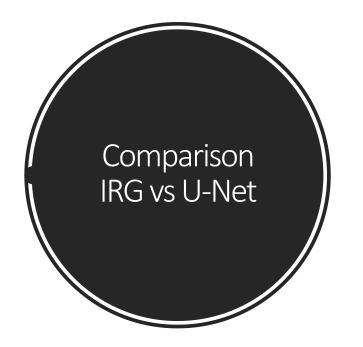




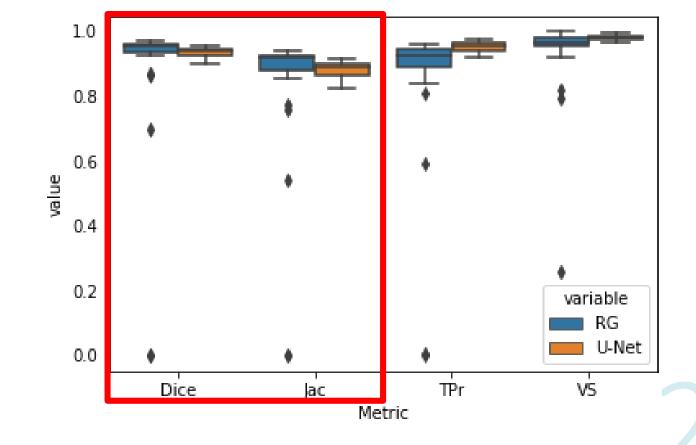


Comparison

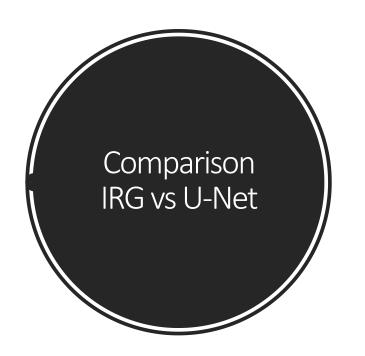




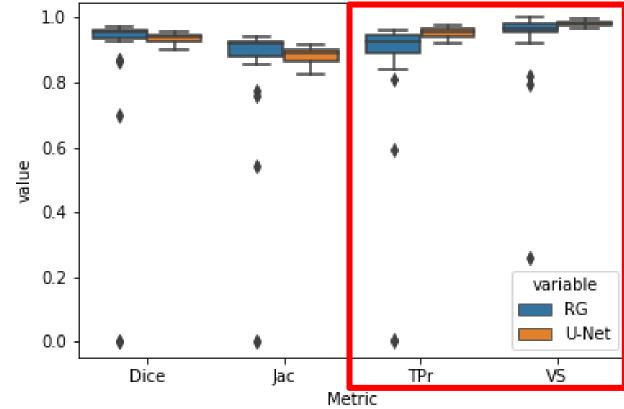
Metric	Iterative Region	Iterative Region		U-Net CNN	U-Net CNN
Metric	Growing mean	Gro	wing median	mean	median
Dice	0.872±0.247		$0.958 {\pm} 0.247$	0.938±0.013	0.944±0.013
Jac	0.826±0.242		0.920 ± 0.242	$0.884{\pm}0.023$	0.894+0.023
TPR	0.844±0.243		0.928 ± 0.243	0.955±0.015*	0.958±0.015*
VS	0.933±0.137		0.968±0.137	0.981±0.008*	0.981±0.008*





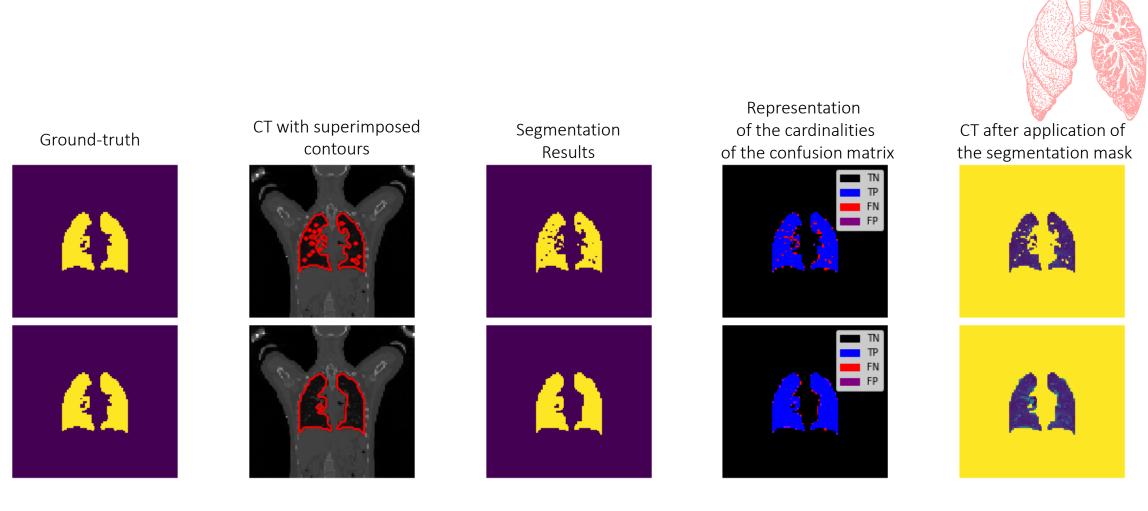


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TPR	0.844±0.243	0.928±0.243	0.955±0.015*	0.958±0.015*
VS	0.933±0.137	0.968±0.137	$0.981 \pm 0.008*$	0.981±0.008*



* Statistically significant results

30



Comparison of the segmentations resultant from the IRG method (top) and U-Net CNN (bottom)



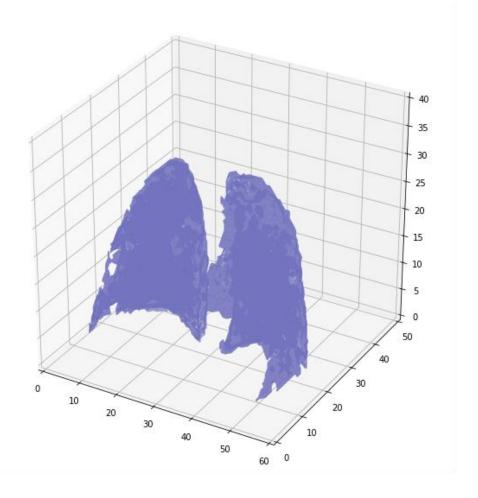
Conclusions

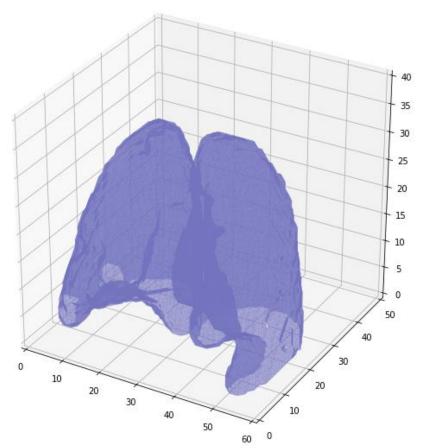
There were significant differences for U-Net on VS and TPr

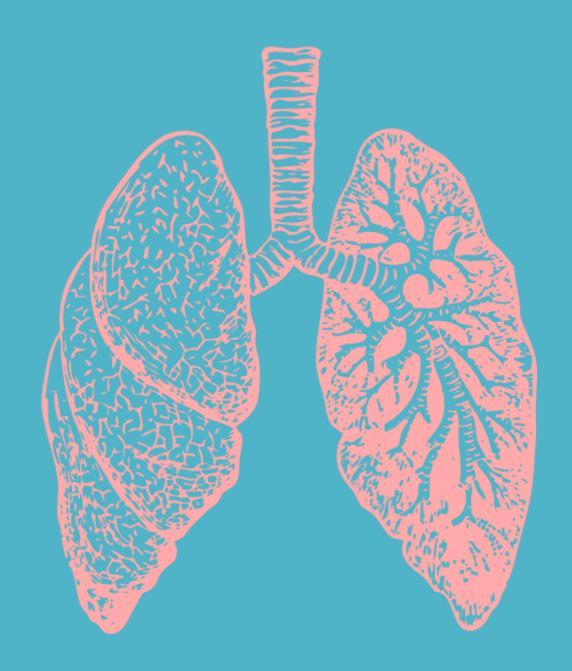
Region Growing is better on DICE and Jac, but there are no significant differences

This algorithms may help to reduce the time spent by clinicians

Future directions







Questions?