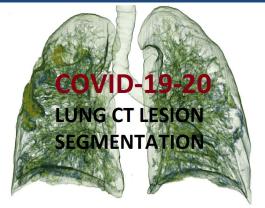




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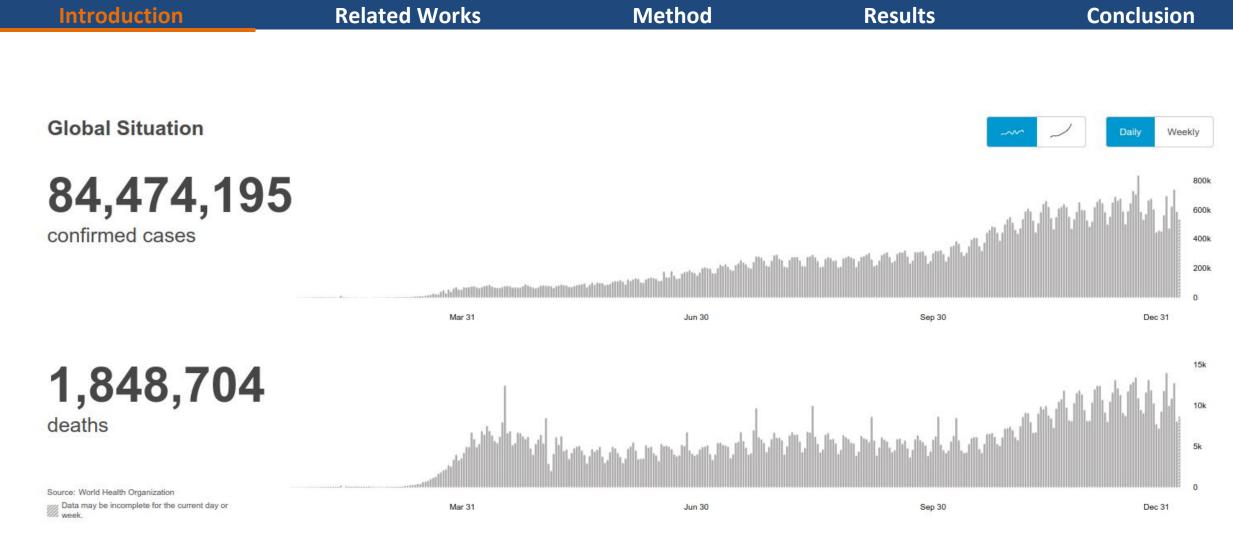




# Semi-supervised Method for COVID-19 Lung CT Lesion Segmentation

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School of Computer Science Northwestern Polytechnical University Xi'an China January 11, 2021



Globally, as of **5:47pm CET**, **5** January 2021, there have been **84,474,195 confirmed cases** of COVID-19, including **1,848,704** deaths, reported to WHO. <sup>[1]</sup>

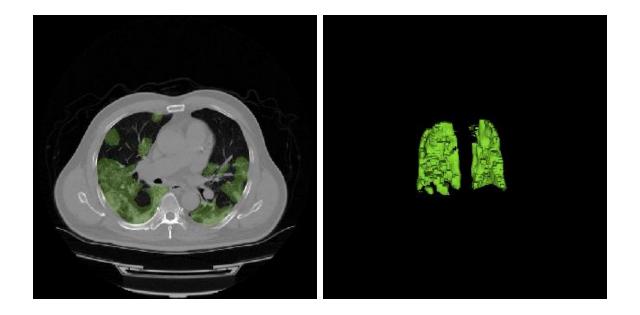
[1] WHO Coronavirus Disease (COVID-19) Dashboard. https://covid19.who.int/

Shishuai Hu et al.

The manifestation of the viral infection in the lung has been one of the earliest indicators of disease and may play an important role in the clinical management of patients. <sup>[2]</sup> - Automated lung lesions segmentation on CT images can accelarate this process.

# Challenges

- Lesion distribution usually multifocal and peripheral.
- Labeled CT images limited.
- Image sources multi-institutional, multi-national and originate from patients of different ages, genders and with variable disease severity.



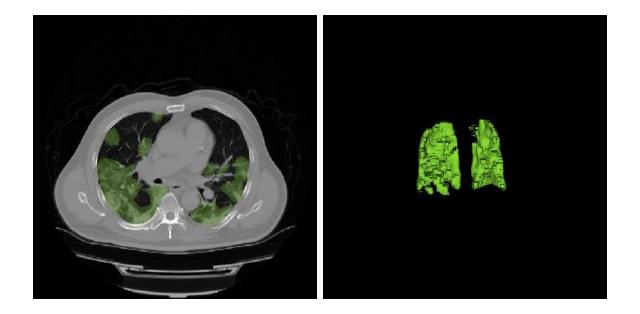
### Lung and viral infection regions

[2] COVID-19 Lung CT Lesion Segmentation Challenge - 2020. https://covid-segmentation.grand-challenge.org/

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### Lung and viral infection regions

[2] COVID-19 Lung CT Lesion Segmentation Challenge - 2020. https://covid-segmentation.grand-challenge.org/



> Reverse Attention <sup>[3]</sup> - improve the sensitivity of the model.

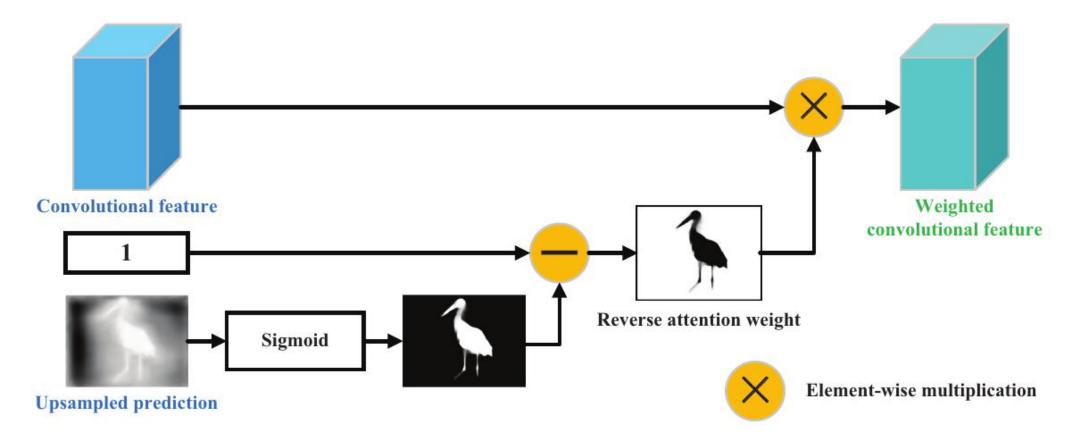


Illustration of the reverse attention block, whose input and output are highlighted in blue and green respectively.

[3] Chen S, Tan X, Wang B, et al. Reverse attention for salient object detection[C]//Proceedings of the European Conference on Computer Vision (ECCV). 2018: 234-250.

Shishuai Hu et al.

Introduction	Related Works	Method	Results	Conclusion
Generalization abili Semi-supervised I	-			ain the model labeled data Model
Labeled CT ima	ges are rare and expens	ive.	to predi	ne trained model ict labels for the labeled data
Unlabeled CT in	nages are much <mark>cheape</mark>	r.	pseudo-labeled data	labeled data
			3. retrained the model with the pseudo and labeled datasets together	lodel

Semi-supervised learning with pseudo labels

[4] Lee D H. Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks[C]//Workshop on challenges in representation learning, ICML. 2013, 3(2).

Shishuai Hu et al.

Introduction Related Works Method Results Conclusion

# **U-Net with Reverse Attention Module (RA-UNet)**

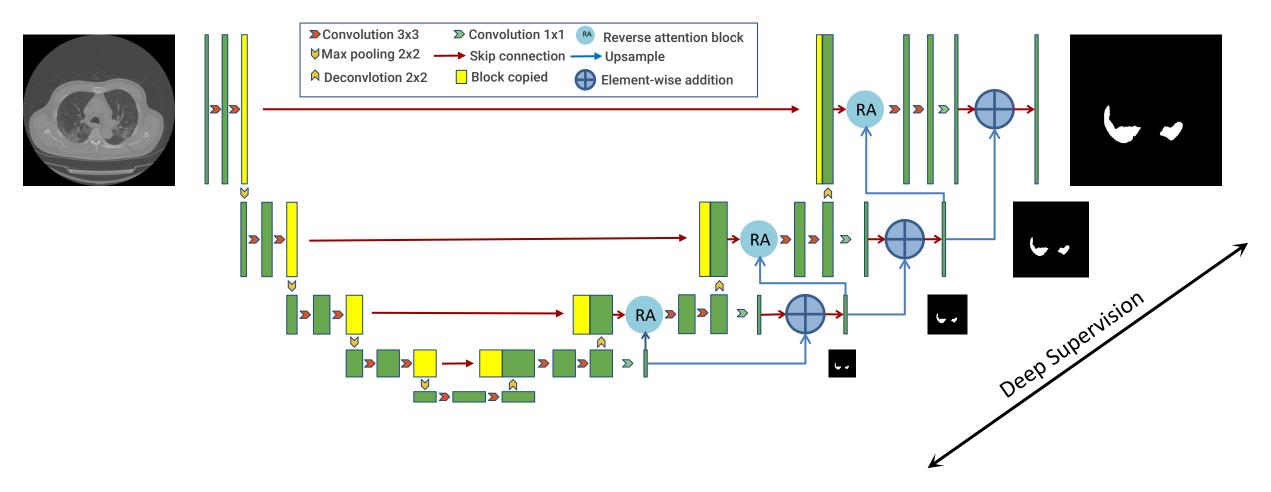
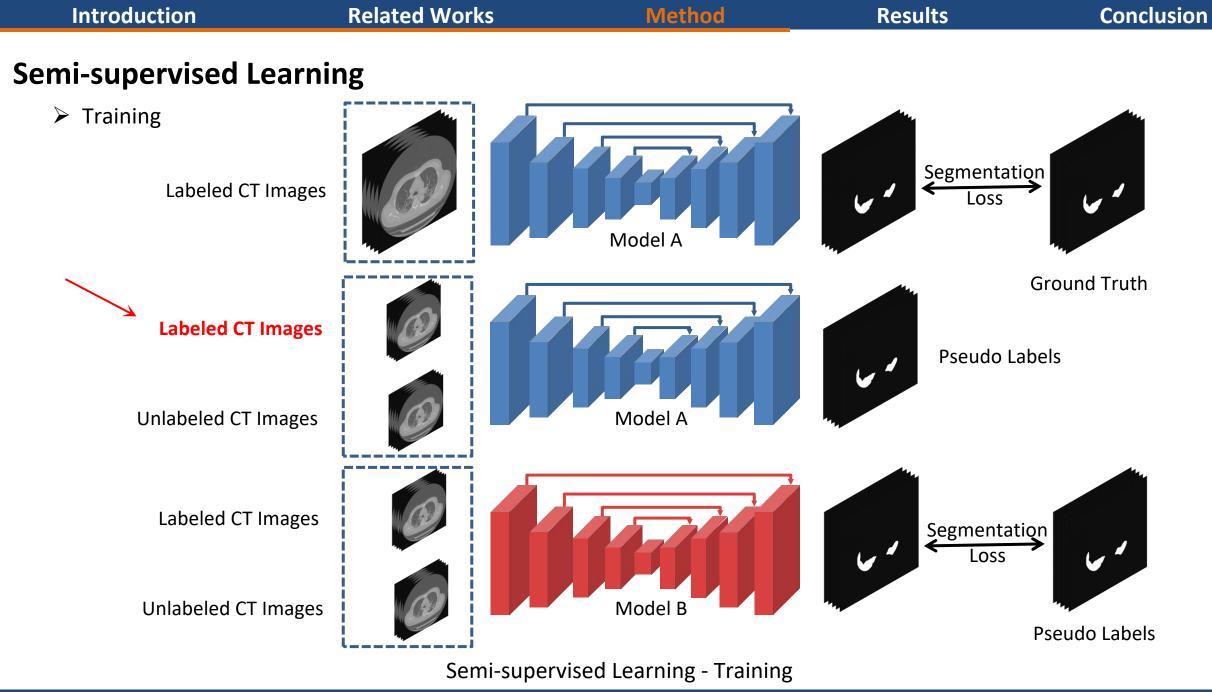


Diagram of 2D RAU-Net

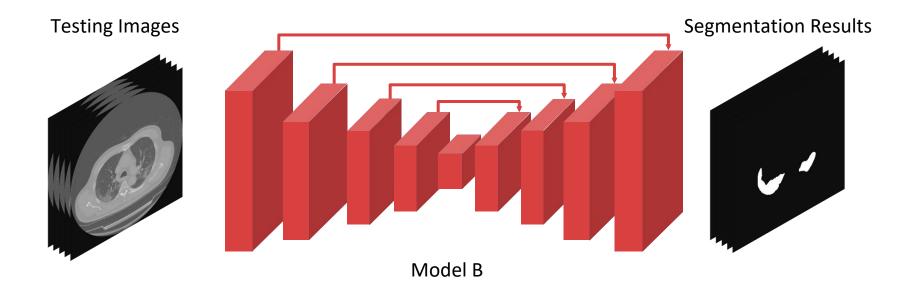


Shishuai Hu et al.

Introduction	Related Works	Method	Results	Conclusion

### **Semi-supervised Learning**

> Testing



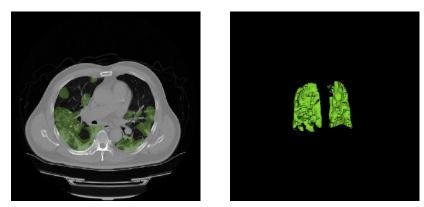
Semi-supervised Learning - Testing

## Datasets

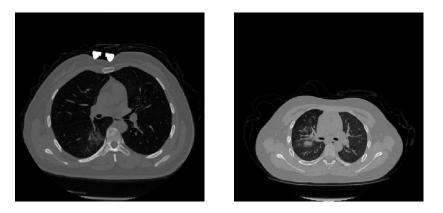
- Labeled data
  - COVID-19 segmentation challenge dataset <sup>[2]</sup> 200 cases (Version 1)
- Unlabeled data (external data)
  - TCIA CT Images in Covid-19<sup>[5]</sup> 400 Lung cases (exclude cases appear in chellenge Lung dataset)

# **Evaluation Metrics**

- Dice similarity coefficient (Dice)
- Precision (Pre.)
- ➤ Recall (Rec.)



Lung CT image slice and lesion annotations from COVID-19 Lung CT Lesion Segmentation Challenge dataset



Lung CT image slices from TCIA Covid-19 CT images dataset

[5] An P, Xu S, Harmon SA, Turkbey EB, Sanford TH, Amalou A, Kassin M, Varble N, Blain M, Anderson V, Patella F, Carrafiello G, Turkbey BT, Wood BJ (2020). CT Images in Covid-19 [Data set]. The Cancer Imaging Archive. DOI: https://doi.org/10.7937/tcia.2020.gqry-nc81

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Introduction	Related Works	Method	Results	Conclusion

### **Backbone Network**

InnUNet <sup>[6]</sup>

## **Ablation Study**

Ablation study on training set (5-fold cross validation)

Methods	Dice	Pre.	Rec.
2D nnUNet	69.01%	77.72%	67.30%
3D Lowres nnUNet	72.38%	79.10%	71.28%
3D Lowres RA-UNet	72.26%	78.86%	72.04%
3D Fullres nnUNet	72.38%	77.98%	72.16%
3D Fullres Semi-nnUNet w GT	76.30%	82.01%	75.67%
3D Fullres Semi-nnUNet w/o GT	76.65%	81.99%	75.94%

[6] Isensee F, Jaeger P F, Kohl S A A, et al. nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation[J]. Nature Methods, 2020: 1-9.

Shishuai Hu *et al.* 

## **Comparision with Other Methods**

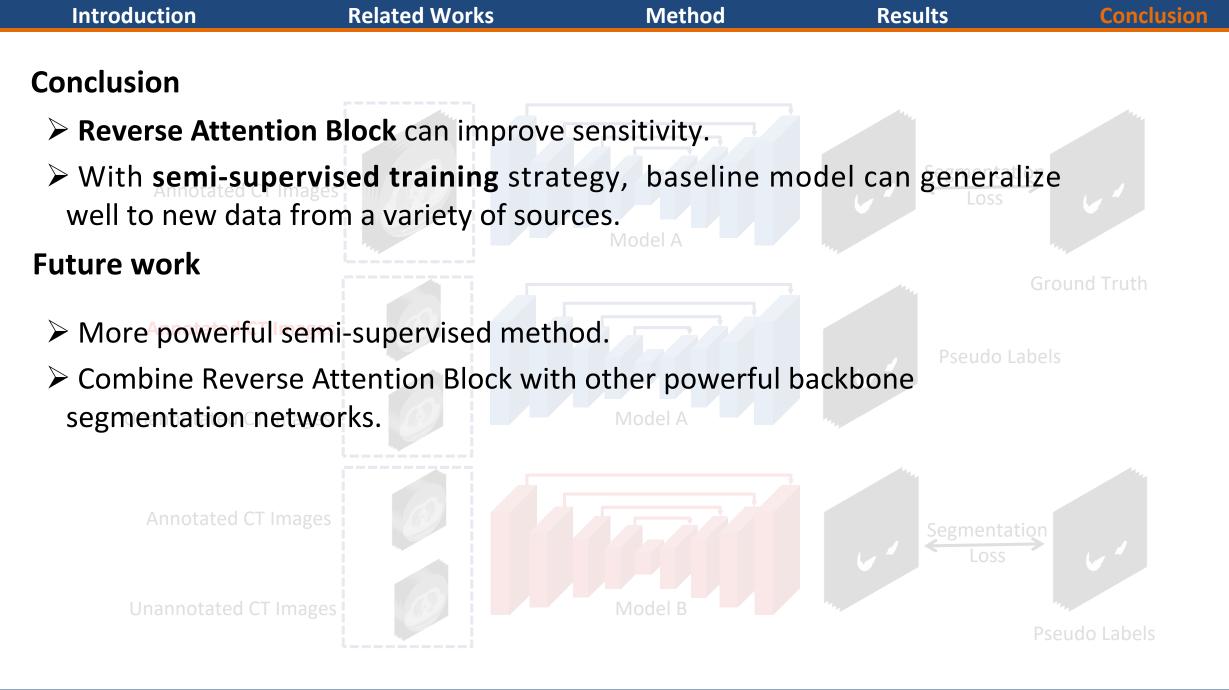
#### Compare with other methods on the testing leaderboard

User	Dice Score	Jaccard Coefficient	Normalized Volume Diff	Hausdorff 95	Surface Dice at 1mm
sshu	0.6659 ± 0.2390	0. 5399	0.7434	134. 3897	0. 5799
CSCYQJ	0.6581 ± 0.2447	0.5327	0. 5713	2320. 5037	0.5719
ttime	0.6577 ± 0.2399	0.5306	0.6356	128.9435	0.5694
Isensee	0.6543 ± 0.2710	0.5369	0.8482	2297.8055	0.5704
dev.sungman	0.6534 ± 0.2495	0.5280	1.2208	154.0145	0.5627
brunomOliveira91	0.6492 ± 0.2451	0.5226	0.8245	118.7694	0.5603
wangliwen1994	0.6485 ± 0.2629	0.5267	0.9662	4473.7645	0.5536
vitali.liauchuk	0.6461 ± 0.2540	0.5212	0. 7203	129.7144	0.5601
LCSBmedAI	0.6448 ± 0.2677	0.5241	1.1581	121.0697	0.5531
claire.tang	0.6441 ± 0.2612	0.5214	0.9285	117.1646	0.5621

Shishuai Hu *et al.* 

Introduction	Related Works	Method	Resul	ts Conclus	sion
Visualization					
CT Image	GT	nnUNet	RAUNet	Semi-nnUNet	

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# **Thanks for your attention!**

#### Acknowledgement

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Shishuai Hu et al.