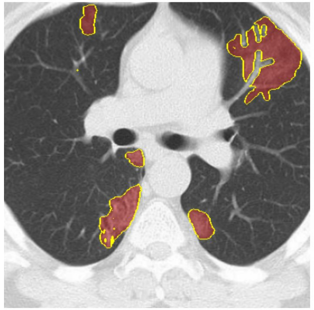
COVID-19 Segmentation:

A Weakly Supervised Consistency-based Learning Method for COVID-19 Segmentation in CT Images



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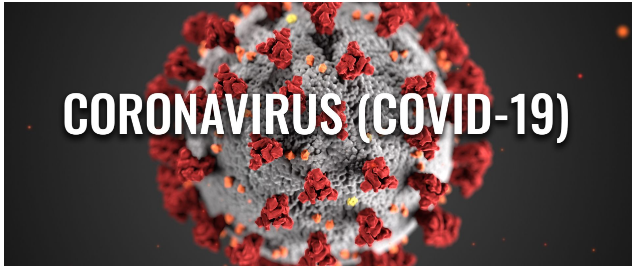
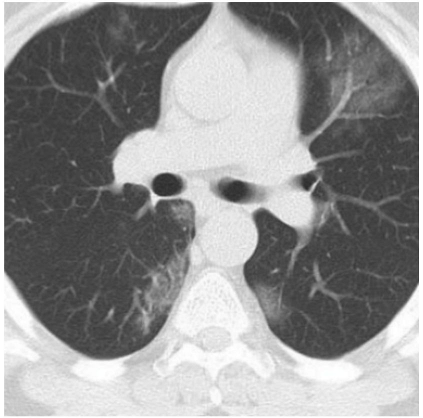
COVID-19 is a global pandemic

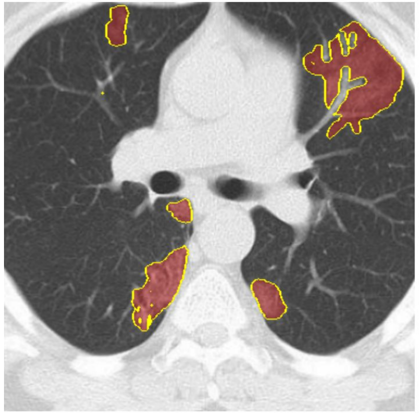
- Over 55 million cases around the world
  - Over 1.3 million deaths
- Hospitals are overwhelmed
- Its long- and short-term effects are still unknown



Develop a System for Analyzing COVID-19

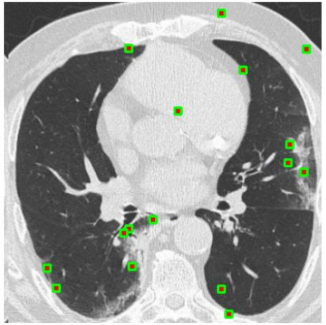
- CT Scans help provide
  - Effective diagnosis
  - Follow-up assessment
  - Disease evolution
- Deep learning (DL) methods have been successful for identifying infected regions
- **But**, successful DL methods need
  - Fully supervised training labels
  - The labels are expensive to acquire



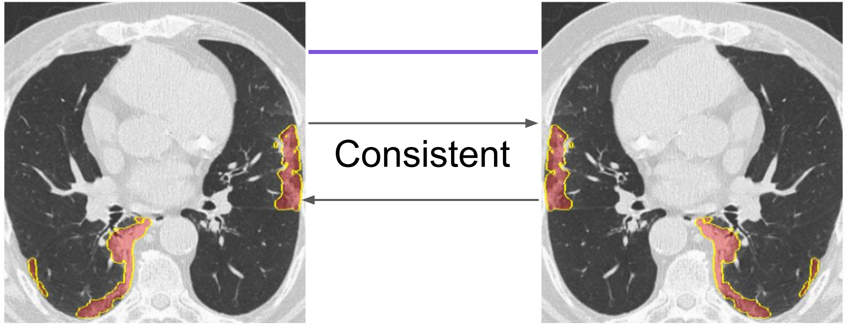


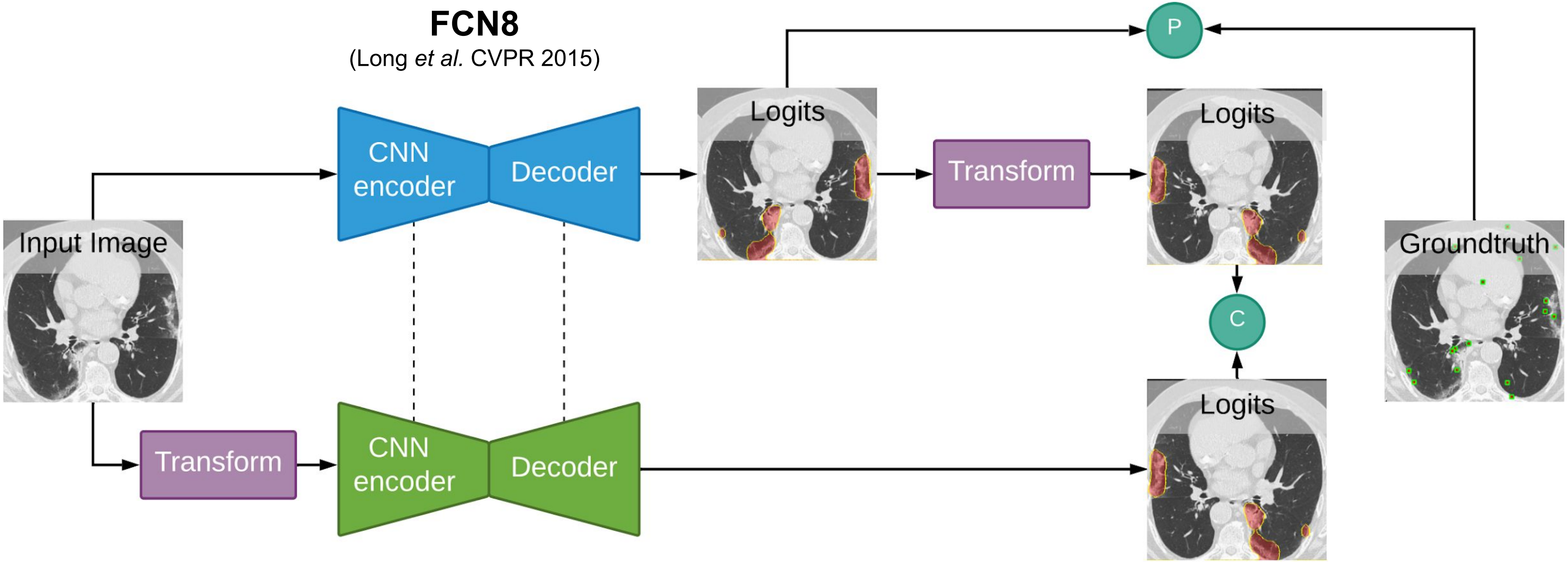
Contributions

- Proposed a deep learning method that can learn segmentation from **point-level labels**
  - A single point annotation per infected region
  - A consistency loss that ensures consistent output under flips and rotation
- Segmentation results on par with the fully-supervised on 3 COVID-19 datasets
  - Although, acquiring mask labels takes around **5 times more** than point-level



Point-level Supervision





P Point-level Loss

$$\mathcal{L}_P(X_i, Y_i) = -\sum_{j \in \mathcal{I}_i} \log(f_\theta(X_i)_{jY_j}) \ , \qquad (2)$$

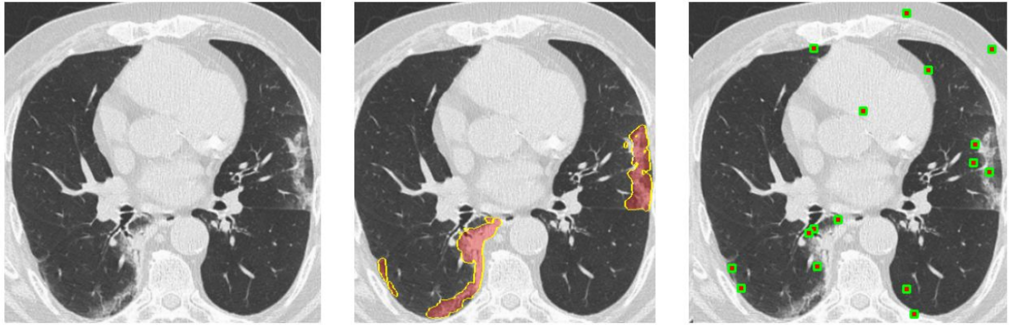
C Consistency loss

$$\mathcal{L}_C(X_i) = \sum_{j \in \mathcal{P}_i} |t_k(f_\theta(X_i))_j - f_\theta(t_k(X_i))_j|, \qquad (3)$$

Datasets and Evaluation

- 3 open source COVID-19 datasets
- For each dataset we have two splits
  - *Mixed*: train, val, test slices come from **different** scans
  - *Separate*: train, val, test slices come from the **same** scans

Name	# Cases	# Slices	# Slices with Infections (%)	# Infected Regions
COVID-19-A	60	98	98 (100.0%)	776
COVID-19-B	9	829	372 (44.9%)	1488
COVID-19-C	20	3520	1841 (52.3%)	5608



Original Image

Full Supervision (Conventional)

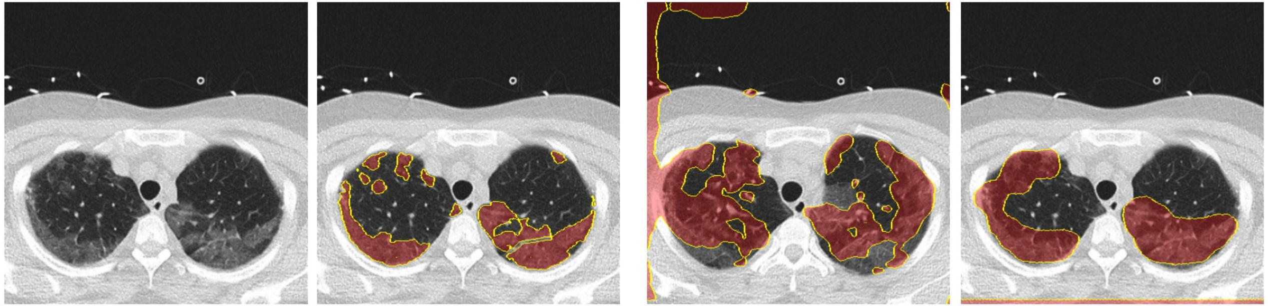
Point-level Supervision (Ours)

Results

Table 5: COVID-19-C-Mixed Segmentation Results

Loss Function	Dice	IoU	PPV	Sens.	Spec.
Fully Supervised	0.78	0.64	0.79	0.77	1.00
Point Loss (PL)	0.12	0.07	0.07	**0.95**	0.82
CB(Flip) + PL (Ours)	0.66	0.49	**0.56**	0.80	**0.99**
CB(Flip, Rot) + PL (Ours)	**0.68**	**0.51**	**0.56**	0.85	**0.99**

$$\mathcal{L}(X,Y) = \sum_{i=1}^{N} \underbrace{\mathcal{L}_P(X_i,Y_i)}_{\text{Point-level}} + \lambda \boxed{\underbrace{\mathcal{L}_C(X_i)}_{\text{Consistency}}\,,} \qquad (1)$$



Original Image | Ground Truth | Point Loss (PL) | Consistency Loss CB(Flip, Rot) + PL

Conclusions

COVID-19 Segmentation

1. A Simple Consistency-based Loss Function

2. Annotators only have to label a single point per region

3. Achieved SOTA for COVID-19 Weakly Supervised Segmentation

Code Available: https://github.com/IssamLaradji/covid19_weak_supervision