



Detection and Segmentation of Lesions in Chest CT Scans for The Prediction of COVID-19

Seminar Presentation at the University of Maryland
Center For Environmental Science



University of Maryland
CENTER FOR ENVIRONMENTAL SCIENCE

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Main Findings



1. Prediction of COVID-19 vs Common Pneumonia (CP) vs Control/Negative on large datasets is a challenging problem.
2. Detected areas with lesions in chest CT scans can be used for predicting the class of the whole image (COVID-19 vs CP vs Control).
3. The use of the advanced methodology like instance detection and segmentation both improves the accuracy of the prediction and reduces the demand for the training data.
4. Instance detection and image class prediction can be trained in a single shot from scratch, with a very high accuracy.



Plan of the Presentation



1. Chest CT scans vs X-rays,
2. Prediction of COVID-19 from chest CT scans,
3. Deep Learning for the detection + segmentation algorithm,
4. Single Shot Model (SSM) For Lesion Detection and COVID-19 Prediction,
5. Results + Future Work,
6. Papers + OS Code + Data.

Chest CT scans vs X-rays

CT vs X-rays

- Axial slices vs frontal,
- Slices are merged into a single scan,
- X-ray: faster, easier to interpret,
- CT: more accurate

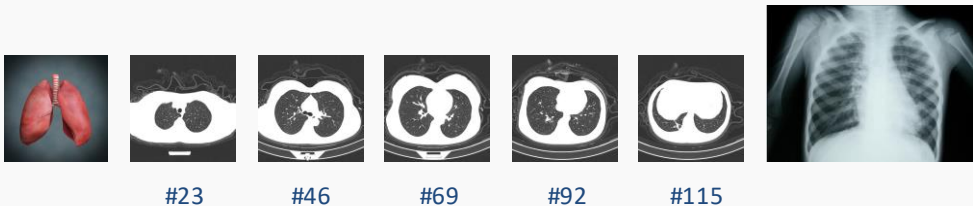


Figure 1: Chest CT Scan slices vs single X-ray. Source: CNCB, OS

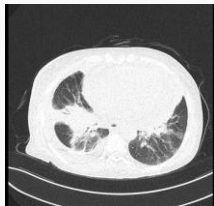
Chest CT scans For Prediction of COVID-19

Chest CT Scans For COVID-19

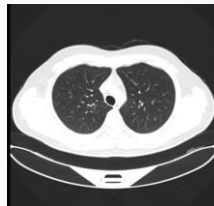
1. More accurate than the X-ray, less labor-intensive than rRT-PCR,
2. Automated prediction of COVID-19 from chest CT scans: a method of supporting doctors and radiologists
3. Pneumonia, incl COVID-19 have various manifestations in chest CT scans (lesions)



(a)



(b)



(c)

Figure 2: Chest CT Scan. (a): COVID-19 positive, (b): Common Pneumonia, (c): Normal.

Source: CNCB

Chest CT Scans For COVID-19

1. The differences between COVID-19 and other types of pneumonia are observable (e.g. D.Zhao et al, 2020; X.Li et al, 2020;), but often not statistically significant.
2. Two types of lesions correlated with both conditions: Ground Glass Opacity (GGO) and Consolidation (C).
3. To distinguish between the two conditions, the configuration of each lesion type is important: location (uni- vs bilateral), distribution (peripheral, diffuse), range, number, attenuation (fade).

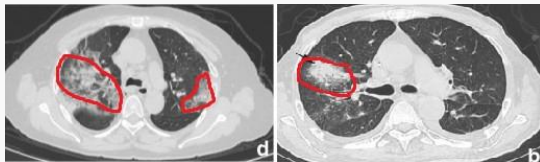


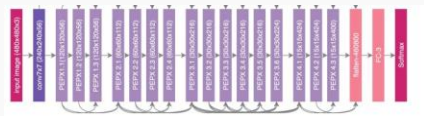
Figure 3: COVID-19 (left) vs CP. Source: X.Li et al, 2020

Lesion Detection Using Deep Learning

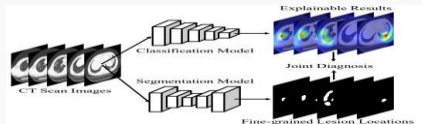
Lesion Detection

Two types of DL solutions exist:

1. Straightforward (feature extractor + class logits, e.g. in Gunraj et al, 2020, Butt et al, 2020) using ResNet, ResNeXt, DenseNet or a tailored solution (e.g. COVNet, COVNet-CT).
2. Feature extractor + semantic segmentation (e.g. UNet): predicted masks are concatenated with the feature maps to predict the image class, e.g. JCS, Y-H Wu et al, 2020.



(a)



(b)

Figure 4: (a): COVIDNet, source: L.Wang et al, 2020 , (b): JCS Source: Y-H Wu et al, 2020



Lesion Detection



The main disadvantage of the existing methods is their dependence on large amounts of data for training, data augmentation tricks, etc. Many were trained on small amounts of data, and therefore their ability to generalize requires additional testing.

1. We can train DL algorithms that detect (bounding box) and segment (contours) lesions in chest CT scans. Using these algorithms has a number of advantages:
 1. They generalize well to the unseen (new) data,
 2. A number of OS solutions (e.g. Torchvision models pretrained on MS COCO 2017) is available that can be finetuned (transfer learning) to the problem at hand,
 3. Training is fast on GPUs
2. The main advantage is their architecture is that it reduces the size of the data required for the training: in addition to using batches of images, they extract training batches from each image.

1. Faster R-CNN (Ren et al, 2015) and Mask R-CNN (He et al, 2017) solve the problem of detecting (predicting the bounding box+class) and segmenting each object (predict a mask of the object) ***independently***, i.e. the model understands objects at the instance level rather than image or pixel and outputs **box+mask+confidence scores/object**.
2. This contrasts with both image classification like ResNet and semantic (pixel-level) segmentation like UNet. Instead of nameless feature maps and image-wide score maps Mask R-CNN can handle partial occlusion and disconnected objects by predicting them explicitly.
3. As a result, Mask R-CNN does a very accurate instance segmentation and prediction.

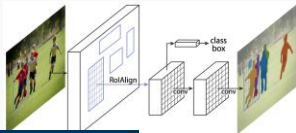


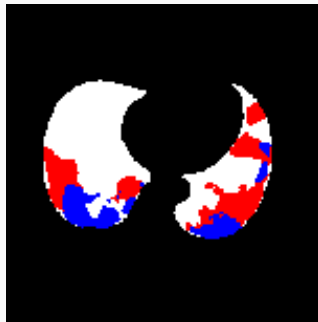
Figure 4 (c): Mask R-CNN. Source: He et al, 2017

Lesion Detection

To train Mask R-CNN on COVID-19 data we need the input images and the image masks, from which everything else is extracted:



(a)



(b)

Figure 5: (a): Input Image , (b): Mask with two types of lesions. Source: CNCB

The Model:

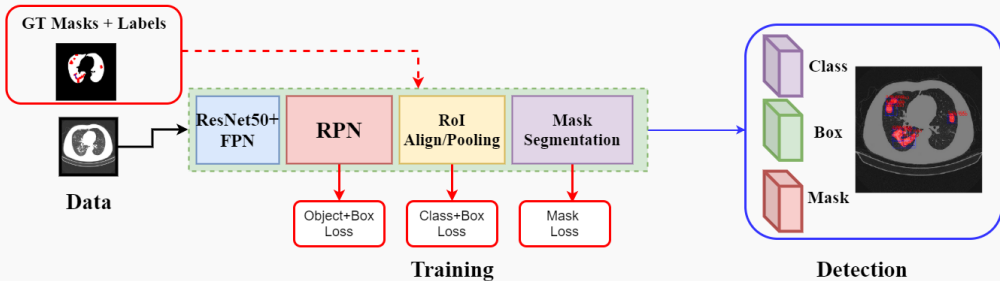


Figure 6: Mask R-CNN training

Lesion Detection

The output/prediction + independent score maps, RoI score threshold = 0.75:

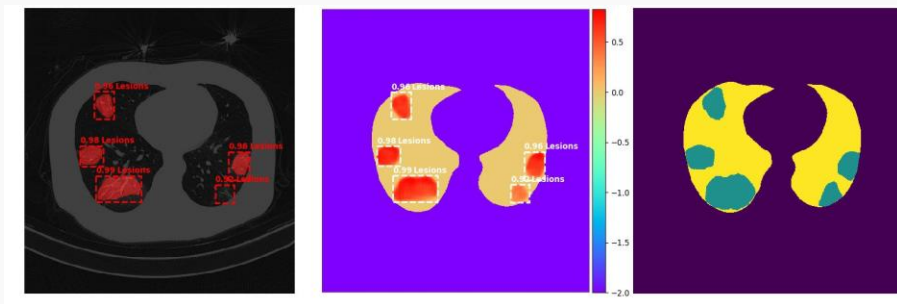


Figure 7: Mask R-CNN output. Left: input image with the overlaid predictions (class, mask, box), center: normalized *independent* score maps overlaid with the lungs mask, right: gt masks

Single Shot Model For Lesion Detection and COVID-19 Prediction



COVID-19 Classifier



1. Mask R-CNN localizes objects, but this says nothing about the global (image) class, i.e. Mask R-CNN doesn't understand the class of the image,
2. Specifically, there are many overlaps between COVID-19 and other types of pneumonia. It is impossible to classify a slice from just a single region. The accurate prediction requires consideration of all regions of interest (Rois) detected by Mask R-CNN,
3. Solution: consider all positive Rois regardless of their score and extract the image class from them/learn their distribution,
4. Solution: Single Shot Model (SSM) extends Mask R-CNN both to classify whole images, and detect separate lesions.

COVID-19 Classifier

Single-Shot Model (Mask R-CNN + Image Classification Module):

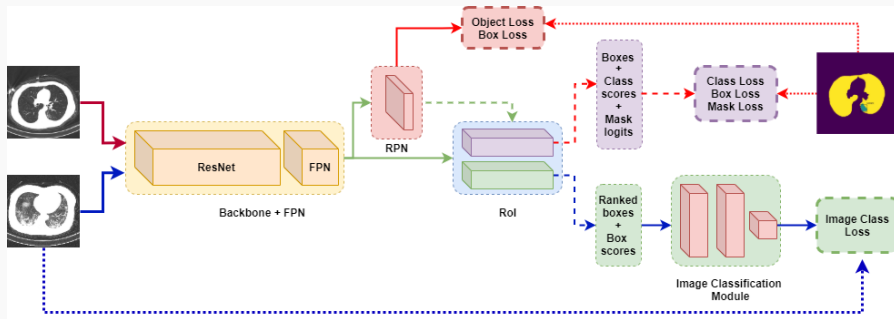


Figure 8(a): SSM. Normal arrows: tensors/features, broken arrows: batches/predictions, dotted arrow: image label, red arrows: only segmentation, blue arrows: only classification, green arrows: both problems.

Single-Shot Model (Mask R-CNN + Image Classification Module):

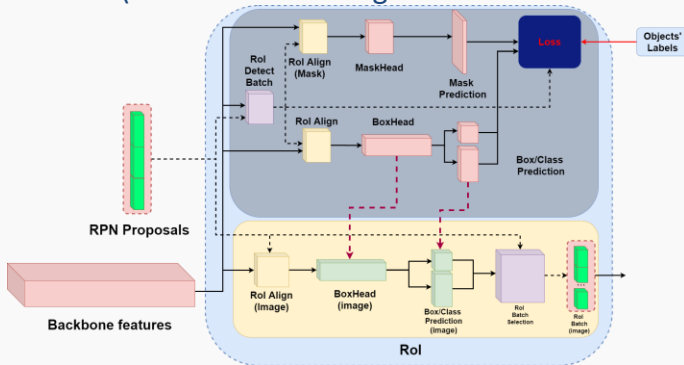


Figure 8(b): SSM Region of Interest (RoI). Normal black arrows: tensors/features, broken black arrows: batches/predictions, broken red arrows: weights copy, red image label, normal red arrow: labels.

COVID-19 Classifier

The model: RoI Batch To Feature Vector

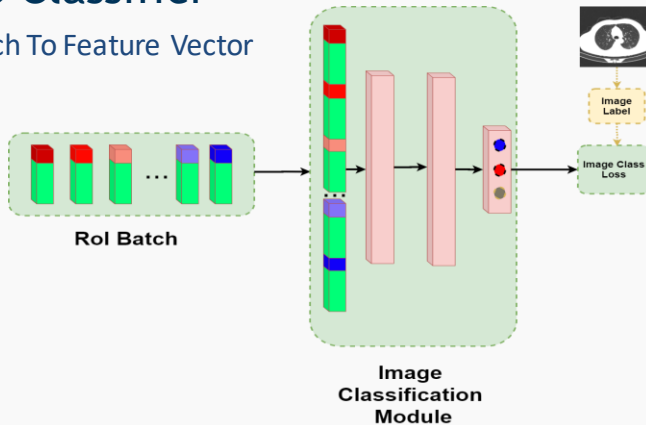


Figure 8(c): SSM. Conversion of the RoI batch to a feature vector.

COVID-19 Classifier

The model's output (RoI score threshold=-0.01)

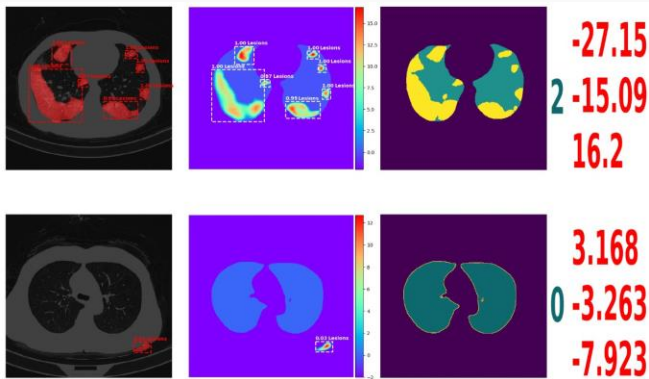


Figure 8(d): SSM. Output of the segmentation (first 3 columns) and classification (last column) modules

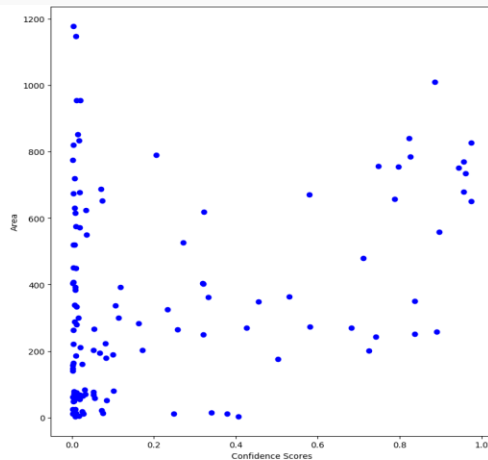
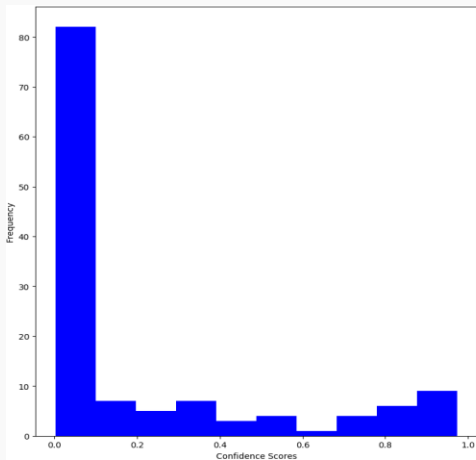


Figure 9(a): SSM. Histogram + score vs size of the positive RoIs: COVID-19

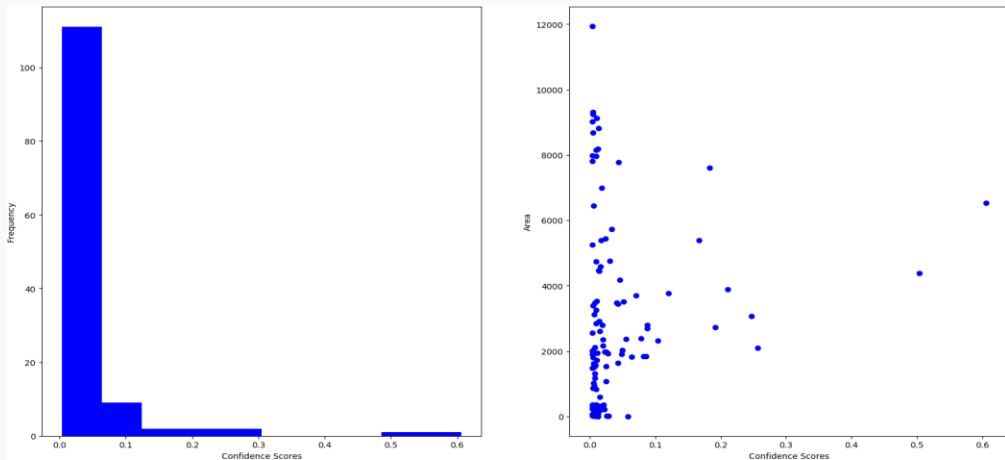


Figure 9(b): SSM. Histogram + score vs size of the positive Rols: Common Pneumonia

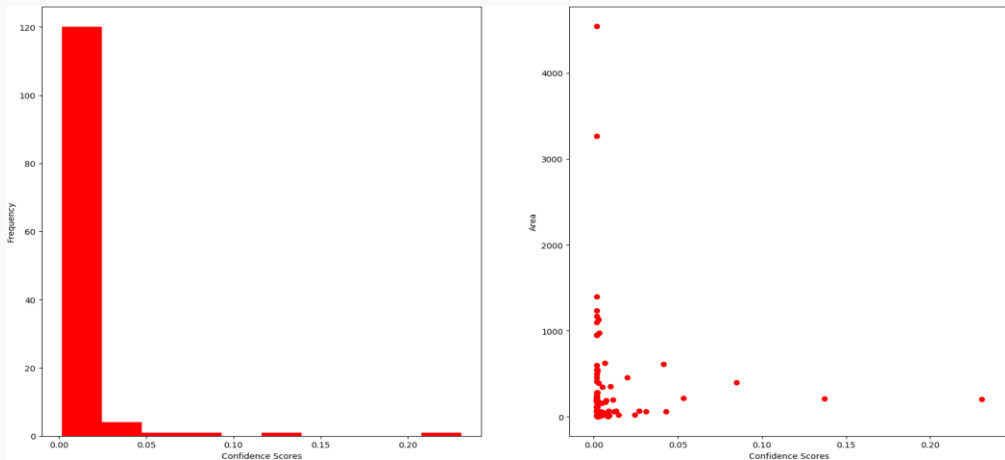


Figure 9(b): SSM. Histogram + score vs size of the positive Rols: Normal

Results + Future Work

| Model (Backbone) | #Total parameters | #Trainable parameters | Training | Validation | Test | Ratio Test/Train | Training Time(min) |
|-------------------------------------|-------------------|-----------------------|----------|------------|-----------|------------------|--------------------|
| SSM ^{2,S} (ResNet18+FPN)* | 6.13M | 6.13M/1.90M | 650/3K | -/20.6K | 100/21.1K | 0.15/7.06 | 348/357 |
| SSM ^{2,S} (ResNet18+FPN)** | 8.27M | 8.27M/1.90M | | | | | 348/341 |
| SSM ^{2,S} (ResNet34+FPN)* | 6.80M | 6.80M/2.56M | | | | | 365/361 |
| SSM ^{2,S} (ResNet34+FPN)** | 13.66M | 13.66M/2.56M | | | | | 371/361 |

Figure 10: Models' sizes and training time. Source: Ter-Sarkisov (2020,d)

| Model | AP@0.5IoU | AP@0.75IoU | AP@[0.5 : 0.95]IoUs | Rank |
|-----------------------------------|---------------|---------------|---------------------|------|
| SSM ^S (ResNet18+FPN)* | 0.5095 | 0.3927 | 0.3923 | 6 |
| SSM ^S (ResNet18+FPN)** | 0.5799 | 0.3828 | 0.4245 | 3 |
| SSM ^S (ResNet34+FPN)* | 0.6291 | 0.4648 | 0.4535 | 1 |
| SSM ^S (ResNet34+FPN)** | 0.5152 | 0.3381 | 0.3579 | 9 |

Figure 11: Segmentation Precision. Source: Ter-Sarkisov (2020, d)

| Model | COVID-19 | CP | Normal | Overall | F1 score | Rank |
|-----------------------------------|---------------|--------|--------|---------------|---------------|------|
| SSM ^S (ResNet18+FPN*) | 93.16% | 95.68% | 96.18% | 95.38% | 0.9542 | 2 |
| SSM ^S (ResNet18+FPN**) | 93.00% | 96.53% | 98.64% | 96.75% | 0.9676 | 1 |
| SSM ^S (ResNet34+FPN*) | 89.62% | 89.99% | 96.76% | 92.93% | 0.9293 | 4 |
| SSM ^S (ResNet34+FPN**) | 91.44% | 95.33% | 92.48% | 93.26% | 0.9333 | 3 |

Figure 12: Classification (class sensitivity, overall accuracy and F1 score). Source: Ter-Sarkisov (2020, d)



Results



Summary of the advantages of Single Shot Model:

1. Trains both segmentation and classification branches from scratch,
2. Requires a fraction of the training data to achieve a very high COVID-19 sensitivity and accuracy,
3. Trains a fraction of model parameters,
4. Generalizes well to the unseen data,
5. Understands COVID-19 and CP correlates explicitly,
6. Can be extended to do single-shot segmentation and detection.



Results



Future Work:

1. Generalize findings to other datasets: SARS-Cov-2 (Soares and Angelov, 2020), UCSD-COVID-CT (X.He et al, 2020), COVID-CTSet (M.Rahimzadeh et al, 2020), and other,
2. Improve the methodology by considering the affinity between different types of lesions,
3. Extend the findings to whole scans (video) and other types of data (x-rays, ultrasound, etc)

Papers + Code + Data



Preprints on medRxiv



```
@article {Ter-Sarkisov2020.10.30.20223586,  
  author = {Ter-Sarkisov, Aram},  
  title = {Lightweight Model For The Prediction of COVID-19 Through The Detection And Segmentation  
of Lesions in Chest CT Scans},  
  year = {2020},  
  doi = {10.1101/2020.10.30.20223586},  
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@article {Ter-Sarkisov2020.10.23.20218461,  
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  title = {Detection and Segmentation of Lesion Areas in Chest CT Scans For The Prediction of COVID-19},  
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@article {Ter-Sarkisov2020.10.11.20211052,  
  author = {Ter-Sarkisov, Aram},  
  title = {COVID-CT-Mask-Net: Prediction of COVID-19 from CT Scans Using Regional Features},  
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Preprints on medRxiv



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article {Ter-Sarkisov2020.12.01.20241786,  
  author = {Ter-Sarkisov, Aram},  
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Github code



Models: <https://github.com/AlexTS1980/COVID-Single-Shot-Model>,

<https://github.com/AlexTS1980/COVID-CT-Mask-Net>

Data: <http://ncov-ai.big.ac.cn>

Splits: <https://github.com/haydengunraj/COVIDNet-CT>

THANK YOU!