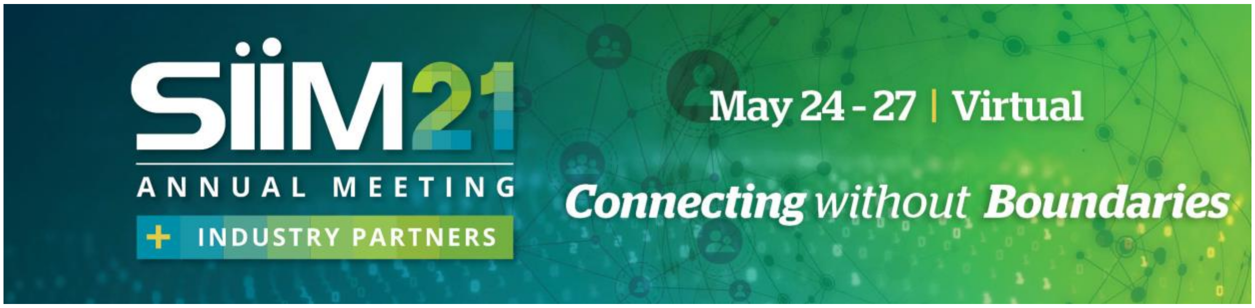

COVID-19 Lung Lesion Segmentation Using a Sparsely Supervised Mask-RCNN on Chest X-rays Automatically Computed from Volumetric CTs

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Introduction

Chest X-rays (CXRs) of COVID-19 patients are frequently obtained to determine the extent of lung disease and are a valuable source of data for creating deep learning (DL) models. Most current work assessing disease severity on chest imaging has focused on segmenting computed tomography (CT) images; however, given that CT scans are performed much less frequently than CXRs for COVID-19 patients, automated lung lesion segmentation and severity quantification on CXRs could be clinically valuable. There is a universal shortage of CXRs with ground truth lesion annotations, and manually contouring opacities is tedious and labor-intensive. To accelerate severity detection and augment the amount of available CXR training data for supervised DL models, a method of segmenting lesions on CXRs of COVID-19 patients that utilizes open-source CT data is needed. We leverage existing annotated CT images to generate frontal projection "CXR" training images for COVID-19 use-cases.

Hypothesis

Coronal chest projections generated from annotated volumetric CTs can be used as training data for supervised DL models tasked with COVID-19 lung lesion segmentation and severity quantification on CXRs.

Methods

We developed the following pipeline for COVID-19 lung opacity segmentation on CXRs:
1. We compute a coronal CXR projection from a volumetric CT via a nested sum of image pixels.
2. We train a Mask-RCNN on a mixed dataset containing annotated CXRs and coronal projections of CTs to segment lung opacities on patient CXRs.

Results

We trained our model on two distinct datasets with ground truth segmentations:
1. 80 CXRs
2. (Mixed) 10 CXRs and 70 projections from CTs

We evaluated our approach on a test set containing 20 CXRs with COVID-19 lung disease; our model achieved DICE scores of 0.88±0.02 and 0.87±0.02 on Datasets 1 and 2, respectively. This suggests that we can replace as much as 87.5% of CXR training images with projections of CTs while maintaining model accuracy.

Conclusion

Our results far exceed the few published prior studies; e.g., Tang et al.'s U-Net segmentation model achieved an IoU score of 0.4755 for the test dataset, which is significantly lower than our model's IoU score of 0.77±0.03.

A limitation of our study is that we used small amounts of publicly available data, so our model may not generalize to other data; however, our results suggest that improved accuracy can be obtained by augmenting CXR data with projections of public CT volumes. Training and testing our model on larger datasets with more representative samples could improve future results.

Figure(s)

Algorithm 1: CT TO X-RAY CONVERSION

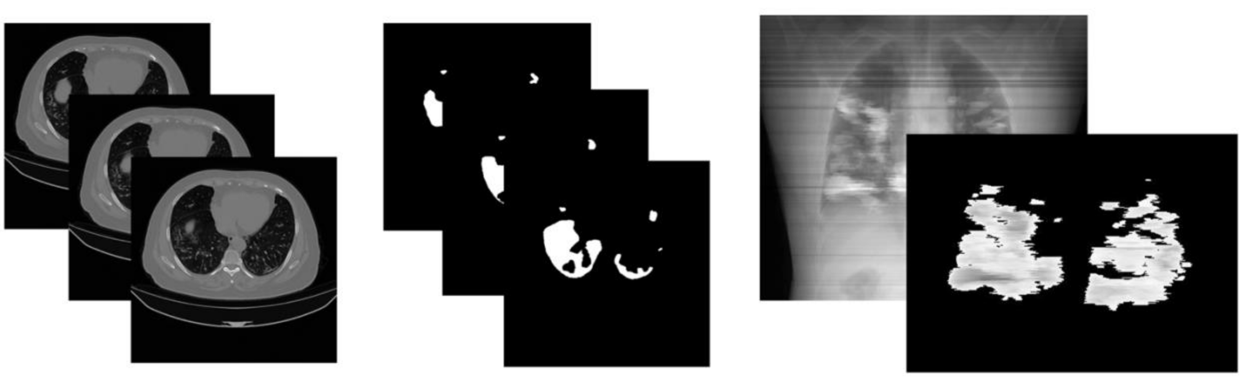
```
Input  : An array of CT slices scans and an array of mask slices masks
Output: A coronal X-ray projection computed from scans and masks

Sort scans and masks by z-position
Z ← length of scans
(X, Y) ← dimensions of each CT slice, in pixels
xray ← empty array of size (X, Z)

for z ∈ [0, Z] do
    data_scan ← pixel values of scans[i]
    data_mask ← pixel values of masks[i]
    For every nonzero pixel value p at location (x, y) in data_mask,
        data_scan(x, y) = p

    for x ∈ [0, X] do
        sum ← 0
        for y ∈ [0, Y] do
            sum ← sum + data_scan(x, y)
        end
        xray(x, z) ← sum
    end
end
return xray
```

(a)



(b) (c) (d)

	Training Dataset		Baseline**		
Metric	Dataset 1 (X-rays Only)*	Dataset 2 (Mixed)*	Training Set	Validation Set	Test Set
Sørensen-Dice coefficient (DICE)	0.8835 ±0.0204	0.8703 ±0.0211	N/A		
Intersection over Union (IoU)	0.7936 ±0.0328	0.7727 ±0.0329	0.5157	0.6724	0.4755

*Margins of error obtained via a 1-sample t-test for population mean (μ) with 95% confidence. Evaluated on test dataset of 20 CXRs.

**Tang, Sun, and Li's U-Net segmentation model, outlined in `https://www.medrxiv.org/content/10.1101/2020.10.19.20215483v1.full`

Keywords

Artificial Intelligence; Imaging Research