

Predicting Severity of COVID-19 From Patients' Chest CT Images Using Self-Supervised Image Segmentation Approaches

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ABSTRACT COVID-19 is the new outbreak of a contagious disease that infects the lungs. Currently, no vaccines or antiviral medicines exist for COVID-19 as COVID-19 is a newly infectious disease that was first discovered around December 2019. As COVID-19 is a very contagious disease, cases appear faster than the amount of test kit available. Currently, the most common testing used is PCR(Polymerase Chain Reaction) test. These test samples are sent to a centralized lab for analysis which would take several days for the test results to be available. Due to the exponential rate of infections, the limited amount of test kits, and the long wait time for the test results to be available, many infected patients are unable to get tested and receive treatments. An alternative approach to test for COVID-19 patients is through computerized tomography (CT) scan of the lungs. CT scan can drastically reduce the time taken for test results to be available and this could speed up the testing time as well as the limiting number of testing kits available. We will propose a deep learning architecture that can evaluate different segmentation of the lungs from CT images to detect if a patient is infected with COVID-19 so that we can reduce the amount of time taken to carry out testing to determine if patients are infected with COVID-19. In addition, we will calculate the severity of the lungs affected by the disease from the CT images. The lungs will be subdivided into different regions, a calculation of the severity of each region of the lungs will be carried out through evaluation of CT severity score (CT-SS) or Dice Similarity Coefficient (DSC).

INDEX TERMS Deep Learning, REMOVE THIS: TODO: update abstract, add multi-seg figure, add severity score performance

IMPACT STATEMENT The authors should include here a significance statement of no more than 30 words. The statement should summarize the main findings of the research work reported in the manuscript.

I. INTRODUCTION

COVID-19 is a newly identified disease that is very contagious and has been rapidly spreading across different countries around the world. The virus that was first identified in Wuhan has now infected more than 3.5 million people around the whole world and causes more than 245,000 deaths. Common symptoms from COVID-19 are fever, dry cough, but in more serious cases, patients can experience difficulty in breathing. As more people are infected, communities that have been in close contact with infected patients are getting tested for COVID-19. The test used to carry out the test for COVID-19 uses PCR(Polymerase Chain Reaction) test which could take several days for the test results to be available as the test samples are sent to a centralized lab for analysis and can be time consuming. There is a limited number of supplies of PCR tests which is a bottleneck for testing to be efficient. Several alternative methods have been considered to test patients that are COVID-19 positive including CT scan of the lungs. CT scans of the lungs are faster and easier to detect COVID-19 presence in patients. As the number of infected patients increases exponentially, it can be hard to provide testing scans for patients because of the limited number of doctors. It is recommended that Artificial Intelligence systems are used to analyse the CT scans of lung patients to determine the severity of COVID-19 and monitor the disease progression as well as

to compensate for the high number of patients. Specifically, we propose using deep learning to analyze and create a pixel-level segmentation of CT scan images of patients' lungs to determine the severity of COVID-19 in their lungs. In order to obtain the severity score, the model is first trained to segment the infected region of the lungs. Then, the severity score will be calculated by calculating the overlapping ratio between the segmented region for infected regions and the parenchyma of the lungs.

II. RELATED WORKS

There are several works that have been proposed to create image segmentation for CT scan lung images of COVID-19 positive patients. They have demonstrated effective solutions using deep neural networks to accurately predict if a patient has COVID-19 positive or negative.

A study has been conducted that uses multiple models for different tasks where the study uses both classification and image segmentation tasks for COVID-19 detection through multi-tasks learning. The study uses Inception Residual Recurrent Neural Network (IRRCNN) for the classification of COVID-19 detection and uses NAbLA-Net (NABLA-N) network for infected region segmentation for X-ray and CT images scan. [1] Transfer learning is used to retrain the IRRCNN model with samples to differentiate between COVID-19 positive samples and negative samples in the classification phase.

Mathematical Morphological approaches are implemented for selecting appropriate contours for chest region selection in the segmentation phase with NABLA-N network. Some classical imaging and adaptive threshold approaches are applied to extract the features to identify infected regions of COVID-19. They used a total number of 5,216 samples of which 3,875 samples are pneumonia and 1,341 samples are normal.

Another study [2] introduces a feature variation block and progressive atrous spatial pyramid pooling block using COVID-segNet, a high accuracy network that is able to create segmentation of COVID-19 infection from chest CT images. The network consists of an Encoder and a Decoder with residual skip connection connecting the encoder and the decoder at their respective layer, following the architecture of UNET [3]. Their main findings include the introduction of an FV block and a PASPP block. FV block consists of three branches - contrast enhancement branch, position sensitive branch, and identity branch. These branches can enable automatic change of parameters to display positions and boundaries of COVID-19. The PASPP block takes features extracted from the FV block to acquire semantic information with a variety of receptive fields. The dataset that they used consists of 21,658 labeled chest CT images, of which 861 CT images are confirmed COVID-19.

The paper above however conducted the study with a good amount of data samples to train the network to achieve a high performance. They obtained their dataset from hospitals through obtaining permission. We would like to create a network that does not require much labeled dataset to be able to achieve good performance. By doing this method, we could bring this network forward to detect new lung diseases when there are not much dataset available. Besides that, the paper is only able to recognize the presence of COVID-19 in a patient, but the papers could not quantify the severity of the disease.

While there is a limited number of public data samples available for CT COVID-19 lung images segmentation, it will not be feasible to train a network to achieve high performance. There are a different number of research that resolve this issue. One method is to use semi-supervised learning to mitigate the problem of having a low number of data samples to improve the performance of deep neural networks. Instead of having to manually annotate the data, semi-supervised learning utilizes the unlabeled data samples to aid in the training for the network.

Deng Pin Fan et al. [14] used semi-supervised learning to enlarge the limited number of training samples for CT lung image segmentation. They developed a model called InfNet and semi-InfNet. The InfNet version of the model uses fully supervised method to predict the segmentation of the CT images for ground-glass opacities and consolidations. The model outputs 4 images of the segmentation for the CT lung images that contains either ground-glass opacities or consolidations with different image sizes. The segmentation of the different image sizes are resized to the same size as the ground truth of the segmentation to compute the loss function. They also uses a edge loss to guide the model to predict the bounding area of the segmentation. To improve InfNet, they use semi-supervised by progressively enlarging the training dataset with

unlabeled data using random sampling strategy. Specifically, they generate pseudo labels for unlabeled CT lung images. The advantage of using semi-supervised learning is that we can generate pseudo labels to increase the number of data samples. However, semi-supervised learning still require the unlabeled CT images before being able to undergo its learning procedure.

Another study [27] uses Task-Based Feature Extraction Network (TFEN) and Covid-19 Identification Network (CIN). They propose to use task-specific feature extraction network that is tailored to CT lung images with three different classes: Healthy, pneumonia, and COVID-19 cases. They also mentioned that dataset for COVID-19 is still limited and there is not enough high quality dataset. They treat the task-specific feature extraction network as autoencoders and train the overall TFEN module to extract the relevant features from the CT images. Then, they use CIN to perform classification on the extracted features from the TFEN module. Due to the fact that by providing a person with limited CT images, they can easily detect the abnormal regions and differentiate between them very accurately by making use of prior information. This helped them develop a semi-supervised feature extraction network that allows obtaining the relevant prior information to perform the classification in order to mimic human behaviours. However, this study does not undergo segmentation of the CT lung images for better diagnosis of the CT lung images. It also does not provide the severity score of the CT lung image.

There is a study that predicts the severity score of COVID-19 on chest x-ray with deep learning [28]. They use a DenseNet model from the TorchXRyVision library as DenseNet models have been shown to predict Pneumonia well. They use a pre-training step to train the feature extraction layers and a task prediction layer. The pre-training step was used to generate a general representations of lungs and other CXRs that they would have unable to achieve from the small set of COVID-19 images available. They use a network that outputs 18 outputs of a representation of the image, 4 outputs that are a hand picked subset which contain the radiological findings (pneumonia, consolidation, lung opacity, and infiltration), and a lung opacity output. This study however did not use infected region segmentation to predict the severity score. They do not use self-supervised learning but pre-training steps to counter the limited data samples available for COVID-19.

III. PROBLEM STATEMENTS

Getting a high performance in deep neural networks requires an abundant amount of annotated samples. Performance can be drastically reduced if there are not enough data samples to compensate for the model's complexity. Likewise, complex data distributions to learn require a higher model complexity to be able to fit the distribution with better performance. The related works utilizes semi-supervised learning to increase the amount of data samples to achieve higher performance. As pixel-level segmentation on CT images is a complex task, pixel-level segmentation requires a high model complexity to fit the distribution. Unfortunately, there is a limited number of publicly available COVID-19 dataset especially in the form of pixel-level segmentation. The limited number of samples

available greatly reduce the performance of modeling complex distribution for pixel-level segmentation of CT scans lung images.

The related works does not also consider the severity of the lungs of patients as a result from COVID-19. We will propose a model and technique that utilizes self-supervised learning to mitigate the limited number of publicly available COVID-19 CT lung images samples as well as a method to calculate severity score of the segmented regions of CT lung images.

IV. METHODOLOGY

In this section, we will show the details of the self-supervised InfNet for imaging segmentation model including the network architecture, the data preprocessing steps, and the loss function. We will show how self-supervised InfNet helps to improve generalisation and performance of the model while having a limited number of data samples. We will also show the extension of our data preprocessing steps which further improves the performance of our model.

Supervised InfNet (Lung Infection Segmentation Network) will be used as our baseline to compare without using any semi-supervised learning algorithm. This is to show that the self-supervised learning method improves the performance of the baseline supervised learning InfNet for imaging segmentation. We will extend our work on supervised InfNet by adding self-supervised method to it.

We will not change the structure of the InfNet model and use the default parameters as included in their GitHub code. There will be two different types of the InfNet model. The first one will create a single-labeled segmentation of the image for the infected region. This model predicts as true of the region is either ground-glass opacities or consolidations. This will act as a prior to be fed into the multiple-labeled segmentation model concatenate with the original CT image as proposed by the author of InfNet. The multiple-labeled segmentation model will be used to predict the background, ground-glass opacities, and consolidations for the infected region. The multiple-labeled segmentation model will give each of the label a different value instead of grouping them as one as what the single-segmentation model does.

A. Self-supervised InfNet for imaging segmentation

We will propose using a self-supervised method to improve the performance of deep neural networks to create pixel-level segmentation for CT scan for lung images of COVID-19 patients. We will integrate self-supervised inpainting to pre-train our network. Since image inpainting is similarly related to image segmentation, we will integrate the pre-training steps as image inpainting for our image segmentation network. By learning features from Image inpainting, the model can learn more features that are related to image segmentation. As creating mask can be a complex task for the network to learn to inpaint, the mask can either be too complex for the network to start learning or too simple to be able to learn good representations. We will be using a coach network that increases the complexity of the masking of the CT images throughout the training of the network. The mask created will

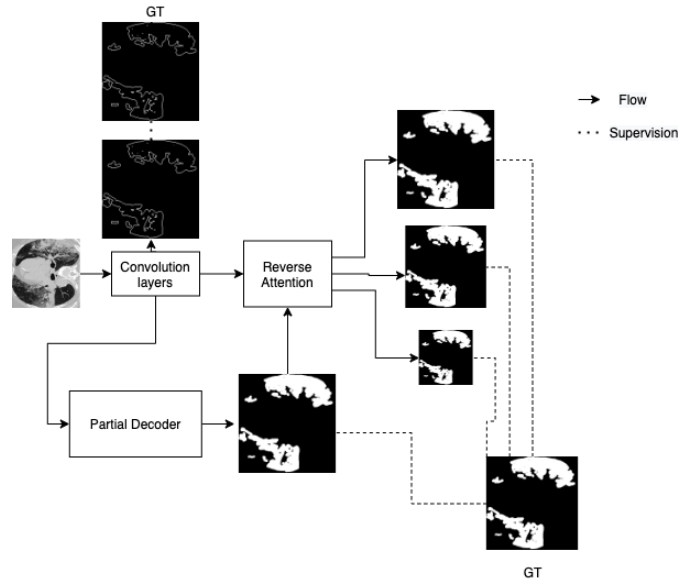


Fig. 1. The architecture of the supervised InfNet. The CT lung image is first passed into the convolutional layers to extract the features of the CT lung image. Then, the features generated from the convolutional layer are fed into the partial decoder module, reverse attention module and the edge detection module. The edge detection module is to help the network with detection of the boundaries of the segmentation. The reverse attention and the partial decoder generates the segmentation of the infection regions of the CT lung images.

initially be relatively simple, once the network is able to predict the inpainting of the CT images with good performance, the coach will increase the complexity of the masking to reduce the performance of the network, similar to how Generative Adversarial Network (GAN) works. The loss function for the coach network is:

$$L_{coach}(x) = 1 - L_{rec}(x \odot M) \quad (1)$$

where $M = C(x)$ which is created by the coach network. A constraint is apply to this loss function because the coach network would just create a mask that masks all region because no context information would be present for the network to learn and a maximum loss will be achieved. The constraint is:

$$\hat{B}(x) = B(x) - SORT(B(x))^{k/B(x)} \quad (2)$$

$$M = C(x) = \sigma(\alpha \hat{B}(x)) \quad (3)$$

The backbone, B , of the coach network has a similar network architecture with the model that inpaints the CT images. $SORT(B(x))$ sorts the features in descending order over the activation map. k represents the k^{th} elements in the sorted list and k helps to control the fraction of the image to be erased. The region that has scores lesser than the k^{th} element will be erased from the images. If k is 0.75 then 0.75 fraction of the images will not be erased. The score is scaled into a range of $[0, 1]$ using a sigmoid activation function. We keep $\alpha = 1$ while training the coach network.

After the self-supervision training is finished, the single segmentation InfNet and multi segmentation InfNet network would reuse the weights that were trained during self-

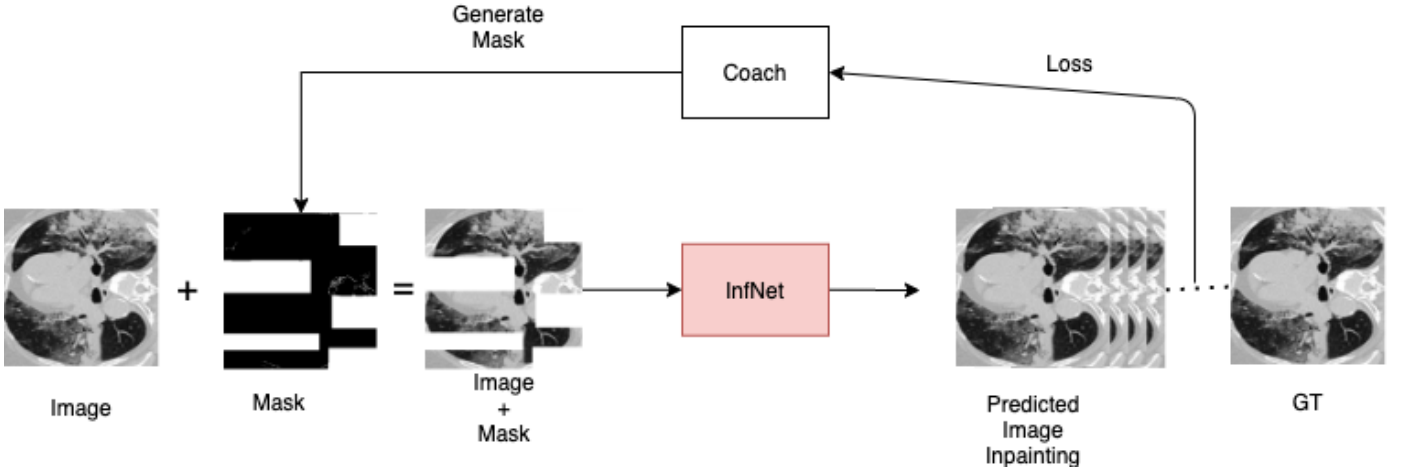


Fig. 2. The architecture of the coach network for self-supervised inpainting. The loss for the coach network is constructed from the loss of the image inpainting from the InfNet. The coach network and the InfNet both work together as a MinMax algorithm. The InfNet will try and minimize the loss to generate better image inpainting while the coach network will try to increase the loss of the image inpainting through generating more complex masks. In the beginning, the masks generated by the coach network will be less complex. Through training of the coach network, as the InfNet gets better at predicting image inpainting, the coach network generates a more complex masks.

supervised training to train normally on the segmentation for the infected regions.

The proposed self-supervised single-labeled segmentation InfNet network architecture can be seen in 3. The last layer for each output prediction is replace to a different linear activation layer. The linear activation layer will re-create the original image that is covered by the masks.

The proposed self-supervised multi-labeled segmentation InfNet network architecture is shown in 4. The changes in the architecture for the multi-labeled segmentation InfNet is similar to the single-labeled segmentation InfNet where the last layer of the layer is replace with a different linear activation layer to output the inpainting of the original image.

We will also implement different data augmentation that includes random cropping, rotation, and random cutout to increase the number of available annotated data samples and labels as well as improve the model generalization as the data samples for CT images from COVID-19 can be limited. We will show that proper data augmentation affect the performance of the model by a marginal amount.

The output of the single segmentation InfNet will include the edge of the segmentation and four single-labeled segmentation of the infected region of the CT lung images with different sizes as shown in 1. A loss will be calculated for each of the output from the InfNet model. The first loss function is the loss edge, L_{edge} which guides the model in representing better segmentation boundaries. The other loss function is the segmentation loss, L_{seg} . The segmentation loss combines both the loss of Intersection over Union (IoU) and the binary cross entropy loss. The segmentation loss equation is as follows:

$$L_{seg} = L_{IoU} + \lambda L_{BCE} \quad (4)$$

The λ is set to 1 for this experiment. The segmentation loss is adapted to all of the S_i predicted output where S_i are created from f_i such that $i = 3, 4, 5$.

Algorithm 1 Pseudo code for self-supervised with InfNet

```

Input:  $D_{labeled} = [(inputImage_1, G_{t1}), ...]$ 
for each epoch do
  for each coach step do
    mask =  $M(x)$ 
    maskedInput =  $mask \odot inputImage$ 
    predictedImage =  $network(maskedInput), inputImage$ 
     $L_{rec} = CrossEntropy(predictedImage, inputImage)$ 
     $L_{coach}(x) = 1 - L_{rec}$ 
    update coach weights
  end for
  for each network step do
     $P_{labeled} = Preprocess(D_{labeled})$  // data aug
    inpaintingOutput =  $network(P_{labeled})$ 
     $L_{rec} = CrossEntropy(InpaintingOutput, inputImage)$ 
    backpropagate and save network weights
  end for
end for
for each batch of  $D_{labeled}$ : do
   $P_{labeled} = Preprocess(D_{labeled})$ 
  trainLoss =  $train(P_{labeled})$ 
  Backpropagate train loss
  testLoss =  $test(P_{labeled})$ 
  save model weights,  $w$ .
end for

```

The total loss function for the baseline InfNet model is then:

$$L_{total} = L_{seg}(G_t, S_g) + L_{edge} + \sum_{i=3}^5 L_{seg}(G_t, S_i) \quad (5)$$

The summation of the loss functions are calculated from the output of the three convolutional layers. G_t refers to the ground truth labels. S_g is the output from the parallel partial decoder to match with the ground truth label.

As for the multiple segmentation infected region InfNet.

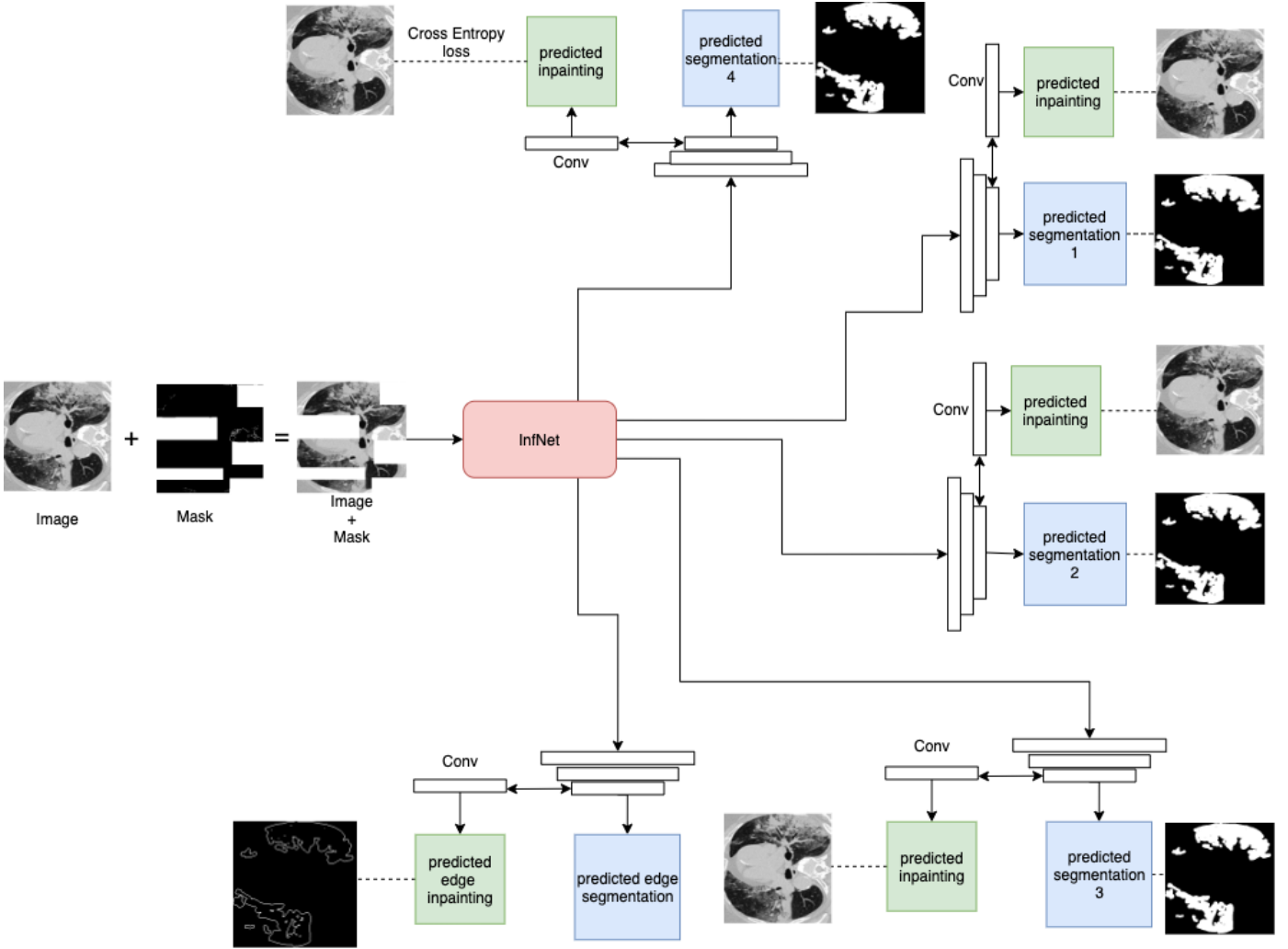


Fig. 3. The architecture of our self-supervised InfNet model. The original InfNet model would generate 5 different predictions: the edge segmentation prediction, and the other 4 are segmentation of the infected regions but of different sizes. In order to utilise the ability of self-supervised method for InfNet segmentation, we generate masks to be fed into the InfNet model. The last layer for each output prediction is not used for the self-supervised case. However, the last layer is replaced with a different layer to reconstruct the image and the edge appropriately. Everything else is kept the same as the InfNet architecture. This way the network will learn meaningful representations of the CT images and we can use these meaningful representations to learn the segmentation of the infected regions of the CT lung images. After learning the self-supervised features for InfNet, the training continues as normal similar to the InfNet algorithm. The training will start with the weights trained using the self-supervised inpainting method. The last layer will be changed to its original layer instead of the replaced convolutional layer.

We also use the default model and hypermaters from the InfNet code. We will however train the network without using any unlabeled images to be used as a supervised version. The CT lung images and prior for the CT lung images are concatenated together before being fed into the multiple segmentation InfNet. The prior is generated from the single segmentation InfNet. The prior would contain the area of the infected region. However, the prior does not contain the labels for ground-glass opacities and consolidations. It just shows the infected regions. The multiple segmentation InfNet will label the CT lung images with background, ground-glass opacities, and consolidations. The architecture for multiple segmentation InfNet can be seen in 4.

In order to improve the performance of the model and to aid in the generalisation, we determine to use self-supervised

learning to learn good representations of the CT scan of lung images. Self-supervised learning generates auxiliary tasks from the labeled data samples. For instance, when undergoing data augmentation with rotation, we could train the network to predict if the images have been rotated 0 degree, 90 degree, 180 degree to learn representations of the images.

B. Estimation of Severity of COVID-19 from CT images

Once the network is able to predict the pixel-level segmentation of the CT scan images, we will use the pre-trained network to predict the segmentation of the infected region. We will then calculate the overlap between the segmentation of the infected region and the segmentation of the parenchyma in the ICTCF dataset. We use the algorithm provided by ICTCF to split the parenchyma from the CT lung images. We remove

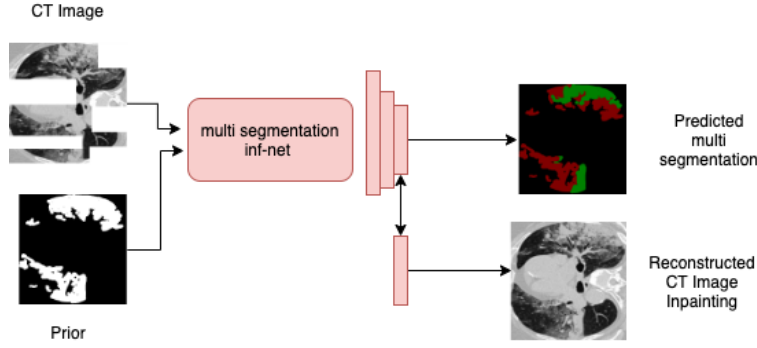


Fig. 4. The architecture of our self-supervised multi segmentation InfNet model. Similar to the supervised version of multiple InfNet, we use the same network weights and architectures. However, the last layer of the multiple segmentation InfNet is replaced with a linear activation layer to predict the inpainting for the CT images. After the self-supervised InfNet has been trained, we will train the multiple segmentation for multiple segmentation InfNet using the weights of the self-supervised InfNet. The last layer however will be changed to its original form instead of using the replaced linear activation layer. This way, all the network weights are loaded from the self-supervised version except for the last layer.

images that the parenchyma were not splitted properly. After cleaning the dataset, we end up with 1305 CT lung images with properly splitted parenchyma. We will then calculate the overlap between the infected lung region predicted by our network with the splitted parenchyma from the CT lung images to determine the severity of the lung. The higher the ratio of the overlap of the infected region to the splitted parenchyma, the higher the severity of the lung.

We will use Dice similarity coefficient (DSC) to evaluate the overlap ratio between the automatically segmented regions by the network and the reference region provided by radiologists. The equation is as follows:

$$DSC(R, S) = \frac{2|R \cap S|}{|R| + |S|} \quad (6)$$

Where R refers to the reference region provided by the radiologists and S refers to the automatically segmented regions by the network. $|\cdot|$ is the operator that is used to calculate the number of voxels in a given region.

We will compare our method against supervised and semi-supervised [13], [14] models trained on COVID-19 dataset. For comparing supervised learning, we will compare against the paper [13]. We will train and follow using the same network structure but change from supervised learning to self-supervised learning and compare the performance between supervised and self-supervised.

When comparing with the semi-supervised model, we determine that our model is successful if our model is able to reach close to or better than the performance of the semi-supervised model as semi-supervised model is able to obtain a higher amount of data samples by looking at both unannotated and annotated data samples while self-supervised model only have access to the annotated labels. A self-supervised learning method will create its own training annotated labels without any manual human labelling and trained without any unlabeled data samples. We will compare our method's performance against InfNet [14] which uses semi-supervised learning by generating pseudo labels from randomly selected unlabeled CT images.

Data split	Source	Segmented	Images	Patients
Training	Med-Seg	Yes	699	39
	ICTCF	No	6654	1338
Validation	Med-Seg	Yes	115	35
Testing	Med-Seg	Yes	118	35

TABLE I. This table shows the data distribution between the datasets that we use to evaluate our model on. Med-Seg refers to the COVID-19 CT Segmentation data set and ICTCF refers to the ICTCF data set.

Our method will be novel compare to the other methods mentioned as our method will be integrating both the segmentation of the CT lung images as well as the calculation of the severity score through calculation of the segmented infected lung areas.

V. EXPERIMENTS

A. Datasets

The dataset that we will be using is an integrative resource of chest computed tomography images and clinical features of patients with COVID-19 pneumonia (ICTCF) [23] which contains the severity score for each CT lung image and CT lung images from medical segmentation website [26].

ICTCF contains 127 types of clinical features and laboratory confirmed cases of COVID-19 from 1170 patients including the severity for the CT lung images. However, ICTCF dataset does not contain the segmentation labels for the ground-glass opacities and the consolidation in the CT lung images. In total, there are 6654 of CT lung images in ICTCF dataset. Originally, there were 1521 patients. However, some of the patients are missing CT lung images. We remove these patients that are missing CT lung images. After preprocessing the patients, the dataset was left with 1338 patients that contains CT lung images. The dataset can be found here: <http://ictcf.biocuckoo.cn/>.

As for the medical segmentation dataset, they contain ground truth label for the segmentation for ground-glass opacities and consolidation of the CT lung images but does not contain the severity score for the CT Lung images. The total amount of

Methods		Dice	Jaccard	Sen.	Spec.	MAE
Single SInfNet	Mean	0.66	0.65	0.45	0.99	14.43
	Error	± 0.06	± 0.05	± 0.07	± 0.00	± 0.77
Single SInfNet + data aug(0.4)	Mean	0.61	0.62	0.38	0.99	16.31
	Error	± 0.06	± 0.05	± 0.07	± 0.00	± 0.90
Single SInfNet + data aug (0.5)	Mean	0.64	0.63	0.41	0.99	14.67
	Error	± 0.06	± 0.05	± 0.07	± 0.00	± 0.82
Single Self-SInfNet	Mean					
	Error					
Single Self-SInfNet + data aug	Mean					
	Error					

TABLE II. Quantitative result for comparison between Single segmentation InfNet and self-supervised single segmentation InfNet

Methods		Ground-Glass Opacity					Consolidation				
		Dice	Jaccard	Sen.	Spec.	MAE	Dice	Jaccard	Sen.	Spec.	MAE
Multi SInfNet	Mean	0.32	0.43	0.40	0.993	0.32	0.18	0.45	0.20	0.996	0.007
	Error	0.004	0.05	0.06	0.003	0.004	0.05	0.04	0.06	0.001	0.003
Multi SInfNet + data aug(0.4)	Mean	0.28	0.37	0.35	0.993	0.01	0.14	0.38	0.16	0.994	0.01
	Error	0.05	0.03	0.06	0.003	0.004	0.04	0.04	0.05	0.002	0.004
Multi SInfNet + data aug(0.5)	Mean	0.30	0.42	0.37	0.993	0.01	0.15	0.45	0.15	0.997	0.007
	Error	0.05	0.03	0.06	0.003	0.004	0.05	0.03	0.05	0.001	0.004
Multi Self-SInfNet	Mean										
	Error										
Multi Self-SInfNet + data aug	Mean										
	Error										

TABLE III. Quantitative result of Ground-glass Opacities & Consolidation on the test data set. Prior is obtained from the single segmentation InfNet

Methods		Ground-Glass Opacity					Consolidation				
		Dice	Jaccard	Sen.	Spec.	MAE	Dice	Jaccard	Sen.	Spec.	MAE
Multi SInfNet	Mean	0.55	0.72	0.60	0.996	0.005	0.21	0.57	0.23	0.998	0.004
	Error	0.07	0.03	0.08	0.003	0.003	0.06	0.03	0.07	0.0007	0.002
Multi SInfNet + data aug(0.4)	Mean	0.54	0.73	0.57	0.996	0.005	0.20	0.59	0.21	0.998	0.005
	Error	0.07	0.03	0.07	0.003	0.003	0.05	0.03	0.06	0.0005	0.003
Multi SInfNet + data aug(0.5)	Mean	0.54	0.70	0.59	0.996	0.005	0.19	0.56	0.20	0.999	0.005
	Error	0.07	0.03	0.08	0.003	0.003	0.05	0.03	0.06	0.0004	0.003
Multi Self-SInfNet	Mean										
	Error										
Multi Self-SInfNet + data aug	Mean										
	Error										

TABLE IV. Quantitative result of Ground-glass Opacities & Consolidation on the test data set. Prior is obtained from the test set.

CT lung images contain in medical segmentation dataset is 932 CT lung images. We randomly assign the CT lung images into training set, validation set, and testing set of which the training set contains 699 CT lung images, the validation set contains 115 CT lung images, and the testing set contains 118 CT lung images.

The assignment of the dataset can be seen in I.

B. Data Augmentation

We used data augmentation to increase our data samples size. The data augmentation that we used includes *vertical flipping*,

horizontal flipping, *random crop*, and *random cutout*. For the random cutout percentage, we experimented that 0.5 cutout of the CT lung images yield higher performance than the rest of the value. This is because entropy at 0.5 is the highest which could increase more variability of the images. Examples of the data augmentation can be seen in figure 5.

VI. RESULTS

In this section, we will show the results of our experiments obtained. We will divide this section into two different subsections: Result for self-supervised InfNet and result for estimation of severity score.

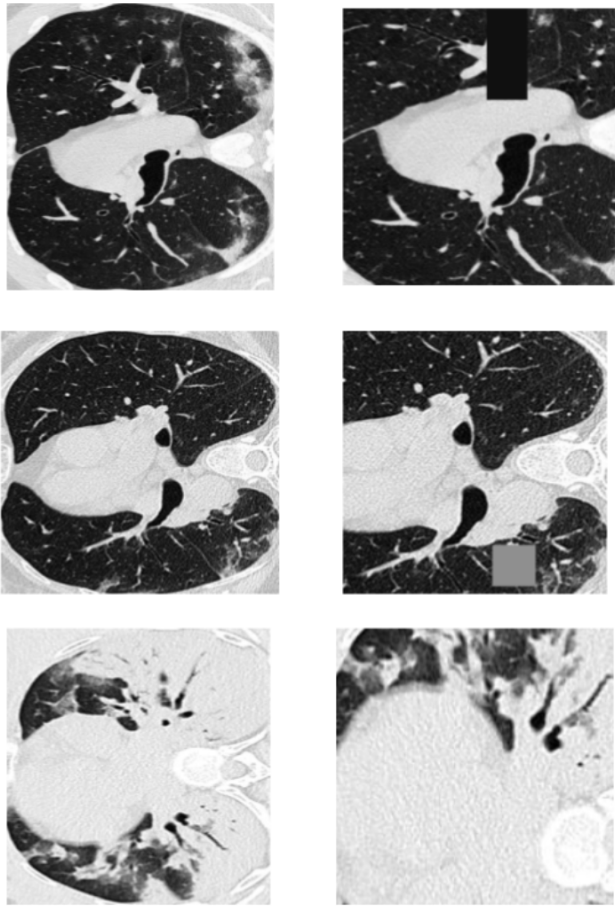


Fig. 5. Example CT lung images of our data augmentation. The left column is the original CT lung images while the right column is the augmented CT lung images. The first row of the CT lung images involves random cropping and random cutout. The second row of the CT lung images involves random cropping and random cutout. The third row of the CT lung images involves random cropping and vertical flipping. We can see the random cutout involves patching the image with colors of the same value of rgb. For instance, if the value of r is 10, then the value of g and b are also 10. If the value of r is 50, then the value of g and b are also 50.

A. Result for self-supervised InfNet

The result for our comparison between the baseline InfNet model and our self-supervised model can be seen in ???. The table is plotted with several metrics: dice, jaccard, sensitivity, specificity, and mean absolute error (MAE).

B. Result for estimation of severity score

VII. CONCLUSION

A conclusion section is required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the major findings and significance of the work or suggest applications and extensions. Do not exceed 300 words for the conclusion section.

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