

# COVID\_MTNet: COVID-19 Detection with Multi-Task Deep Learning Approaches

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## Abstract

*COVID-19 is currently one of the most life-threatening problems around the world. The fast and accurate detection of the COVID-19 infection is essential to identify, take better decisions and ensure treatment for the patients which will help save their lives. In this paper, we propose a fast and efficient way to identify COVID-19 patients with multi-task deep learning (DL) methods. Both X-ray and CT scan images are considered to evaluate the proposed technique. We employ our Inception Residual Recurrent Convolutional Neural Network with Transfer Learning (TL) approach for COVID-19 detection and our NABLA-N network model for segmenting the regions infected by COVID-19. The detection model shows around 84.67% testing accuracy from X-ray images and 98.78% accuracy in CT-images. A novel quantitative analysis strategy is also proposed in this paper to determine the percentage of infected regions in X-ray and CT images. The qualitative and quantitative results demonstrate promising results for COVID-19 detection and infected region localization.*

## 1. Introduction

COVID-19 is a highly contagious and unsafe coronavirus that has not been previously identified. The coronavirus disease 2019 (COVID-19) family is causing thousands of deaths per day around the world. Even though this virus first started from Wuhan, China in Dec. 2019, it is spreading around the world so quickly that presently more than one million people from around 188 countries have been infected with this dangerous virus as of this writing. Due to coronavirus, more than 70 thousand people have already died worldwide, and the number of new deaths has been increasing rapidly day by day. There is no treatment specifically approved for this virus. Thus, the World Health Organization (WHO) has declared COVID-19 as a pandemic disease. The mutation of this virus moving faster than align and more deadly too. This is one of the fastest progressive disease ever seen before [2]. Since it is a new type of virus and it changes formation quickly, there is no specific guideline for the assessment or examination process, and proper treatment. According to findings from Wuhan, Hubei province in China, isolation of infected

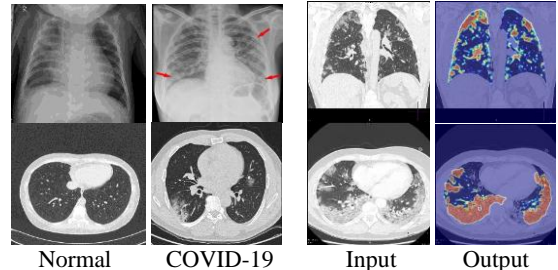


Figure 1: Example X-ray and CT images for normal versus COVID-19 detection and outputs for infected region localization with NABLA-3 network.

patients through home quarantining is the best way to protect people not already infected with this deadly virus [2]. Thus, patients with COVID-19 symptoms must remain isolated and wear masks when near others. For primary examination, a sample of nasopharyngeal exudate is taken to test reverse transcription polymerase chain reaction (RT-PCR) followed by a chest X-ray. If the chest X-ray film is normal, then the patient can go home and take rest. If COVID-19 is confirmed, the patient must be admitted to a hospital. At the initial stages, COVID-19 affects both lungs, particularly the lower lobes, and especially the posterior segments, with a fundamentally peripheral and subpleural distribution. The chest CT is used for detecting COVID-19 in practically 50% of patients in the first two days. The researcher from Tongji Hospital in Wuhan, China, has concluded that the CT should be used as the primary screening or diagnostic method to identify COVID-19.

Even though the RT-PCR has been considered as the gold standard for SARS-CoV-2 diagnosis, due to the limited supply and strict requirements for the laboratory environment, it delays the accurate diagnosis of suspected patients. Hence, this is very difficult to pose the unexpected spreading of infection of COVID-19 diseases. By combining the clinical symptoms and signs, the chest computed tomography (CT) is a faster and easier approach to identify COVID-19 in clinical practices. According to doctors and researchers in China, CT image analysis is the key method to examine suspected patients for COVID-19 confirmation. Recent reports also support this phenomenon [2,3]. It is crucial to detect COVID-19 infections at an early stage for suspected patients. It is also important for patient

prognosis, control of this epidemic, and public health security. As the rate of newly affected global regions is increasing every day, and the number of new patients added is increasing geometrically in those areas, it has become a burden or sometimes impossible to provide the necessary treatment for them [3,4,5]. Hence, an Artificial Intelligence (AI) system can be helpful to identify the COVID-19 patients quickly and accurately using X-ray and CT images as shown in Figure 1.

There are several motivations behind this research. First, accurate and faster detection of COVID-19 patients is very important for the prevention and control of this pandemic. Most importantly, it can protect human lives around the world. Second, deep learning-based radiology image analysis methods have been providing state-of-the-art testing accuracy by far compared to existing methods [6]. Recently, several Deep Learning (DL) based methods have been proposed and shown to be highly accurate for COVID-19 detection from CT images [7,12,17]. Third, around 70,000 people around the world have already died due to the COVID-19. Thus, there is a strong demand for faster and accurate detection of patients infected with COVID-19.

In this study, we apply advanced deep learning methods to investigate both X-ray and CT manifestations of coronavirus (COVID-19) pneumonia using multiple models. These include classification and segmentation for analysis of samples from two different modalities for detection and localization. For chest X-ray image analysis, due to the scarcity of publicly available COVID-19 X-ray samples, we have trained our model with a pneumonia dataset, and then utilized a Transfer Learning (TL) method for training with samples for COVID-19. The contribution of this paper can be summarized as follows:

- Proposed an end-to-end COVID-19 detection and infected region detection method using deep learning approaches
- The proposed methods are evaluated for both X-ray and CT images and achieved promising detection and infected region localization tasks.
- Training and validation are performed on publicly available samples which are collected from different sources around the world.

The paper is summarized as: section 2 discusses related works. Section 3 represents the method and the model used in the implementation. The experimental setup is discussed in Section 5. Sections 6, 7, 8 explain about detail discussion on results, limitations, and conclusion respectively.

## 2. Related works

There are several AI systems that have been proposed for COVID-19 detection from X-ray and CT images. Some studies demonstrate the efficiency of X-ray and CT scans image analysis for detecting the COVID-19. On the other

hand, other papers have demonstrated artificial Intelligence (AI) and image analysis-based methods for COVID-19 detection. In most of the cases, the Deep Learning based approaches are applied and have achieved very promising detection accuracy for COVID-19.

A study has been conducted to illustrate the importance of early detection and management of COVID-19 patients in [8]. A literature review was published recently and claimed that the ground-glass and consolidative opacities on CT are sometimes undetectable on chest radiography. The study has also suggested that CT is a more sensitive modality of medical imaging. The COVID-19 infection pulmonary manifestation is predominantly characterized by ground-glass opacification with occasional consolidation on CT [9]. The pros and cons of using X-ray and CT image analysis and its effectiveness for the screening of COVID-19 patients were explained in recent studies. In most of the cases, chest X-ray is considered as the primary screening method. In cases of patients without predominant disease, COVID-19 can be defined by chest X-ray. Otherwise the CT was recommended for determining COVID-19 infection. Another study demonstrates that Chest CT has a pivotal role for the diagnosis and assessment of lung involvement in COVID-19 pneumonia [10]. The CT plays a central role in the diagnosis of COVID-19 pneumonia and the decision has been taken by conducting an evaluation with 366 CT scans which were reviewed by two groups of radiologists. The objective of the study was to define disease progression and recovery of the illness and found that the peak period during illness were days 6-11 [11]. The performance of the Radiologists has been analysis and observed the radiologist has high specificity but moderate sensitivity in differentiating COVID-19 from viral pneumonia on CT scan [12]. For COVID-19 detection, a CT scan image analysis method found that in 20 (56%) patients out of 36 patients about 2 days after symptom onset had normal [13]. Furthermore, for critical cases, images from both modalities are recommended for decision making.

Meanwhile, there are several DL based systems that have been proposed for X-ray and CT images in the last few months for COVID-19 detection. A DL based method has been proposed for COVID-19 detection from chest X-ray which was named COVID-19 Detection Neural Network (COVNet). The ReseNet50 was used as the backbone for COVNet. This model is tested on 4356 chest CTs from 3,322 patients and showed 0.96 and 0.95 score for Area Under Curve and community acquired pneumonia (CAP) score respectively [14]. The study also demonstrates CT findings were compared for asymptomatic and symptomatic patients for COVID-19 detection and the results showed that there were no significant differences in age, sex distribution, or comorbidities for symptomatic and asymptomatic cases [14]. One of the most relevant recent

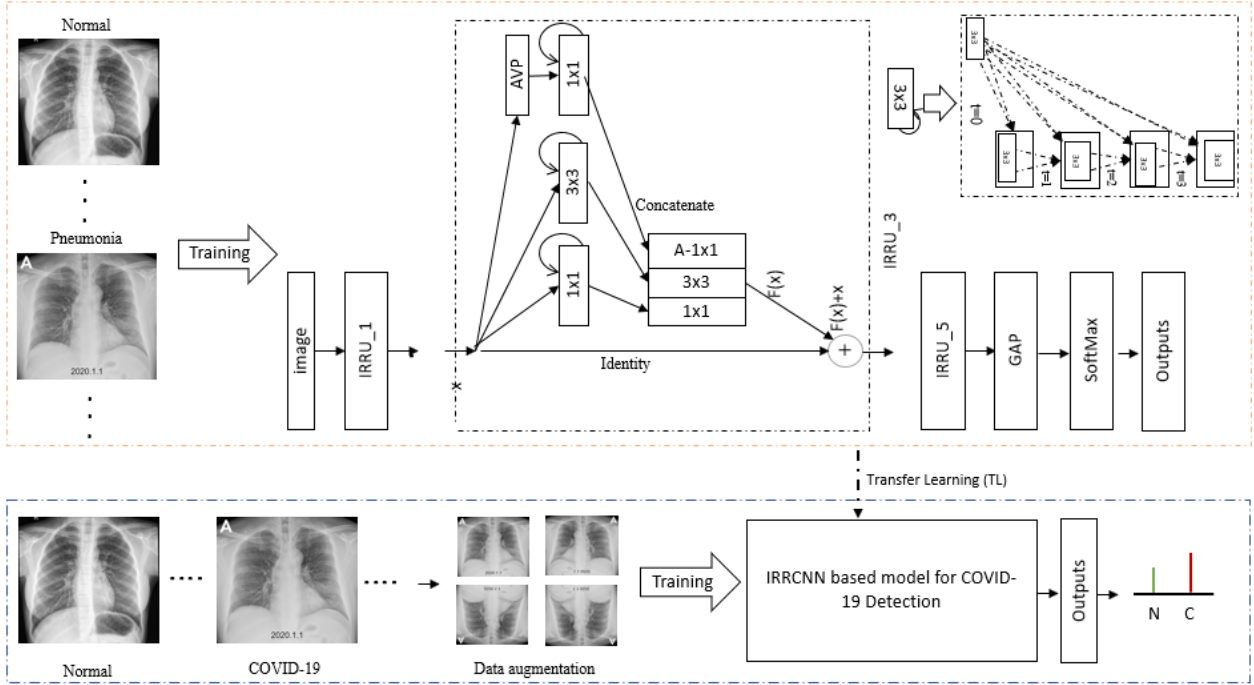


Figure 2: COVID-Det\_X-ray: End-to-end system for pneumonia detection in the top row and COVID-19 detection with TL learning from pneumonia detection at the bottom. Bottom row shows the training phase for COVID-19 which include inputs, data augmentation, training model with TL and outputs (N: normal and C: COVID-19).

models, COVID-Net [15]), uses a deep neural network with high architectural diversity and selective long-range connectivity. The model experimented on two open access data repositories, one for COVID-19 detection dataset and another for pneumonia detection dataset. The experimental results show around 83.5% testing accuracy. In this case, both databases were merged for performing training and testing of the proposed method [15]. However, in our proposed approach, we have trained a model with a pneumonia dataset and used Transfer Learning (TL) for training the same model with a COVID-19 dataset.

A deep learning-based detection for COVID-19 from Chest 3D CT volumes with weak labeled samples has been proposed recently. For each patient, a pretrained UNet model was applied for 3D lung region segmentation and then a 3D-CNN model was applied for predicting the probability of COVID-19 infections. The model was trained on 499 CT volumes and tested on 131 CT volumes and obtained 0.959 ROC AUC with 0.907 and 0.911 sensitivity and specificity respectively. Overall, this model shows around 90% accuracy [16]. In addition, the recent study shows very promising accuracy for pneumonia detection tasks where the model developed grouped three different categories: COVID-19, Influenza-A viral pneumonia, and healthy cases from CT images. The VNet based VNET-IR-RPN is used for region of interest

segmentation for pulmonary tuberculosis. The proposed deep learning-based method shows around 86.7% testing accuracy from CT images [17].

According to the literature studies, the X-ray and CT scans have been used very often to recognize the patients with COVID-19. Hence, we present here an end-to-end deep learning-based system for COVID-19 detection and infected regions detection from both X-ray and CT images.

### 3. Methodology

In this implementation, we have used multiple models for different tasks where the classification model is for COVID-19 detection and the segmentation model is used for Region of Interest (ROI) detection for COVID-19. The Inception Recurrent Residual Neural Network (IRRCNN) model is used for the COVID-19 detection task [18]. The NABLA-N network is applied for infected region segmentation from X-ray and CT images.

**COVID-19 Detection from X-ray-Image (COVID-Det\_X-ray):** first, we have used the IRRCNN model to classify the normal and pneumonia detection from chest X-ray images. Then, the Transfer Learning (TL) method is used to train with samples to determine COVID-19 and normal images from Chest X-ray images. The end-to-end training method is shown in Figure 2. The

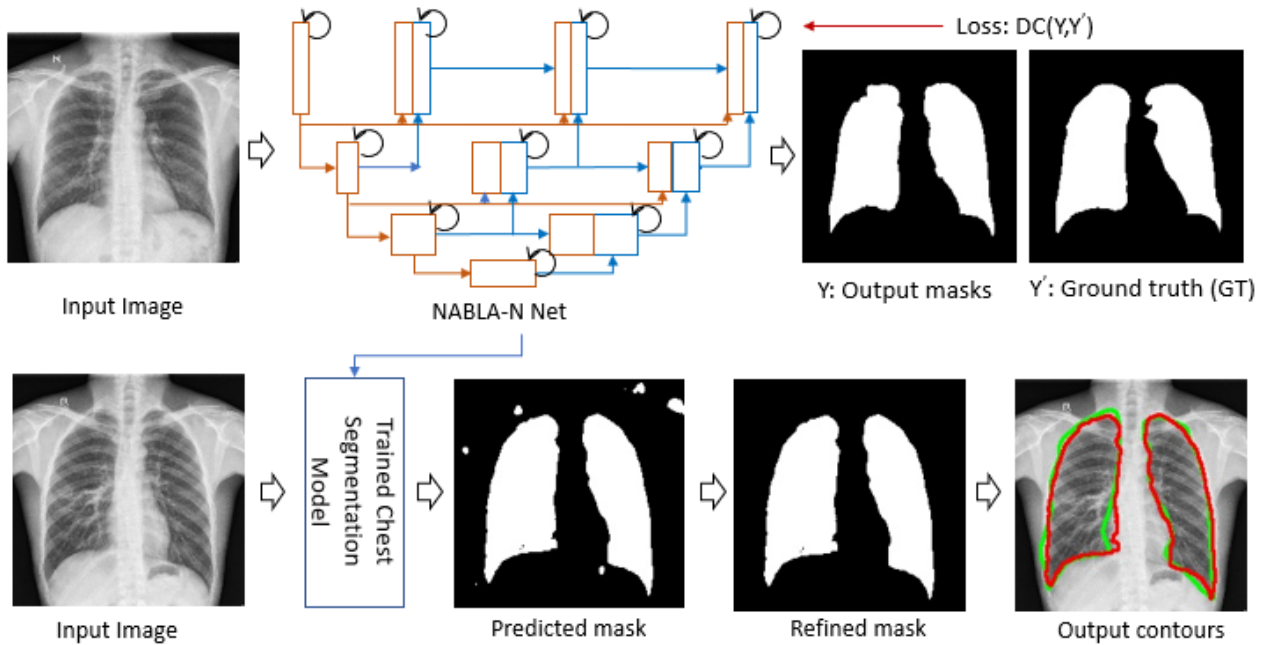


Figure 3: Chest segmentation model for X-ray (Chest-Seg\_X-ray): the top row of the figure shows the training method and bottom row demonstrates the different steps for testing phase.

IRRCNN model is used for this implementation where five Inception Recurrent Residual Unit (IRRUs) are used [18]. The IRRUs are shown for unit 3 in the top of Figure 2. After successfully training the model for COVID-19 detection, the system has been tested with completely new samples collected from new patients.

**COVID-19 segmentation from X-ray-Image (COVID-Seg\_X-ray):** another system is developed for detecting infected regions for COVID-19 in X-ray images. In this case, the NABLA-N model is applied for only chest segmentation [19]. The end to end training and testing method for chest segmentation method (Chest-Seg\_X-ray) is shown in Figure 3. Mathematical morphological approaches are applied for selecting the refinement and selecting appropriate contours for chest region extraction, which is shown in the last column of the second row in Figure 3. In the testing phase, precise chest regions are extracted. After generating segmentation masks for the chest regions, the mask is used to extract only the chest regions from the input images, which is shown in Figure 4(a). A classical image processing method and adaptive thresholding approach are applied for extracting the features to identify the infected regions of COVID-19 from the segmented chest region in Figure 4(b). Finally, the output heatmap image with COVID-19 infected regions are shown in Figure (c).

**COVID-19 detection from CT scans (COVID-Det\_CT):** CT scans are also used for detecting coronavirus which is very effective to detect the infection of COVID-19 within a couple of days after infection. This is stated according to

the assessment system followed by the expert in Wuhan, China. For COVID-Det\_CT, we have used the IRRCNN classification model, which is trained on our own datasets. The database samples are collected from normal CT and CT scan with COVID-19. From this implementation, the same methods are followed as described for COVID-Det\_X-ray.

**COVID-19 segmentation from CT scans (COVID-Seg\_CT):** for mining the specific infected region of COVID-19 virus in lung region, we have developed an end to end system for segmentation of lung region from 2D

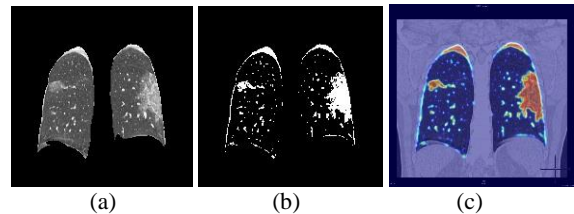


Figure 4: The pipeline processing for COVID-19 infected region detection: (a) chest regions, (d) mask for COVID-19 infected regions and (c) final heatmap image.

images where the same NABLA-N model is used as mentioned in COVID-Seg\_X-ray. First, we have trained the model on publicly available 2D lung images, which is called Lung\_Seg\_CT. Then the trained Lung\_Seg\_CT model is directly applied to segment the lung region from the entire set of CT images. Classical image processing and morphological analysis are then applied to extract infected

regions with COVID-19. The entire system is named “COVID-Seg\_CT”. For the testing phase, the same processing pipeline CT is used, which is demonstrated for X-ray, as demonstrated in Figure 3 and 4.

**Architecture details:** The IRRCNN model consists of an input layer, five IRRUs, a Global Average Pooling (GAP) layer, and a Softmax output layer. For this model, we have applied  $1 \times 1$ , and  $3 \times 3$  kernels for IRRU. The entire model utilizes around 34M network parameters. On the other hand, the NABLA-N network consists of an encoding and three decoding units. The model architecture is as followed:  $3 \rightarrow 16 \times (3 \times 3) \rightarrow 32 \times (3 \times 3) \rightarrow 64 \times (3 \times 3) \rightarrow 128 \times (3 \times 3) \rightarrow 256 \times (3 \times 3) \rightarrow 512 \times (3 \times 3) \rightarrow 256 \times (3 \times 3) \rightarrow 128 \times (3 \times 3) \rightarrow 64 \times (3 \times 3) \rightarrow 32 \times (3 \times 3) \rightarrow 16 \times (3 \times 3) \rightarrow 1$ . The general notation of  $F_N \times (M \times N)$  where  $F_N$  represents the number of feature maps and  $(M \times N)$  represents the kernel size which is  $(3 \times 3)$  kernels used in each layer except the last layer. The Rectified Linear Unit (ReLU) activation function is used all through the network in this implementation. At the end, a  $1 \times 1$  convolutional layer is used to reduce the dimension of the feature maps to the single channel outputs with a sigmoid activation function. In addition, we have utilized the up-sampled feature maps from 3 different encoding layers including the bottleneck layer. Therefore, we named the model NABLA-3 network. The NABLA-3 model utilizes totally 18.98 Million (M) network parameters. The network is initialized with the He initialization method [21].

## 4. Experiments

### 4.1. Experimental setup

The COVID-19 detection system is developed using multiple models for classification and segmentation tasks which is implemented with TensorFlow deep learning framework on four NVIDIA GTX2080 Ti single GPUs. For testing, the end-to-end system was run on the single GPU system.

### 4.2. Database

We have collected several datasets for implementing this multi-modality learning method. The pneumonia detection samples are collected from publicly available datasets in [22]. The total number of samples are 5,216, where only 1,341 samples are for normal and 3,875 samples for pneumonia. The average size of the images is around  $1168 \times 984$  pixels. Due to the limitation of our computing system, we have resized the images to  $128 \times 128$  pixels. To resolve the class imbalance problem, we have applied class specific data augmentation. The example images are shown in Figure 5. The COVID-19 dataset has been collected from different sources around the world and a publicly available dataset [23]. Due to the scarcity of training samples, we

have applied data augmentation techniques for increasing the number of samples.

For segmentation of the chest regions, we collected 704 chest X-ray images and corresponding masks, which are shown in Figure 5[24]. The original average size of the sample is  $2437 \times 2806 \times 3$ . We have resized the image to  $192 \times 192 \times 3$  pixels images. As a result, input samples significantly lose essential information. From the total number of samples, 80% of samples are used for training and the remaining 20% are used for validation and testing of the COVID-Seg\_X-ray model. This is the first step of infected regions extraction from input chest X-ray images. The randomly selected X-ray images and corresponding masks are shown in Figure 6.

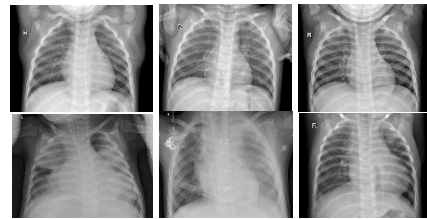


Figure 5: Randomly selected samples without pneumonia in first row and second row shows the X-ray image with pneumonia.

In addition, for COVID-19 detection from CT images, there is no labeled dataset available for this specific task. Hence, we have collected samples from different sources for normal CT scans. The COVID-19 CT images are considered from different CT scans from confirmed patients. A total of 420 samples are collected where 247 samples are for normal and 178 samples are for COVID-19. We have observed the variant sizes of the samples, the lowest dimension of the images  $450 \times 338$  pixels and highest  $630 \times 630$  pixels.

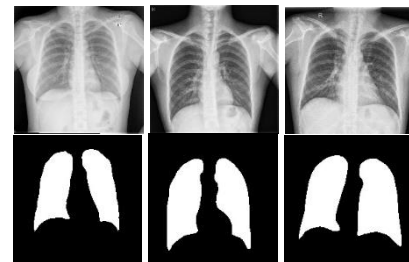


Figure 6: Example image for Chest X-ray segmentation.

Thus, all samples are resized to  $192 \times 192$  pixels. From the total samples, we randomly selected 375 samples for training and validation, and the remaining 45 samples are used for testing. To increase the number of samples, a data augmentation method is applied during the training. Randomly selected samples are shown in Figure 7.

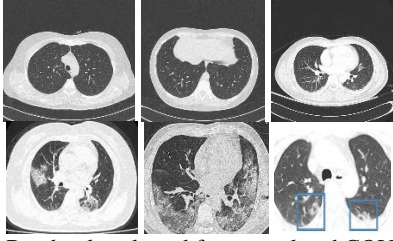


Figure 7: Randomly selected for normal and COVID-19 CT images.

For lung segmentation from CT images, we have used a publicly available 2D CT scans from Kaggle competition [25]. This dataset contains 267 samples with corresponding masks in total with corresponding labels images. Some example samples and mask are shown in Figure 8.

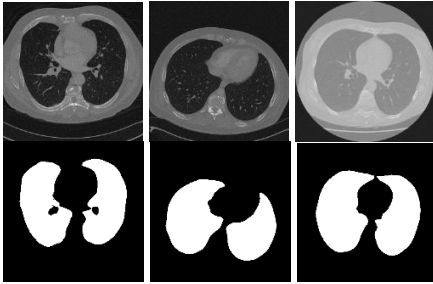


Figure 8: Example image for lung segmentation from 2D images. First row shows the input image and second row show corresponding masks.

The actual size of the images is  $512 \times 512$ . We resized them to  $256 \times 256$ -pixel single channel images. The total number of samples was 267, where 80 percent of the images were used for training and the remaining 20 percent used for validation and testing.

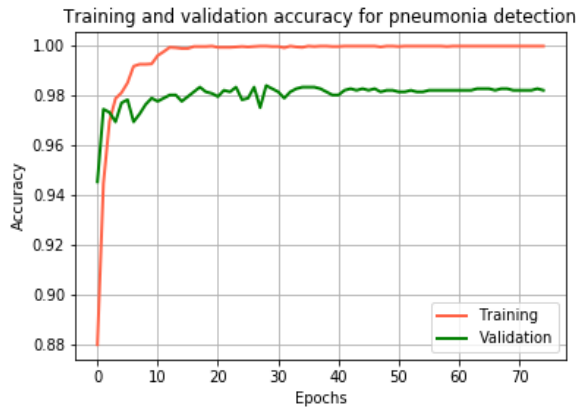


Figure 9: Training and validation accuracy for pneumonia detection task for 75 epochs.

#### 4.3. Training methods

The IRRCNN model is trained and tested on pneumonia dataset. For COVID-19 detection method for X-ray (COVID-Det\_X-ray), the model is trained with the following hyperparameters: Adam optimization method

with learning rate  $1 \times 10^{-3}$ , and Batch size 32. The system is trained for 75 epochs in total where the learning rate is decrease with respect to the factor of 10 after each 25 epochs. The training and validation accuracy for pneumonia detection method is shown in 9. From the figure, it can be seen that the proposed pneumonia detection method shown around 98.2% validation accuracy. For COVID-Seg\_X-ray is trained with Adam optimizer with learning rate  $3 \times 10^{-4}$ , Dice Coefficient (DC) loss.

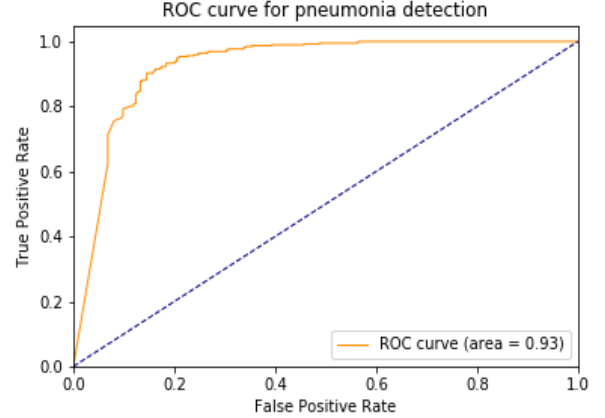


Figure 10: Receiver operating characteristic (ROC)-AUC curve for COVID-19 detection.

The classification model (COVID-Seg\_CT) is trained with same parameters as COVID-Seg\_X-ray, however, due to the less number of training samples, the model is trained 150 epoch with batch size of 16. For COVID-Seg\_CT is trained with Adam optimizer with learning rate  $3 \times 10^{-4}$ , DC loss, As the number of images is less, therefore, we have used the batch size of 8. In this implementation, we have used max min normalized single channel images for training and testing.

#### 5. Results

**COVID-Det\_X-ray outputs:** After successfully training the model, we have tested the pneumonia detection system with completely new 624 which includes 234 normal and 390 pneumonia samples. The quantitative results show around 87.26% testing accuracy for pneumonia detection. Then, the same IRRCNN model is used for training and testing for the COVID-19 detection where the pretrained weights from pneumonia are used as initial weights for training the COVID-19 model. We have achieved around 84.67% testing accuracy on the completely new 67 COVID-19 testing samples. The Receiver operating characteristic (ROC)-AUC for pneumonia is shown in Figure 10. This shows an AUC of 0.93.

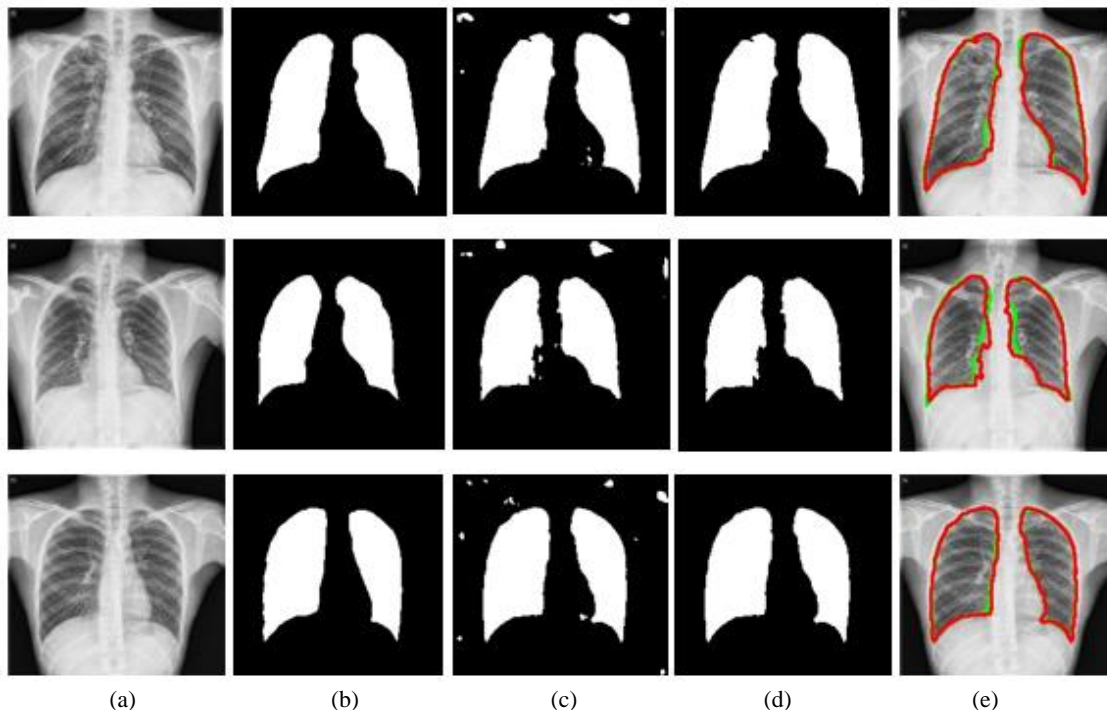


Figure 11: Chest segmentation (Chest-Seg\_X-ray) results: (a) input chest images (b) Ground Truth (c) Model outputs (d) Refined outputs and (e) Final outputs with contours where the green and red contour represent the ground truth and detection respectively.

**COVID-Seg\_X-ray outputs:** For further evaluation and to define the specific infected regions with COVID-19, we have implemented an end to end segmentation system for extracting the chest regions from the entire X-ray image. The NABLA-N network is used for chest segmentation from X-ray images. This model has been trained on the chest-x-ray segmentation challenge dataset. After successfully training the model, the performance is evaluated on the testing samples provided by the organizer. We have tested on completely new 57 chest X-ray images. The model shows 0.9452 and 0.9466 in terms of global accuracy and F1-score respectively. In addition, it shows around 0.8650 and 0.8846 for Intersection over Union (IoU) and Dice Similarity Coefficient score (DC).

The experimental results for the segmentation model for COVID-19 X-ray samples are shown in Figure 12. The first column shows the inputs images, the second column shows the outputs from COVID-Seg\_X-ray, the third column shows the polished segmentation masks, the fourth column represents outputs for only chest regions, and the fifth column shows the final outputs with COVID-19 infected regions. The qualitative results clearly demonstrate that the proposed model is able to segment and detect contaminated regions of COVID-19 accurately from the chest X-ray images.

In addition, for quantitative justification, we have calculated the total number of pixels of the lung regions and the total number of pixels for infected regions with COVID-19. The percentage is calculated with respect to the total areas of the lung, which can be used for measuring the contingency and severeness of corona-virus patients. For the first row and third column in Figure 12, the number of total pixels for lung is 6696 and total number of infected pixels with COVID-19 is 2245. Thus, the percentage of infection is 33.52% with respect to the total pixels of lung regions. In the last row of Figure 12, the total number of pixels for lung regions is 9601 and the total number of infected pixels with COVID-19 is 3609. Thus the percentage of infection is 37.58%. This quantitative analysis can be applied to define the severeness of the COVID-19 disease. For the second, third and fourth column, the percentage of infection is around 51.23%, 27.66%, and 47.89% respectively.

**COVID-Seg\_X-ray outputs for COVID-19 from Abdominal CT:** We have also observed that for some cases, patients have been confirmed with COVID-19 after analysis of the abdominal CT images. Thus, we have evaluated the same model for X-ray as has been tested on abdominal CT images. The outputs for abdominal CT images are shown in Figure 13. The first column shows the input images, the second column represents the refined segmented mask, where only large regions have been

selected among a set of segmented regions, and the fourth column shows the extracted lung region with respect to the refined mask in Figure 13(b). The classical image processing method and adaptive thresholding method are applied to extract the pixels to represent COVID-19, and the sixth column demonstrates the heatmaps for the infected regions for COVID-19. For the first row, the total

number of pixels for the lung regions is 5184 and the total number of infected pixels with COVID-19 is 1599. Hence, the percentage of infection is 30.84%. For the second and third row, the percentage of infection is 80.39% and 23.18% respectively. The quantitative and qualitative results clearly show that the proposed classification and segmentation for X-ray images demonstrate promising

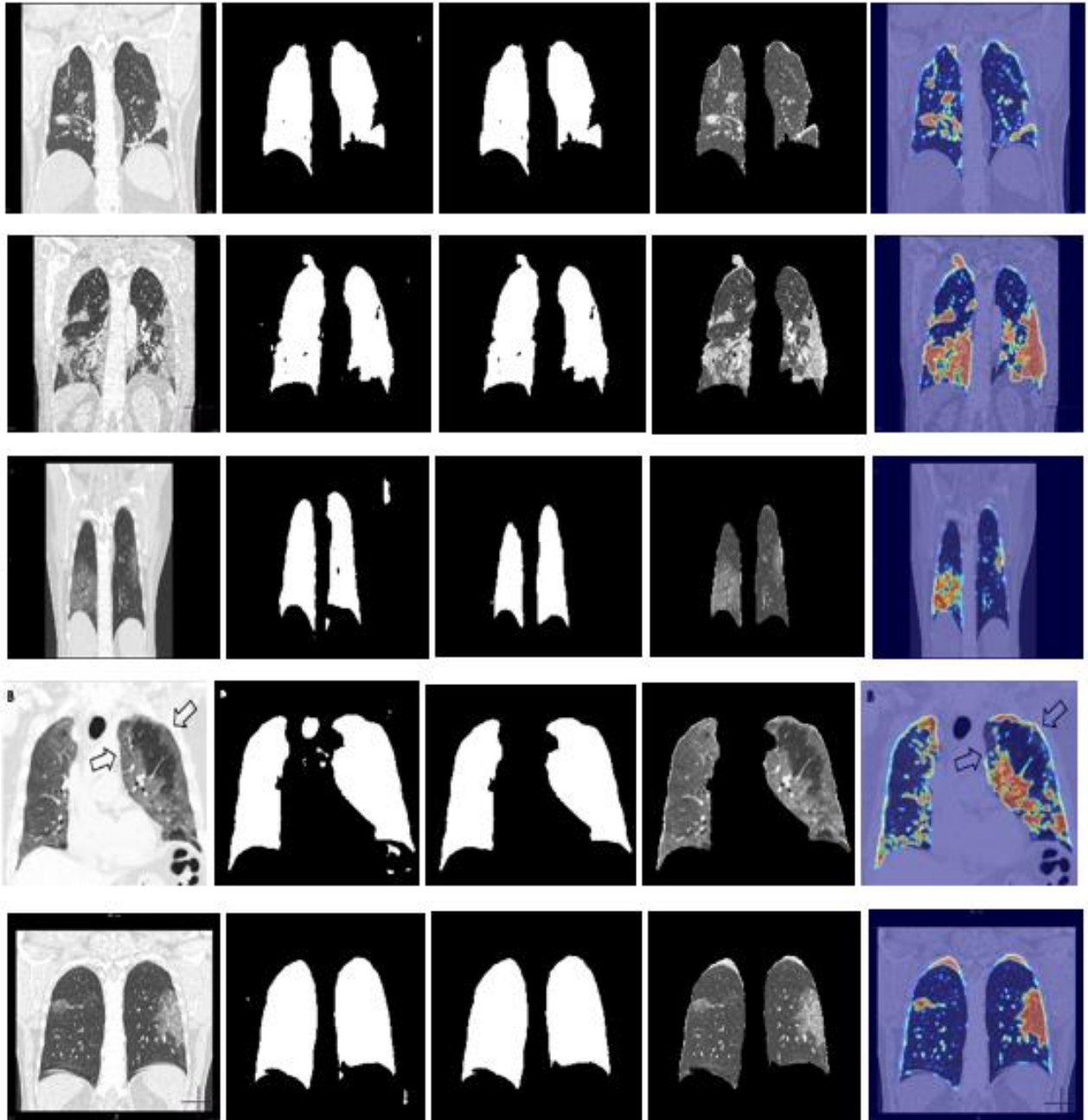


Figure 12: Experimental results of COVID-Seg\_X-ray model: first column represents the input images, second column shows the predicted segmentation masks, third column shows the refined outputs with chest regions, fourth column represent only chest regions, and fifth column represent the heatmap in the infected regions.



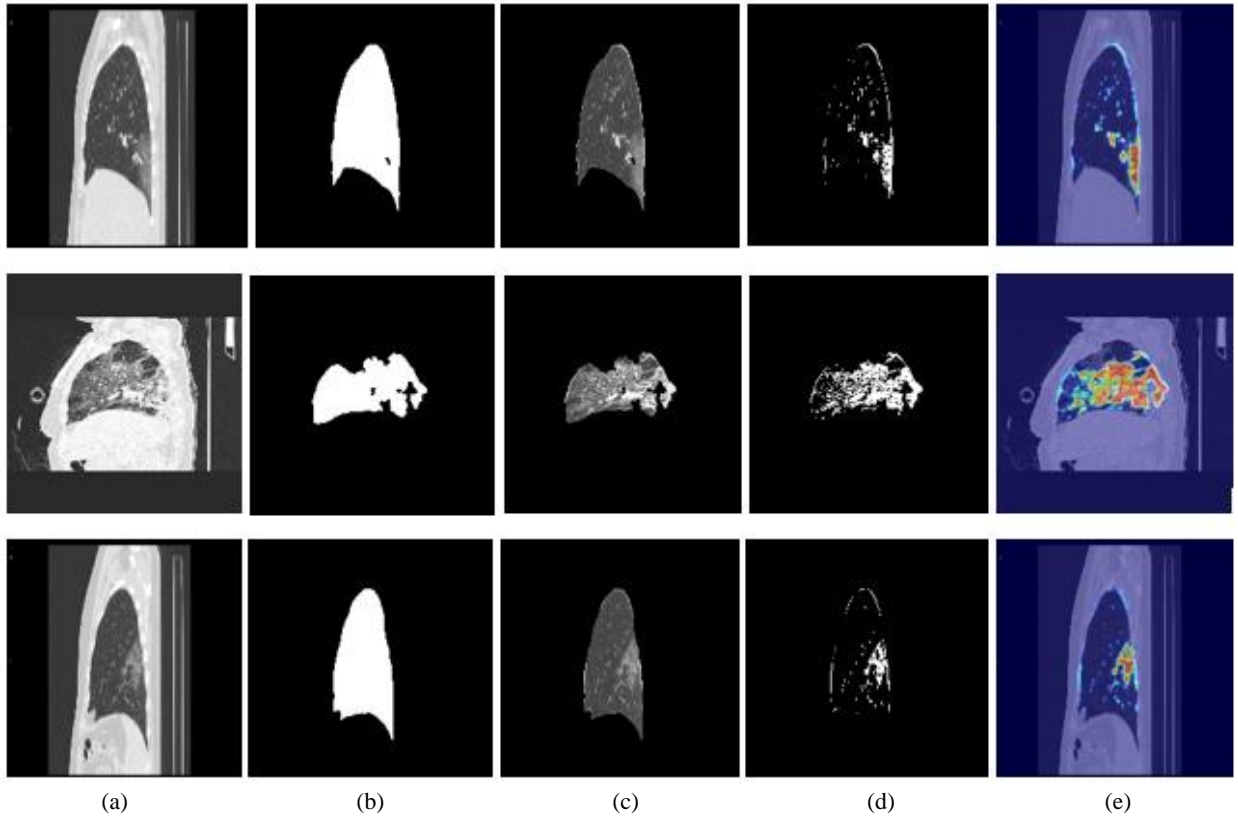


Figure 13: Experimental results of COVID-Seg\_X-ray model for abdominal CT: (a)inputs, (b) segmented masks, (c) lung regions, (d) extracted pixels for COVID-19, and (e)final heat with heatmap.

detection and infected region extraction.

**COVID-Det\_CT outputs:** From the literature survey, we have observed that CT scans are used to identify the COVID-19 detection directly. In some critical cases, Doctors fail to take a decision directly from the X-ray analysis. Instead, the CT scans are used to take final decisions on the patients. Different studies have claimed that CT is most efficient to confirm the COVID-19 patients. Thus, we have included a detection model for CT images which is named COVID-Det\_CT. The system is trained and tested on our own dataset. The COVID-Det\_CT shows around 98.78% testing accuracy for 45 samples.

**COVID-Seg\_CT outputs:** For extracting infected regions with COVID-19, the NABLA-N network-based segmentation model is trained and tested on a publicly available 2D lung segmentation dataset. This model is named COVID-Seg\_CT. After training the COVID-Seg\_CT model, the testing is done on completely new samples. The quantitative results demonstrate 0.9885 and 0.9956 for F1-score and global accuracy respectively. The qualitative results are shown in Figure 14. The first column shows the input images, the second column shows the ground truth, and the third column shows the outputs from the COVID-Seg\_CT model. The results clearly

demonstrate that the proposed model produces very accurate segmentation results compared to ground truth

Since, we did not have any label samples for COVID-19 for

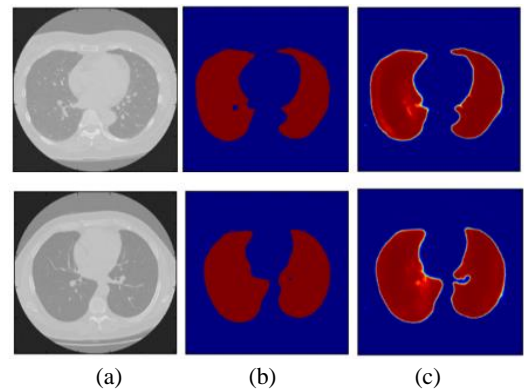


Figure 14: COVID-Seg\_CT outputs for testing samples: (a) inputs (b) Ground Truth (GT) and (c) model outputs.

segmentation tasks, the COVID-Seg\_CT model is directly applied to segment the lung regions from the samples with COVID-19. After segmenting the lung region from CT images, mathematical morphological operations are

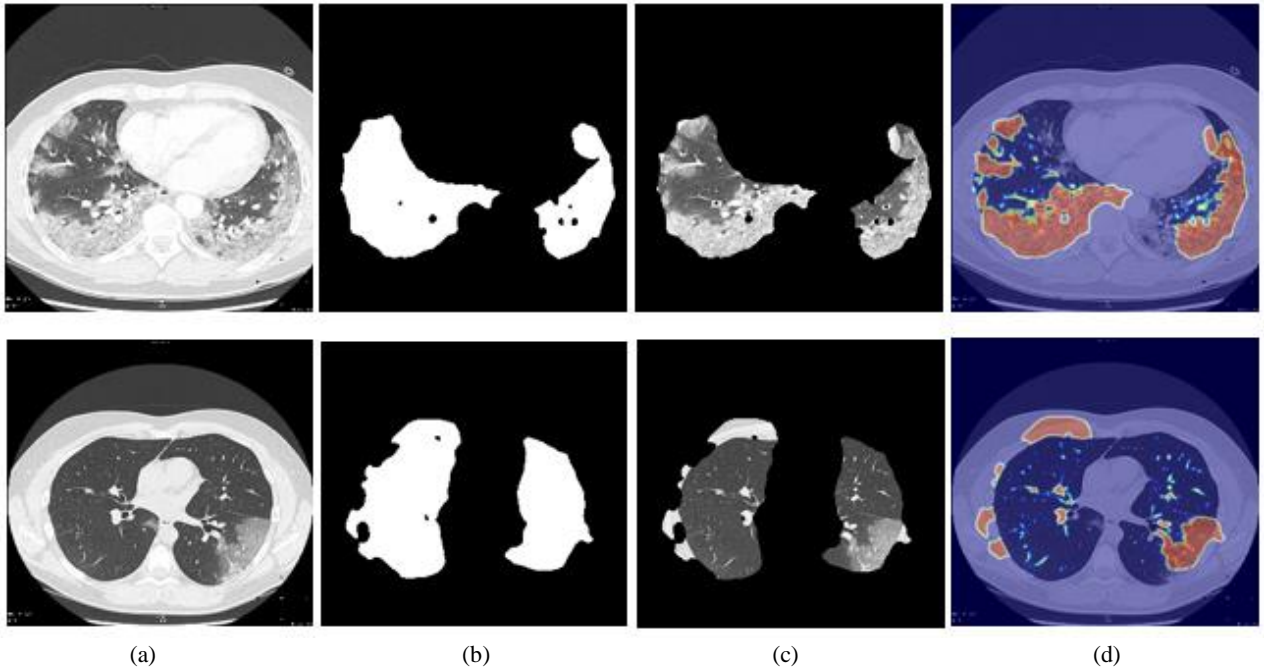


Figure 15: The COVID-19 infected region detection results from lung CT images: (a) inputs images, (b) segmented and refined masks with TL learning approach, and (d) infected region with heatmaps.

performed to refine the segmentation masks. Lung regions are then extracted with respect to the mask. The segmentation results of COVID-Seg\_CT model for COVID-19 samples are shown in Figure 15. The first column shows the input images, the second column shows the lung segmentation results, the third column represents lung regions, and the fourth column represents the result with heatmap. In most of the cases, the proposed model provides good accuracy of detection. However, in some cases, we have observed false detection, as shown in the second row in Figure 15(d).

## 6. Discussions

The proposed pneumonia detection method shows around 87.26% testing accuracy whereas the recently published paper shows 84.67% testing accuracy in [15]. Thus, our IRRCNN based detection model shows around 3.76% better testing accuracy for pneumonia detection tasks. In addition, most of the COVID-19 infected region detection methods proposed are based on patch-based detection methods for infected region extraction, where there is a big possibility to have false positive and false negative detection as the decision is taken based on the class [17]. On the other hand, we proposed an infected region with different level of evaluation for pixel level analysis. Thus, the qualitative results clearly demonstrated the infected region from the lung part and the proposed COVID-19 detection significantly reduces the possibility

of false positive and false negative detection for COVID-19.

## 7. Limitations

Both detection and segmentation methods for X-ray images provide very promising accuracy. However, there are some limitations of this study which need to be addressed in the near future. First, the COVID-Det\_X-ray model needs to be trained and tested with more COVID-19 samples. Second, as the COVID-Det\_CT model is trained and tested on only 300 samples in the initial implementation, the model provides very good detection accuracy. From our point of view, the COVID-Det\_CT model needs to be trained and tested with more samples to generalize and make the model more robust and accurate. Third, due to the scarcity of the label samples for lung segmentation from CT for COVID-19, the COVID-Seg\_CT provides outputs with false positive detection shown in the second row in Figure 15 (d). This needs to be improved.

## 8. Conclusion

In this study, we propose an end-to-end system for COVID-19 detection and infected region localization from two different modalities of medical imaging. For classification, and segmentation tasks, our improved Inception Recurrent Residual Neural Network (IRRCNN)

and NABLA-3 network models are applied. The models are tested on X-ray, abdominal CT, and full body CT images on publicly available datasets. The observed results show very promising detection results with 84.67% and 98.78% testing accuracy for COVID-19 from X-ray and CT images respectively. In addition, the qualitative results clearly demonstrate high accuracy in the segmentation and detection of infected regions by COVID-19 in both X-ray and CT images. In the near future, we would like to collect more samples of COVID-19 affected subjects to develop a robust and more accurate system.

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