Automated Detection of COVID-19 Infected.pdf

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Automated Detection of COVID-19 Infected Lesion on Computed Tomography Images Using Faster-RCNNs

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***Abstract*—The gold standard of a definitive test for the 2019 novel Corona Virus (SARS-CoV-2) is reverse-transcription polymerase chain reaction (RT-PCR). However, its sensitivity ranged between 50% - 90% with high false negatives. Currently, false negatives are real clinical problems, caused by the absence of antibodies formation during sampling (incubation period), impaired antibody formation in immunocompromised patients, apart from sample acquirement technique and transportation issue. Thus, repeated RT-PCR testing is often needed at the early stage of the disease, which may prove to be difficult in a pandemic situation. In some research, the chest computed tomography (CT) image was a rapid and reliable method to diagnose patients with suspected SARS-CoV-2 with higher sensitivity compared to RT-PCR test, particularly the lab test is negative. In this study, 420 CT images with 2,697 features from seven patients infected by SARS-CoV-2 and 200 CT images from healthy individuals are used for analyzing. The convolutional neural networks (CNNs) with Faster-RCNNs architecture is proposed to process the infected lesion detection. As a result, the proposed model shows 90.41% mAP, 99% accuracy, 98% sensitivity, 100% specificity, and 100% precision of classifier performances. All performance produces a 100% score when it tests on external data CT image. It can be seen from the detection result that Ground-glass opacities (GGO)-principal lesions on CT images in the peripheral and posterior sections of the lungs should be strongly suspected of developing SARS-CoV-2 pneumonia. On average, it took less than 0.3 seconds per image to detect the abnormalities from a CT image from data pre-processing to the output of the report. For a frontline clinical doctor, the proposed model may be a promising, supplementary diagnostic process.**

***Index Terms*—Lesion detection, SARS-CoV-2, COVID-19 pneumonia, CT images, Convolutional neural networks, Faster-RCNNs**

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I. Introduction

NOVEL coronavirus, also known as SARS-CoV-2 or COVID-19 (Corona Virus Disease 2019) has now infected more than 784,381 people in the world and spread to more than 190 countries. These numbers were reported only in less than 100 days since it was first identified in Wuhan, China, at the end of December 2019. SARS-CoV-2 belongs to the genus Betacoronavirus, one of the genera of viruses in the Coronaviridae family, the type that can infect the respiratory system [1]. In many cases, this virus only causes mild respiratory infections, with flu-like symptoms [2][3] However, the newly emerging virus can also give rise to severe respiratory infections, such as pneumonia, similar to the previously known Middle-East Respiratory Syndrome (MERS), and Severe Acute Respiratory Syndrome (SARS) [4]. There are several techniques to detect the novel COVID-19 that infected in the lung, such as reverse-transcription polymerase chain reaction (RT-PCR), gene sequencing for respiratory or blood specimens, chest X-Rays, and computed tomography (CT) chest images [3].

Currently, the gold standard of a definitive test for COVID-19 is the RT-PCR test, which is considered to be highly specific. Unfortunately, the sensitivity interval for the test result only ranged between 60-97% [1][3][4]. Therefore, false negatives are a real clinical issue, and repeat testing may be appropriate in one case to be sure about eliminating the disease. In some previous papers, CT scan imaging had been shown to yield better sensitivity than RT-PCR testing [4][5]. A research paper in the Radiology journal emphasized the importance of CT to diagnose patients with suspected SARS-CoV-2 infection, particularly when the lab test result is negative [6][7]. Another study that used data from 1,014 patients who underwent both chest CT imaging and RT-PCR test within three days revealed sensitivities of 98% and 71%, respectively [8][9]. It implies that a large number of RT-PCR tests cannot be identified quickly for treatment, probably related to a difficulty in sampling acquirement techniques or transportation in a pandemic situation. The false positives and false negatives need to be considered in diagnostic interpretation due to unestablished validity in different laboratory measurements (variability in sensitivity and specificity). False-positive RT-PCR test results may result from the cross-reactive antibodies with other various other viruses (e.g. coronavirus, dengue virus), and past infection by a coronavirus. Meanwhile, false-negative for COVID-19 can occur if the sampling test is carried out during the incubation period when the antibodies are not yet formed, or in immunocompromised patients (impaired antibody formation) [10][11].

Another alternative method that can diagnose the SARS-CoV-2 is image analysis based on the CT scans imaging data. The results of chest CT scans in SARS-CoV-2patients can show the severity of pneumonia from coronavirus. The lungs are the organs most affected by the viral reaction, with evidence of lesser damage in other organs [6][12][13]. SARS-CoV-2causes exudative inflammation with pathological features similar to those caused by SARS and MERS syndrome. However, the pulmonary fibrosis caused by the new coronavirus was not as serious as SARS [14]. Blood vessels are damaged during the reaction of the human immune system against viruses. It then allows fluid to leak into the lung tissue, which can be seen as white spots on CT images in the chest. Some CT features of lung abnormality that can be observed during the early phase of SARS-CoV-2 infection are as follows : [2][4][6] (i) lung changes in ground-glass opacities (GGO), consolidation, GGO, and reticular pattern, vacuolar sign, microvascular dilation sign, fibrotic streaks, subpleural line, and subpleural transparent line; (ii) bronchial change in air bronchogram and bronchus distortion; and (iii) pleural change in thickening of pleura, pleural retraction sign, and pleural effusion. However, the frequency of lung change, especially GGO scores, was significantly higher in early-phase disease than in advanced-phase disease [11].

In the previous study, it was determined, the majority of patients with SARS-CoV-2 pneumonia had a GGO turbidity rate of 86.1 %, or mixed and consolidated GGO of 64.4 %, and vascular enlargement in the lesion of 71.3 %. GGO are areas with interstitial thickening in the lungs [6]. The lesions on CT images of SARS-CoV-2patients were more likely to have a peripheral distribution of 87.1%. In addition, bilateral involvement, dominancy in lower lungs and multifocality were 82.2%, 54.5% and 54.5%, respectively [12]. The architectural distortion, traction bronchiectasis, and pleural effusion, possibly reflect the viral load, virulence or the level of pathogenicity of SARS-CoV-2 [12]. Such a condition can be evaluated from lung images. Chest CT severity score (CT-SS) can help to evaluate the severity and level of pneumonia caused by the coronavirus [13]; however, there were variabilities in the performance of radiologists to differentiate SARS-CoV-2with viral pneumonia [14].

Currently, deep learning (DL), one of the Artificial Intelligence (AI) approaches, has been proposed as a potential technique in CT image region detection. Based on automatic feature learning, it produces a robust model in shape, region, and spatial relation features. Specifically, Convolutional Neural Networks (CNNs) proven in automatic feature learning in medical applications like endoscopy, cardiovascular, cancer, lung infections and others [13]–[19]. It indicates the feature learning-based CNNs with CT images in the chest for detection of the SARS-CoV-2produce good performances [20]–[23]. The main features of SARS-CoV-2 are the bilateral distribution of patchy shadows and GGO [2][7]. According to hallmarks, the CNNs can process the automated feature learning that might be difficult for the conventional visual recognition approach. While typical CT images-help to screen suspected cases early on, the small CT images for early screening pneumonia caused by infectious and inflammatory lung diseases are difficult to be detected [8][9][11]. Hence, the deep investigation to diagnosis the SARS-CoV-2pneumonia is desirable.

II. Material and Method

CT image patterns of viral pneumonia caused by SARS-CoV-2shown by different pathogens. The radiologists differentiate viral infections to diagnose SARS-CoV-2

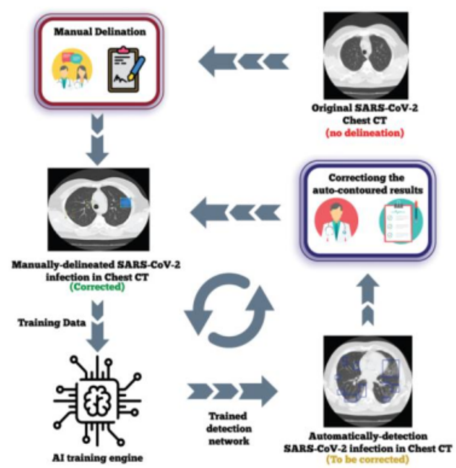


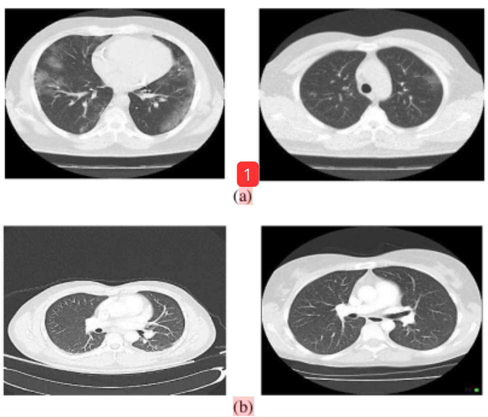
Fig. 1. The framework of Faster-RCNNs investigation for SARS-CoV-2 infected lesion detection

pneumonia by using CT imaging findings of these emerging pathogens. In this study the framework to make the CT pattern interpretation based on framework is presented in Fig. 1.

The CT image as raw data, and it is delineation by radiologists to assign the region infected by viral. All the delineation data is divided into data training, validation, and testing. The AI approach uses for learning with deep structure by using CNNs-based region detection. When the region is detected, it is validated again by radiologists to ensure the result for making the robustness of CNNs model.

A. Data Preparation

A number of data used in this study were collected from 419 CT scan images SARS-CoV-2 infected cases from seven patients, and 200 CT scan images of normal condition from two patients from a well-known website [23]. The view of CT images from 4 ways, axial lung window, axial non-contrast, coronal lung window, and coronal non-contrast. In this study, three radiologist experts create manual delineation for the infected region before the learning process. In this study, the CT patterns of viral pneumonia only are related to the pathogenesis of SARS-CoV-2 infections by using region of interest (ROI) images to define the inflammatory lesions based on ground-glass opacity, mosaic sign, and interlobular septal thickening as presented in Fig. 2 (a), and health condition in Fig. 2 (b).



(a)

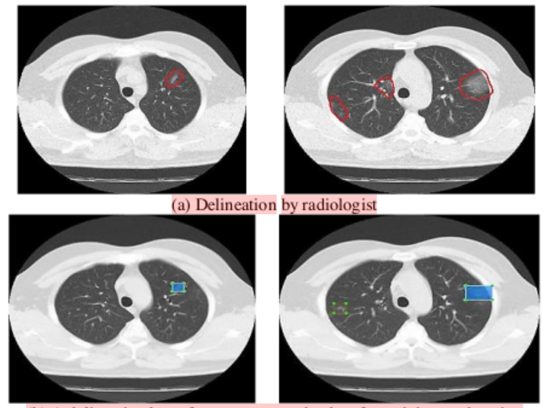
(b)

Fig. 2. (a) Sample of CT scan images SARS-CoV-2 infected; (b) sample of CT scan images of healthy condition.

B. Pre-processing

In this stage, data delineation from the radiologist is annotated again for custom classes of CT images dataset with bounding boxes process as presented in Fig. 3 (a). In addition, an example of delineation by the software is presented in Fig. 3 (b). The input data which contains a bunch of images with their bounding boxes information. All data infected by SARS-CoV-2 were about 419 images with a pixel size that varies from 256 x 256 pixels until 1500 x 1800 pixels. Prior to the learning process, the data is splitting into two, i.e. (1) 80 % for training about 335 images and (2) 20% remaining for testing about 84 images.

All process to detect infected lesion by SARS-CoV-2 is presented in Fig. 4. There are four stages of completing the whole process, i.e. (i) pre-processing of the CT images to extract effective pulmonary regions; (ii) multiple candidate image cubes were segmented using a 2D CNN model, the center image was collected along with the two neighbors of each cube for further steps; (iii) an image detection model was used to categorize all the image patches into two types normal and infected with average precision (AP) score to select the confidence value of candidate recognition as a whole; and (iv). The probability function uses to measure the lesion as normal or infected by SARS-CoV-2. The ROI is sketched on the CT images based on at least three features of pneumonia, including ground-glass opacity, mosaic sign, and interlobular septal thickening [2][8][11]. For ROI, it is sized approximately from 600x600 pixels up to 1024x1024 pixel.



(a) Delineation by radiologist

(b) A delineation by software to create the data for training, and testing

Fig. 3. CT scan images preparation for the learning process.

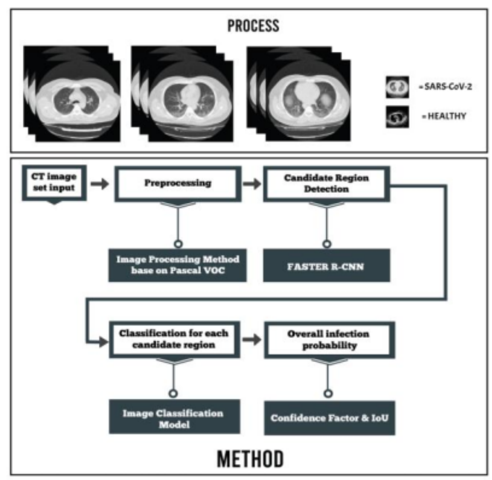


Fig. 4. The process of infected lesion detection.

C. Faster-RCNNs

CNNs, with the strong ability of nonlinear modeling, have extensive applications in medical image processing as well [24][25]. One of the CNNs architecture is based on an object detection approach for exploring the infected region by SARS-CoV-2, named Faster-RCNNs used in this study [26]. The proposed architecture with Faster R-CNNs is presented in Fig. 5. The architecture consists of the region proposal network (RPN) as an algorithm for region proposal and the Fast R-CNNs as a network for detectors. The RPN starts with the input image, which is fed into the backbone CNNs. The backbone network is used to recognize the infected region caused by SARS-CoV-2 in the lung as a pneumonia condition. VGG16 and ResNet50 architecture are created to produce high accuracy of region detection. The Faster R-CNNs detector also consists of a backbone of the CNNs, a pooling layer of the ROI and fully connected layers followed by two sibling branches for classification and bounding box regression. A detail of the Faster R-CNNs general architecture, as shown in Fig. 5.

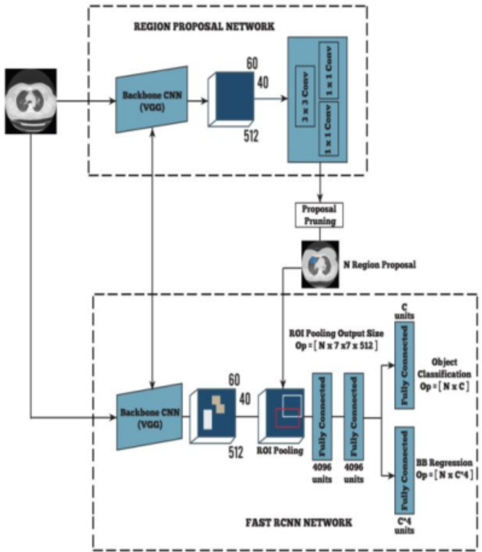


Fig. 5. The Faster-RCNNs architecture.

The proposed model must tune the hyperparameter to reduce the false negative and false positive of bounding box detection. Therefore this system is warranted to be further optimized and tested. Training and testing both region proposal and object detection networks on CT images are developed of a single scale of about 600 pixels and up to 1024 pixels. Two backbone CNNs architecture models, such as VGG16 and ResNet50 will be compared to select the best model. For the RPNs backbone modeling with hyperparameters 50 epochs to 200 epochs, one batch size, 0.0001 learning rate, and 0.9 momentum. For achieving the best sensitivity and specificity of the CNNs detection, Stochastic Gradient Descent (SGD), and Adam optimizer utilized for the pre-trained VGG16. All hyperparameter tuning for feature learning of 2,697 "bounding box" from 275 images. In the fine-tuning for Faster RCNN architecture

TABLE I
FASTER-RCNNS STRUCTURE

Layer	Number of Filter	Kernel size	Stride
Convolution	64	3x3	1
Convolution	64	3x3	1
Max Polling	-	2x2	2
Convolution	128	3x3	1
Convolution	128	3x3	1
Max Polling	-	2x2	2
Convolution	256	3x3	1
Convolution	256	3x3	1
Convolution	256	3x3	1
Max Polling	-	2x2	2
Convolution	512	3x3	1
Convolution	512	3x3	1
Convolution	512	3x3	1
Max Polling	-	2x2	2
Convolution	512	3x3	1
Convolution	512	3x3	1
Convolution	512	3x3	1

was used anchor box scale: 128, 256, and 512 pixels with ratio: (1:1), (1:2), and (2:1) respectively. All bounding box is the same object as lung region infected by SARS-CoV-2, therefore the overlap RPNs is set at min = 0.3 and max = 0.5, also overlap classifier ROI is set a min = 0.1 and max = 0.5. The Faster-RCNNs structure, as seen in Table 1. In the last filter, 512 pixels used, induced by the large stride, provide good results, although accuracy can be further improved with a smaller stride.

D. Performances Evaluation Metric

In this study, the CNNs-based object detection is based on regression and classification process with two performances evaluation values such as, mean intersection over union (mIoU), and mean average precision (mAP). The concept of mIoU and mAP use to computes how much the predicted boundary (bounding box) overlaps with the ground truth in the two process, good performance model that implies two bounding boxes perfectly overlap. If the overlap value above the threshold are considered positive, and below the threshold are considered negative. The confidence score for each object identified by the model in the image needs to be considered as well. It expected to have a confidence score above a certain threshold. In our proposed model, all objects in the bounding box are associated as areas infected by SARS-CoV-2 in different sizes. From very small to large in one lung area. So if the bounding box prediction cuts at least 0.3 part of the ground truth, it is assumed that the infected area has been detected; therefore, the IoU threshold is tuning between 0.3 to 0.5. The proposed model also calculates the accuracy (Acc.), sensitivity (Sens.), specificity (Spec.), and precision (Prec.) to know the whole object detection performances. To ensure the process of object detection run in a good performance, an Intel i9-9900k CPU together with NVIDIA GPU RTX 2080ti 11GB was used as server for testing. The processing time depended largely on the number of convolution layers in one CT image set.

III. RESULTS AND DISCUSSION

The gold standard for the SARS-CoV-2 diagnosis has nucleic acid identification based on RT-PCR for the existence of specific gene sequences. However, the high number of false negatives also occurs due to many factors, such as methodological drawbacks, disease stages, and specimen collection methods that may delay diagnosis and control of disease. Recent data suggest that nucleic acid testing accuracy is only around 50-90% [3][6][7]. Due to the limitation of RT-PCR test, there is an immediate need to look for other simple alternative approaches which can be used by frontline health care workers to diagnose the disease rapidly and accurately.

Our study represents the AI-based region-CNNs technologies for effectively screening of CT images caused by SARS-CoV-2. In terms of CT image lesion distribution, SARS-CoV-2 patients were more likely to have peripheral distribution (87.1%), bilateral involvement (82.2%), lower lung predominance (54.5%), and multifocal distribution (54.5%), consistent with the findings of previous studies [10][11]. To develop a detection algorithm, two physicians in radiologists delineation the 420 images with 2,697 features as ground truth for a prediction and two physicians for validation of the result. By using Faster-RCNN, it achieved an accuracy of about 99% in the best model (see Table 2). Other performance to indicate the proposed model produce good detection such as 98 % sensitivity, 100 % specificity, and 100% precision for each image at the testing stage with 0.3 of IoU. Moreover, in this study, mAP is also used to measure the overlapping area between ground truth and predicted image (see Table 3). In Fig. 3, the Faster-RCNN produce high mAP with VGG16 architecture as RPN backbone about 90.41% greater than Resnet50 architecture backbone about 84.55%. It means VGG16 produce good performance to detect the image infected by SARS-CoV-2.

TABLE II
PRE-TRAINING AND FINE-TUNING PROCESS OF FASTER-RCNNS ARCHITECTURE FOR SELECTING THE BEST MODEL WITH 200 EPOCHS

Training with	Back-bone	IoU	Sens. (%)	Spec (%)	Prec . (%)	Acc. (%)
SARS-CoV-2 image 1024 pixels	VGG16	0.3	98	100	100	99
SARS-CoV-2 image 1024 pixels	VGG16	0.4	98	85	96	96
SARS-CoV-2 image 1024 pixels	VGG16	0.5	98	71	87	88
SARS-CoV-2 and healthy image 1024 pixels	VGG16	0.3	95	90	98	94
SARS-CoV-2 and healthy image 1024 pixels	VGG16	0.4	95	82	96	93
SARS-CoV-2 and healthy image 1024 pixels	VGG16	0.5	94	70	84	82
SARS-CoV-2 and healthy image 600 pixels	VGG16	0.3	95	82	96	93
SARS-CoV-2 and healthy image 600 pixels	VGG16	0.4	94	64	91	88
SARS-CoV-2 and healthy image 600 pixels	VGG16	0.5	94	75	80	79
SARS-CoV-2 and healthy image 1024 pixels	ResNet50	0.3	90	86	98	90
SARS-CoV-2 and healthy image 1024 pixels	ResNet50	0.4	90	67	94	87
SARS-CoV-2 and healthy image 1024 pixels	ResNet50	0.5	88	62	76	72

TABLE III
THE FASTER-RCNNS ARCHITECTURE PERFORMANCE FOR MEASURING THE OVERLAPPING BETWEEN GROUND TRUTH AND PREDICTED IMAGE IN MAP METRIC

Back bone	IoU	mAP (%)
VGG16	0.5	90.41
Resnet50	0.5	84.55

The result of CT images detection for two conditions, including SARS-CoV-2 infected and healthy, is presented in Fig. 6. Multiple infected regions of SARS-CoV-2can have single or double lesions, lower lobes are more commonly affected than upper and middle lobes and the right middle lobe is the least infectious (see Fig. 6 (a)). The result shows that the majority of COVID-19 cases have common characteristics on CT images, including early ground-glass and late-stage pulmonary consolidation opacities. The pathogenic feature in CT imaging is associated with their specific pathogenesis of the lung lesion, such as patchy, nodular, honeycomb, grid, or strips. Some of the images in which the lesion density is often irregular with the primary appearance of ground-glass opacity followed by interlobular or intralobular septa thickening. The lesion can also present aggregation and development of fiber stripes as paving stones. By using CNNs based region infected, all feature can detect with some bounding box in the whole images.

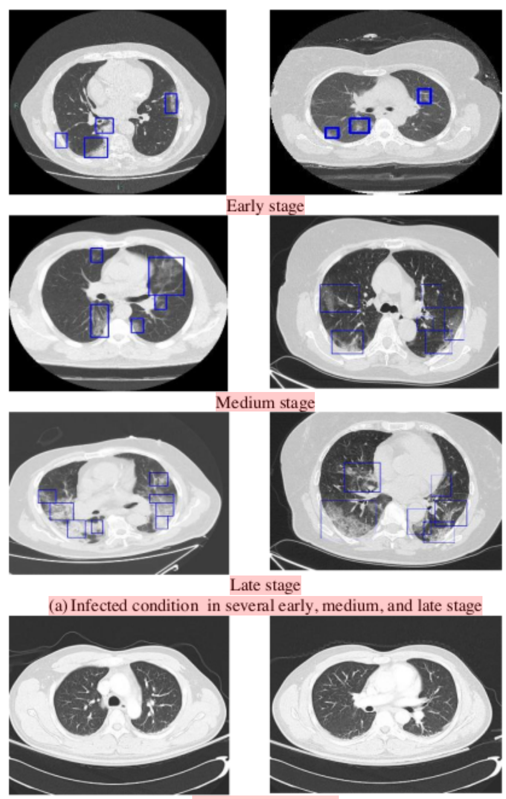


Fig. 6. The object detection in CT images results with two conditions infected lesion by SARS-CoV-2 and healthy.

In this study, the most surprising result, when the proposed model predicted the external data positive and negative cases. The proposed model still managed to predict 100% for all metrics in terms of accuracy, sensitivity, specificity, and precision certainty that the lungs with the

TABLE IV
RESEARCH BENCHMARKING FOR LUNG IMAGE DETECTION IN THE TESTING STAGE

[illegible]	[illegible]	Acc.	Sens.	Spec.
[illegible]	[illegible]			
Song et. al. [27]	SARS-CoV-2, bacteria, and healthy	-	93	-
Chen et. al. [28]	SARS-CoV-2, and other viral	95.2	100	93.6
Narin et. al. [29]	SARS-CoV-2, MERS, SARS, and healthy	98	-	-
Hemdan et. al. [30]	SARS-CoV-2, and healthy	90	-	-
Zheng et. al. [31]	SARS-CoV-2, and healthy	90.1	-	-
Proposed model	SARS-CoV-2, and healthy	99	98	100
	External data without training	100	100	100

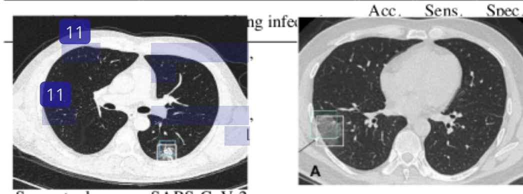


Fig. 7. Sample of testing results with external data.

infected region in the images are positive for SARS-CoV-2 as presented in Fig. 7.

The amounts of studies have used the DL approach for the SARS-CoV-2 infected CT image lung classification given its superior performance. However, such detection requires high sensitivity and specificity to avoid generating many false negatives that may cause excessive anxiety in the patient. The comparison between our model with another DL approach can be seen in Table 4. The result found that our model improves performance. All the results have been produced in this research make it a promising good screening tool for SARS-CoV-2. During the existing outbreaks and potential pandemics of COVID-19, the DL, especially CNNs model, can potentially serve as a powerful tool for lung CT imaging screening. Using the supercomputer system, by using our proposed model the time for detection, each case only takes about 0.2-0.3 seconds, and can be done remotely via a shared public platform. Therefore further improvement of this method will greatly shorten the diagnostic time for control of disease. Hence, the proposed AI approach should significantly contribute to the control of COVID-19. The detection result can be reducing (i) the number of persons under investigations for timely quarantine and treatment, and (ii) human-to-human transmission.

However, there are some drawbacks due to the comparatively large number of variable objects around 2,697, such as CT images reflect a difficult task of classification, especially those outside the lungs that are irrelevant to pneumonia diagnosis, (ii) the training data patients set is relatively small variation about nine patients, the predicted performance can increase with increased training volume, (iii) the features of the CT images examined were in late-stage patients with severe lung lesions, (iv) the research must enroll some cases of SARS-CoV-2 patients with early-stage for making the algorithm robustness, (v) this study not include the data patient with a false negative in the RT-PCR test as a case in the robustness test, and (vi) comprehensive investigation with other virus infections can enable us to distinguish between SARS-CoV-2 pneumonia and other lung infections.

IV. CONCLUSION

To identify COVID-19 with higher sensitivity, the combination of clinical symptoms, exposure history, typical CT lung imaging features, and dynamic changes must be considered. Since single RT-PCR testing only produces a low sensitivity, it should not exclude the diagnosis of SARS-CoV-2, especially if clinical suspicion is high. To provide early recommendations based on CT lung imaging, this study developed the CNNs model with an object detection approach. As depicted in the results, the proposed model can detect the infected region by SARS-CoV-2 on CT chest radiography 99% accuracy, 98% sensitivity, 100 % specificity, and 100% precision. The testing by using external data produce 100% accuracy, 100% sensitivity, and 100% specificity. In the present study, the number of model samples was limited. Therefore, to achieved a better model with high-performance, high efforts should be made to improve the bounding box, segmentation, and classification model. Moreover, the efficiency of this generalization algorithm should be validated with a larger set of data. Hence, the training and testing of the number of samples should be expanded to improve performance in the future. It can be concluded that our proposed CNNs architecture model can overcome the limited number of CT images data with good value in all performance metrics in the object detection approach. It could be a helpful, additional diagnostic tool for clinical doctors on the frontline.

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