



# Non-Invasive Technique-Based Novel Corona(COVID-19) Virus Detection Using CNN

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**Abstract** A novel human coronavirus 2 (SARS-CoV-2) is an extremely acute respiratory syndrome which was reported in Wuhan, China in the later half 2019. Most of its primary epidemiological aspects are not appropriately known, which has a direct effect on monitoring, practices and controls. The main objective of this work is to propose a high speed, accurate and highly sensitive CT scan approach for diagnosis of COVID19. The CT scan images display several small patches of shadows and interstitial shifts, particularly in the lung periphery. The proposed method utilizes the ResNet architecture Convolution Neural Network for training the images provided by the CT scan to diagnose the coronavirus-affected patients effectively. By comparing the testing images with the training images, the affected patient is identified accurately. The accuracy and specificity are obtained 95.09% and 81.89%, respectively, on the sample dataset based on CT images without the inclusion of another set of data such as geographical location, population density, etc. Also, the sensitivity is obtained 100% in this method. Based on the results, it is evident that the COVID-19 positive patients can be classified perfectly by using the proposed method.

**Keywords** Coronavirus · CT scan · Diagnosis · Convolution neural network

**Mathematics Subject Classification** 94B10 · 62M45

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## Significant Statement

1. This work proposes an expedite, accurate imagining approach to diagnose COVID19.
2. Small shadow patches, interstitial shifts in the lungs due to the virus are traced through CT images and are trained using ResNet architecture in CNN to obtain 95.09% accuracy.
3. When compared with RT-PCR method, this gives high accuracy, sensitivity, specificity.

COVID19 is an acute, often critical respiratory disorder induced by a novel SARS-CoV2 coronavirus. COVID-19 is confirmed by the Reverse Transcription Polymerase Chain Reactors (RT-PCR) or breathing gene sequences or blood samples as the primary predictor of hospitalization [1]. It can be seen that many researchers are undergoing treatment and vaccination research for coronavirus [2–4]. As radiology is frequently the first destination for patients with an immediate febrile condition, the treatment of such patients plays a significant role in the detection and infection control of the particular patients [5]. The deep learning was applied to the detection of cancer cells [6–13] and tumour [14] from CT scan images are performed. This work supports a novel computer-aided diagnosis system for Covid-19 detection based on a Deep Convolution Neural Network (D-CNN). Here, ResNet-16 network architecture is used for training and labelling the dataset. In the early stage of COVID-19, images indicate many irregular patches and cross-sectional shifts in the lungs. As the disease progresses, multiple ground glass shadows and cross-sectional shift gets developed in the images. Lung consolidation may happen in severe cases. Pleural effusion is rarely observed in COVID-19 patients.

The sequential procedure for automatic diagnosis of COVID19 by CNN is given in Fig. 1. The fine-tuned Convolution Neural Network is implemented for automatic diagnose of COVID-19 patient. In this method, the two types of dataset are considered. One is the COVID-19 image dataset (Fig. 2a) has taken from the GitHub repo [15]. The sample dataset of the healthy patients is taken from the Kaggles CT dataset (Fig. 2b) as the reference images or training dataset. Training the CNN is performed by automated segmentation of the lung image to extract the patches of corona, non-corona and background images. Initially, the CT scan image is divided into blocks, and the average and variance are calculated for each block from Eqs. 1 and 2. With these calculations, the pixels of whole image are classified.

$$AVG_{x,y} = \frac{1}{k^2} \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} L(x+m, y+n) \quad (1)$$

$$VAR_{x,y} = \frac{1}{k^2} \sum_{m=0}^{k-1} \left( \sum_{n=0}^{k-1} L(x+m, y+n) - AVG_{x,y} \right) \quad (2)$$

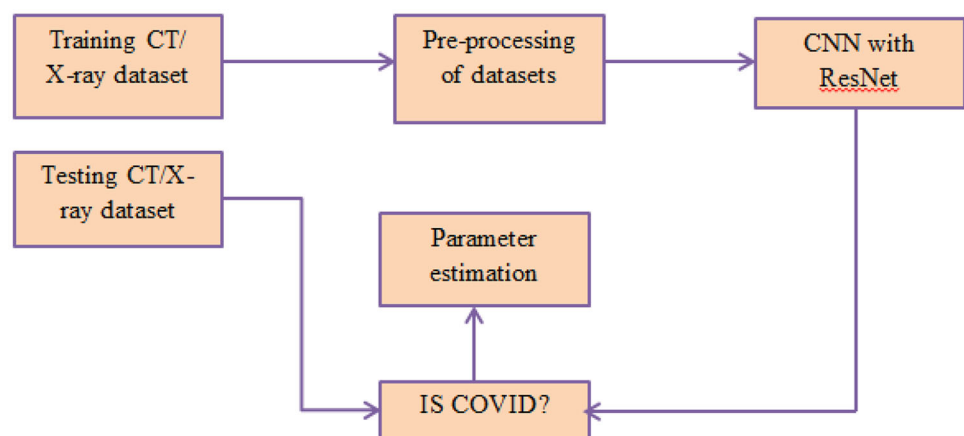
$$A = \frac{1}{W \times H} \sum_{x=0}^W \sum_{y=0}^H AVG_{x,y} \quad (3)$$

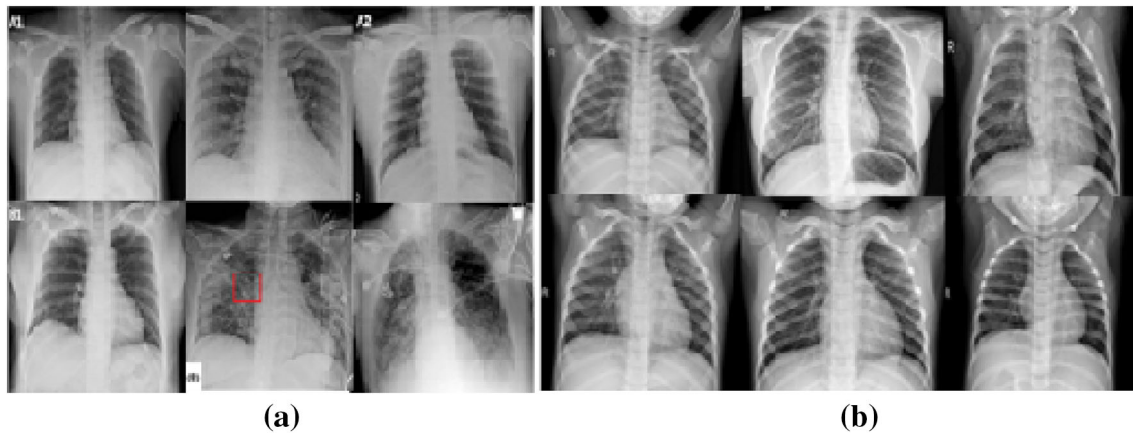
$$V = \frac{1}{W \times H} \sum_{x=0}^W \sum_{y=0}^H VAR_{x,y} \quad (4)$$

$L$  is the lungs image with the size  $x \times y$ ;  $AVG_{x,y}$  is the average of a block with a size of  $k \times k$ . Corresponding to entire image, Eqs. (1) and (2) are substituted in Eqs. (3) and (4). When the  $AVG_{x,y}$  is less than the  $A$  and  $VAR_{x,y}$  is less than  $V$ , then the block is consider being lungs. Finally, the training patches are segmented. When the segmented area in the each segregated part is less than the certain ratio, the area is considered as the background. It is adaptive in nature.

The overall CNN consists of 50 convolution layers, 3 pooling nodes, 16 identity layer and one fully connected (FC) layer. The convolution operation is achieved with a  $7 \times 7$  kernels and 35 training echoes and hyper parameters to certain range. The core aspect of a convolution operation is exchange of weight. The output of convolution layer passes through Rectified Linear Unit (ReLU) activation function which is nonlinear in nature. The output of convolution layer is given to the  $4 \times 4$  MaxPooling that executes standard down-sampling operation that decreases the plane dimension of feature maps such that minor shifts and distortions are introduced and the amount of corresponding learning parameters are decreased. The identity block contains two  $1 \times 1$  convolution and one  $3 \times 3$  convolution block and all the convolution output are added at last. This process is repeated for 16 times. The feature maps are translated into single dimension by average pooling. The final stage of the CNN is the fully connected layer. The obtained single-dimension average polling is connected to the FC layers. The FC layer subnet maps the features derived in the previous layers into the final network outputs including the probability of classification work for each level. Finally, 1-D probability is passed through activation function which is totally different from the other layers. Hence, the activation function used in this layer is softmax function. The function of softmax is to normalize the output real values. From this layer, the output is obtained whether the patient is COVID or not. At the time of testing, the grid method for extracting the feature is not required when utilizing the FCN [16, 17]. On comparison with the grid method, it doesnt required segmentation of image at the testing time. The final determination about the Covid and non-covid is done by comparing the probabilities values and the threshold value. The value of optimal threshold is determined by eliminating and normalizing method. The patches are available in the infected CT image which are used for differentiating the infected and disinfectected patients. By comparing the test and training images,

**Fig. 1** Schematic Diagram





**Fig. 2** a COVID-affected CT image; b Reference CT image

the COVID19-affected patient is diagnosed. The accuracy and specificity are obtained 95.09% and 81.56%, respectively, on the selected sample dataset based on the CT images without the inclusion of another set of data such as geographical location, population density, etc. Also, the high sensitivity is also obtained as denoted in Table 1. The CNN architecture is compared in terms of their accuracy. In proposed method, the ResNet architecture is used. The accuracy parameter of ResNet is compared with the other architectures such as Alexnet, ZFNet, GoogLe Net and VGG Net. The accuracy obtained for our data is tabulated in Table 1. Among all the architecture, ResNet seems to have higher accuracy(95.09%). Eventhough VGG Net is the most commonly used architecture in CNN, it has less accuracy compared to the ResNet. Using the proposed method, COVID-19 positive patients are identified accurately and indicated as true positive patients whereas non-affected patients are indicated as true negative. The parameters such as the accuracy, sensitivity, period for diagnosis and specificity are compared with both CT scan method and RT-PCR method in Table 1. It is inferred that the CT scan with ResNet CNN architecture provides more precision as compared with the RT-PCR.

Chest CT imaging can be accurate, realistic and speedy approach of diagnosing and testing COVID-19, particularly in comparison with RT-PCR. Hence, the image-based detection of COVID-19-affected patients is suggested. The proposed method gives the accuracy of 95.09% with a smaller number of images, and it is user friendly for the physician who can interpret medically. In comparison, around 60 percent of cases had standard CT characteristics associated with COVID-19, and nearly all patients had positive nucleic acid tests [18]. In the other side, “false-positive” result in the nucleic acid test may give true-positive result in CT scan. 95.09% of the patients were initially positive for the chest CT which was compatible with COVID-19 before the initial positive RT-PCR report based on repeated RT-PCR tests and CT scans [18]. Chest Xray may also be considered for performing this task. It is concluded that the chest CT imagery has a strong susceptibility to COVID-19 treatment. To screen COVID-19, the CT scan should be considered, thorough assessment and follow-up, especially in crisis areas.

**Table 1** Parameter comparison for RT-PCR method and CT scan method

Method	Accuracy	Period	Sensitivity	Specificity
RT-PCR	95% (After 4 tests) [8]	Requires 2–4 h for each test	Low	High
	<b>Architecture</b>	<b>Percentage</b>		
	Alexnet	78.85		
	ZFNet	79.54		
	GoogLe Net	90.78		
	VGG Net	89.91		
CT image	ResNet	95.09	Maximum 1 h	High

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