

Covid-19 Detection Based on Cascade-Correlation Growing Deep Learning Neural Network Algorithm

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Abstract

COVID-19, is a dangerous disease, that is widely spread among humans by inhalation of the virus, and it harms and may damage the lung. The aim of this paper is to detect COVID-19 using our new algorithm called “Cascade-Correlation Growing Deep Learning Neural Network Algorithm (CCGDLNN)” from Computed tomography (CT) scan images of a patient’s chest. We apply the algorithm over 48,260 computed tomography scan images from 377 persons divided into 282 normal persons and 95 patients were infected by COVID-19. Our system is divided into two stages: Firstly, the system removes unclear computed tomography-scan lung images by analyzing them. Secondly, we run our algorithm based on the exception model that begins with a small network without any hidden layers but has input and output layers only. The algorithm after that, adds new neurons and connects them to the last layer or add a new layer with one neuron. Finally, after performing these two stages, the system can be able to detect COVID-19 patients from their lung computed tomography-scan images. We train the data using two different models and compared the results with our model. In the image classification process, our model achieved 98.8% accuracy on more than 7996 test images.

Key Words: Deep learning; constructive deep learning; diagnosis systems; COVID-19; CT scan; automatic medical diagnosis.

1 Introduction

COVID-19 is an infectious disease resulting from the new virus called “severe acute respiratory syndrome Coronavirus 2” (SARS-CoV-2). COVID-19 can be transmitted between persons by contacting directly with a diseased person.

The infection can happen when a patient sneezes, coughs, or even talks close to another person and the infected respiratory droplets are transmitted to the normal person [12, 16, 27].

For Covid-19 diagnosis, scientists used several methods like: “Reverse Transcriptase-Polymerase Chain Reaction” (RT-PCR),

medical imaging, and medical tests like isothermal nucleic amplification, antibody, and serology [47]. The most popular method to diagnose the viral disease like COVID-19 is the RT-PCR.

However, The RT-PCR requires high experience and many experimentations to develop novel measurements [15]. Also, the shortage of the number of diagnostic tools at some areas around the world forced the scientists and researchers to find an easier way to detect COVID-19. The researchers found that the medical imaging devices like (X-rays and CT scans) are available at many labs and centers, so they used these devices to diagnose COVID-19. COVID-19 virus attacks the patient’s lung, so the medical imaging can diagnose the disease from the lung image only. Hence, a chest CT scan has become strong evidence for disease confirmation [26].

Fang et al. noted that the accuracy of CT (98%) was higher than RT-PCR (71%) when diagnosing COVID-19 [14]. Covid-19 appears in the patient’s lung using CT scans after at least four days from Covid-19 symptoms [5]. CT scans can help for early COVID-19 diagnosis to prevent the virus to transmit to others, but this method is not recommended at final diagnosis [2]. In [5, 48] some patients who had negative results at their RT-PCR test, were found that their lungs were infected by Covid-19 by using CT scan device. So, when the RT-PCR was repeated twice for these patients, the result converted to positive and confirmed the CT scan examination. However, a manual diagnosis of COVID-19 from chest CT images takes time and it might not be possible to manually check every CT image in emergency situations. So, we need tools that help in diagnosis of COVID-19 automatically by analyzing CT images of patient’s lung. Artificial Intelligence (AI) and deep learning can be used to build an AI based tool that accelerates the diagnosis process [39]. The viral infections can be visualized using machine vision and medical imaging. Deep learning is considered as the best method at machine vision [19]. Deep learning has many applications in medicine [31], agriculture [35], economics [18], etc. In [23], the automated method that was used for diagnosing COVID-19 (90%) was better than a manual diagnosis (70%).

All neural networks (NNs) algorithms define the architecture of the network before the beginning of the training process. However, there is another type of NN called constructive (or adaptive) neural network, which allows the structure of the network to be constructed during the training process. The

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constructive algorithm can solve a real-life problem as it is a supervised learning algorithm. The constructive algorithm begins by a small network that might not have any hidden layers but have input and output layers only. The algorithm then adds the neurons and layers gradually during training processes until reaching the optimal result of classification [29].

In this paper as in Figure 1, we used the CCG-DLNN algorithm [29] that we previously developed at [29] for diagnosing COVID-19 cases from the CT scan lung images.

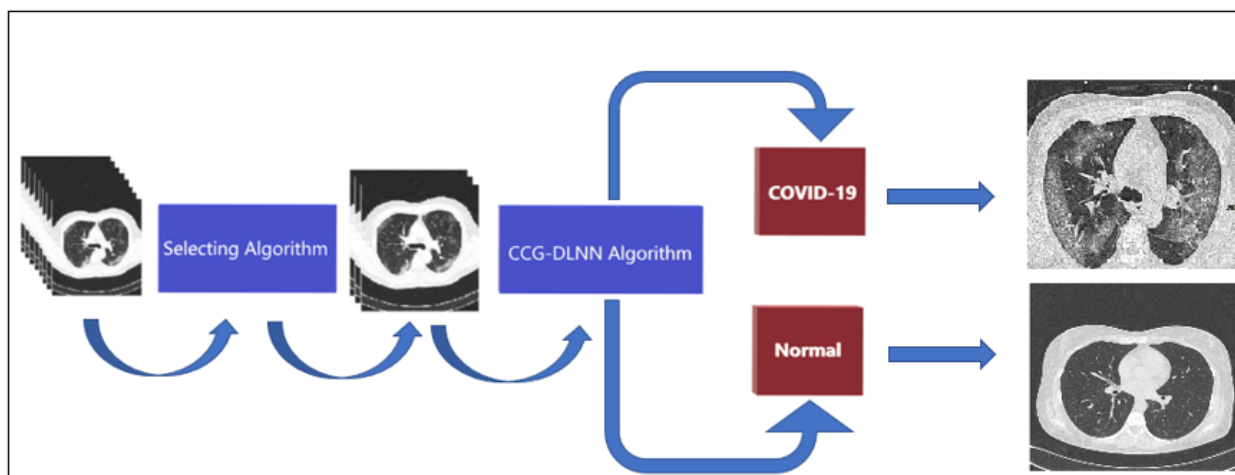


Figure 1: The steps of our proposed system for COVID-19 CT scan chest images classification

This system detects the infected patients using CT scans of these patients.

The dataset that had been used was COVIDCTset [36], and it was divided into 95 patients (15,589 COVID-19 images) and 282 normal persons (48,260 normal images). Our work has two stages:

1. A selecting algorithm: selecting the most noticeable infected lungs.
2. Run the CCG-DLNN algorithm.

After these two steps, we trained and tested two constructive algorithms other than CCG-DLNN algorithm and compared the three algorithms. Finally, we evaluated CCG-DLNN algorithm on more than 7996 images by single-image classification. Then, we examined the system by testing it on 245 patients and 41,892 images. The COVID-19 infected areas are explored in resulting images using a feature visualization algorithm.

The paper organization is: In Section 2, we will describe the related works. In Section 3, the dataset and the proposed algorithm will be discussed. In Section 4 we will present the experimental results. And finally in section 5, the conclusion of the paper was discussed.

2 Related works

Until the time of writing this paper, many trials have been done and several research studies published to deal with the new

pandemic virus COVID-19. There are two types of studies that diagnosed COVID-19 which are: binary classifications or multiple classifications. These studies used chest medical imaging by using X-rays or by CT-scan. This type of studies sometimes used raw data and others used feature extraction.

Almost all studies used convolutional neural network (CNN) and the amount of used data was different from one to another. [30, 45] it was determined COVID-19 was diagnosed using the current deep learning networks and X-ry images of chest. They

have a high accuracy on their results. However, [46] developed a new deep learning (DL) system and evaluated it to make a three-class data classification. This study used 5372 cases from many hospitals around China and used their CT scan chest images for the proposed DL. In [20] the X-ray images and VGG19 and DenseNet models also detected COVID-19.

In [23, 34] the Xception architecture and X-ray images of the chest were used to diagnose COVID-19. In [24] the cases were classified into 3 classes: normal, bacterial, and viral pneumonia. In [34] Resnet50v2 networks along with Xception architecture were used to classify 11,302 images into 3 classes: normal, pneumonia, and COVID-19 patients. The accuracy was 99.5 for this classification.

In [25] developed a new network called COVNet. COVNet was evaluated by using 3322 from 3506 chosen CT scan images. In [7] proposed an eXplainable deep learning approach and used 2482 CT scan images of 120 people to classify the COVID-19 infected patients, and the normal persons. The accuracy reached to 97.38% at this study. In [23] a new algorithm was developed called CovidCTNet. They used CT scan chest images to classify 287 patients into three classes: normal people, COVID-19 patients, and community-acquired pneumonia (CAP). The accuracy of the results was 90%. A segmentation of COVID-19 infections has been performed by using CT scans at [44].

The CNN and machine learning techniques have been used by [1, 8, 10, 28, 31-32, 37, 49] using CT scan or X ray chest images. In [36] it achieved 0.9849 accuracy of CNN when they developed a new method by modifying the feature selection

pyramid network and used the ResNet50V2 network.

An evolutionary neural network [9] is used to detect COVID-19 automatically using a common pneumonia and pneumonia that causes COVID-19. They used transfer learning to detect different abnormalities with small medical image datasets. Multi-objective differential evolution (MODE) [42] is based on CNN for classifying CT scan chest images to diagnose COVID-19. New deep transfer learning model that was based on DenseNet201 by using CT scan chest images as classification of the COVID-19 patient [22]. A new multi-class segmentation technique called Residual Attention U-Net was proposed in [11]. This new technique can be used to diagnose COVID-19 and its related pneumonia using CT scan chest images. In [3] detected infection areas and the diseased part by using a new proposed network "Auto Diagnostic Medical Analysis". They used X-ray and CT scan chest images. DenseNet network has been used for removing the infected spots at the lung. In [6] two methods: the first method is based on AOCTNet, MobileNet and ShuffleNet CNNs; the second method is based on removing the features at X-ray images and make a classification using many different algorithms to diagnose COVID-19. In [17] COVID-19 was detected by using Bayesian CNN model based on the dropweights and chest X-ray images.

The SqueezeNet model is based on Bayesian optimization and diagnosed COVID-19 using X-ray images in [43]. Five models (VGG16, VGG19, ResNet, DenseNet and InceptionV3) diagnosed COVID-19 by using X-ray images [38] and in [33] used five methods to extract features. Then, they classified features using SVM and two, five, and ten-fold cross-validation methods. COVID-19 was diagnosed by using three models (ResNet, InceptionV3, and Inception-ResNet) [10] and they worked on chest X-ray images. In [4] they used small dataset by developing a new deep neural network (DNN) that was based on diagnostic solutions and Capsule Networks.

All these previous researches diagnosed COVID-19 or classified medical images into two or more classes using CNN models.

CNN is based on a fixed network that has a fixed number of layers and neurons. So, all these researches must choose the most suitable network (number of layers, and number of neurons) manually.

In this paper, the structure of the DL network is determined dynamically based on the number of images and the type of them at each problem. We performed CCG-DLNN algorithm that we previously proposed at [29] to diagnose COVID-19 on CT scan chest images. The following section will describe the proposed system in detail.

3 The Proposed System

3.1 The Dataset

We used COVID-CTset1 [36] dataset in our system. This data was collected by Negin radiology in Sari, Iran. The COVID-CTset1 dataset was collected from March 5th to April 23rd, 2020. These CT images were captured and visualized

using a scope model called SOMATOM and software called SYNGO CT VC30-easyIQ. The captured images were at format 16-bit grayscale DICOM, and resolution 512*512 pixels. It converted the format of the resulted images from DICOM to TIFF to remove the patient's private information that attached to each image [18]. COVID-CTset1 dataset has 63,849 images for 377 patients. These images were divided into 15,589 COVID-19 images for 95 COVID-19 patients, and 48,260 normal images for 282 normal people in Tables 1 and 2.

3.2 CT Scans Selection Algorithm

In this paper, we used a selection algorithm that was performed in [18]. The idea of this selection algorithm is to discard the CT scan images of the closed lung. The lung CT scan produces a sequence of images (consecutive frames). At the beginning and the end of consecutive frames of the CT scan lung images, the lung is closed (Figure 2). In these closed lung images, the COVID-19 infection part does not appear. These types of images are useless at classification process. Figure 3 shows the steps of a selection algorithm as discussed in [36].

1. Extracting a region from the middle of each CT scan lung image. This region has pixels numbers $[x;y] = [120;240]:[370;340]$ as in Figure 4.
2. Selecting the dark pixels from the extracting region in step 1 which has values < 300 .
3. Return the maximum (Max) and minimum (Min) number of dark pixels of all images in the CT scan lung sequence.
4. Calculating the threshold in equation (1).

$$\text{Threshold} = \frac{\text{Max}(\text{dark pixels}) - \text{Min}(\text{dark pixels})}{1.5} \quad (1)$$

5. Comparing the number of dark pixels of each image with the amount of threshold that is calculated in step 4.
6. If the number of dark pixels is less than the threshold, then remove this image from the sequence (closed lung).
7. Finally, we will have a number of images that appear inside of the lung.

Figure 5 shows the deleting images that have a closed lung and the remaining images of the sequence that will be used in the classification process that will be discussed in detail at the next subsection.

3.3 CCG-DLNN Algorithm

Constructive algorithm is used for generating an acceptable network in an automatic manner. In constructive algorithm, the neural network is built gradually during the training process. The network starts with a minimum number of layers (may be input and output layers only). The hidden layers, nodes and connections are added gradually at each step of the training process, until reaching the most suitable model for solving an appropriate problem [40].

Table 1: Number of COVID-19 and normal patients

COVID-19 Patients	Normal People	Total
95	282	377

Table 2: Number of COVID-19 and normal images

COVID-19 Images	Normal Images	Total
15,589	48,260	63,849

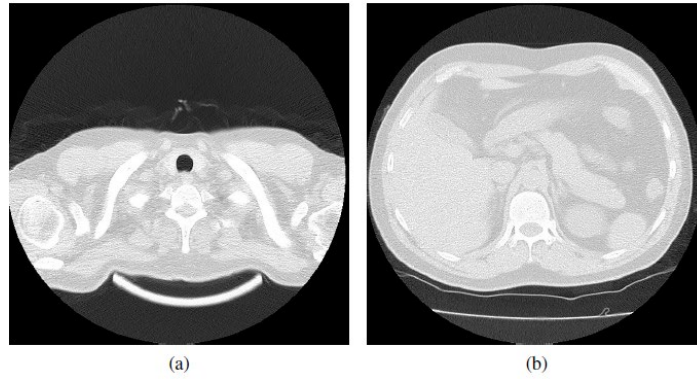


Figure 2: Closed lung at the beginning of CT scan lung sequence (a) and at the end of CT scan lung sequence (b)

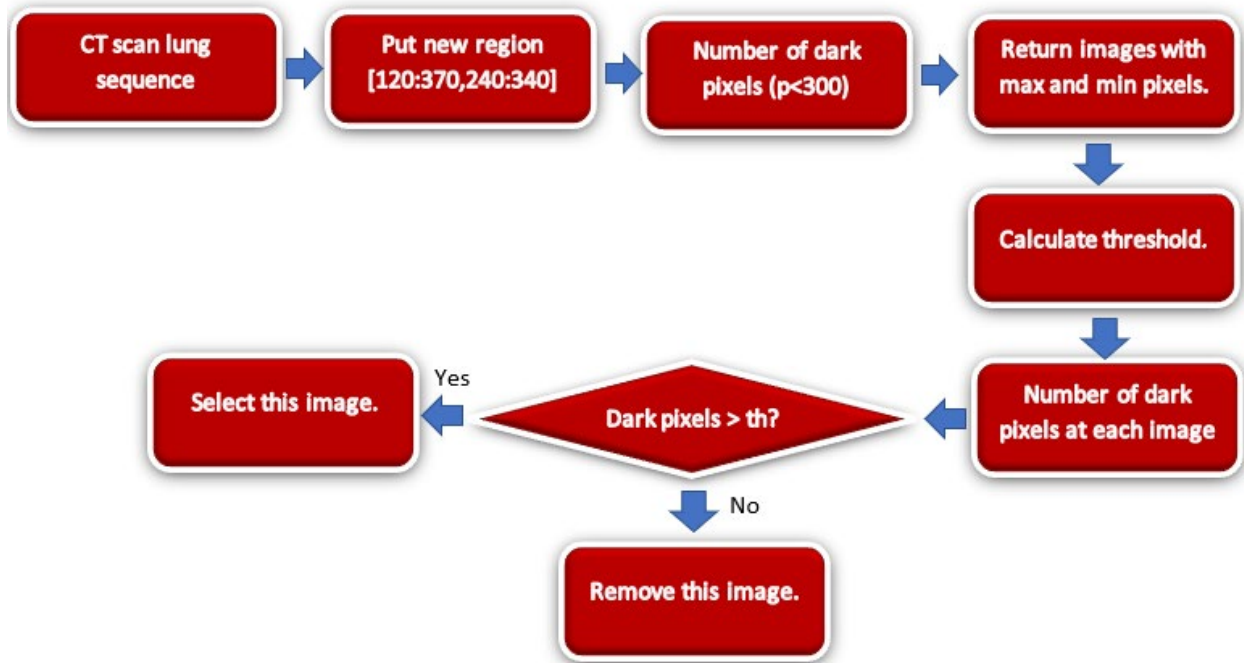


Figure 3: The steps of the selection algorithm

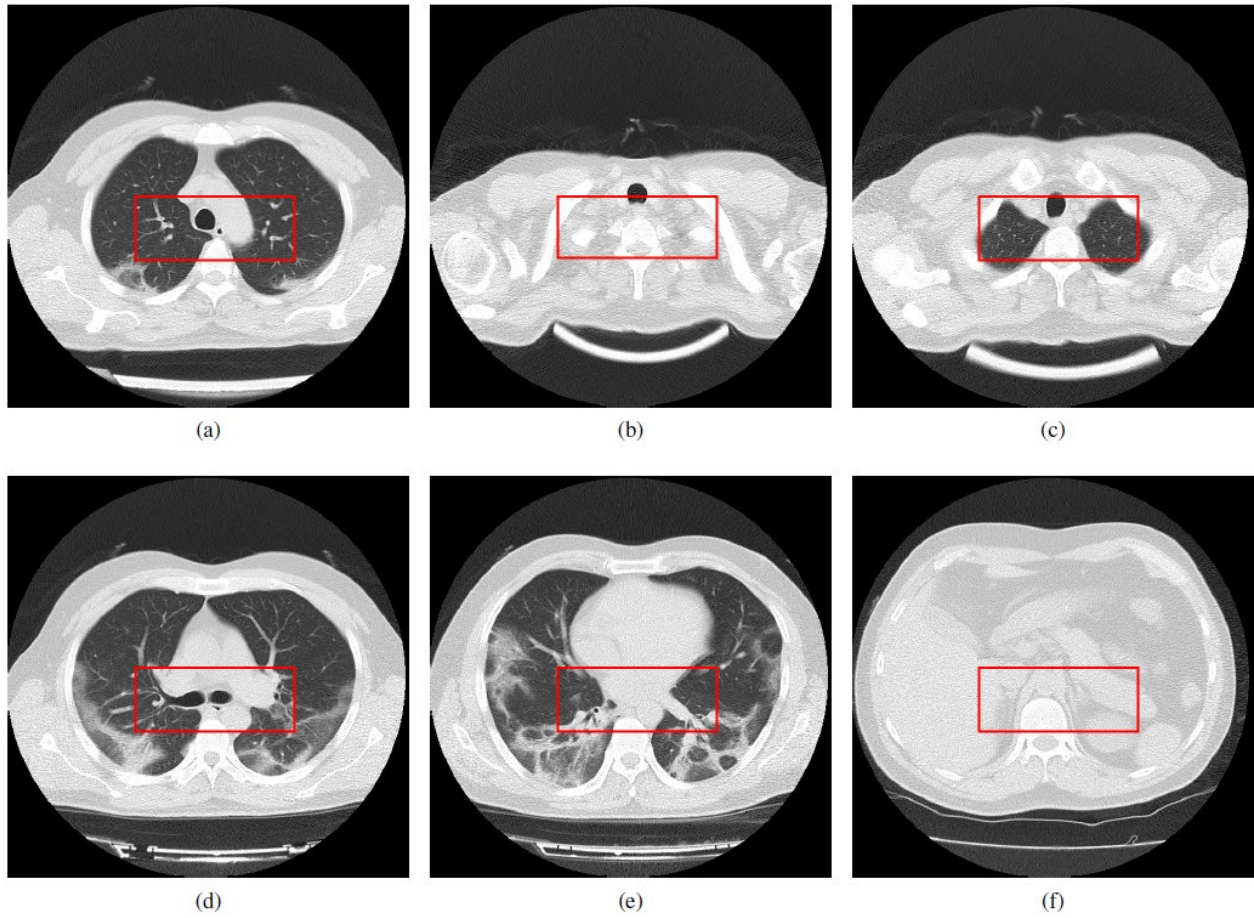


Figure 4: Extracting a specific region from the CT scan lung images



Figure 5: CT scan lung sequence of a patient after deleting closed lung images

The classification problems can be solved by the constructive neural network. The constructive neural network has many benefits such as [41]:

1. It requires few numbers of computations.
2. It requires small topology.
3. It learns faster.
4. It performs the classification process with high accuracy.

In this paper, we used the CCG-DLNN algorithm that we previously proposed at [29] to classify the COVID-19 CT scan lung images that resulted from the selection system. The CCG-DLNN algorithm is a constructive algorithm that begins with only input and output layers. Then the algorithm adds new neurons or new hidden layers gradually during the training process [29]. The CCG-DLNN algorithm uses the same technique as Cascade Correlation Neural Network (CCNN). The difference between CCG-DLNN algorithm and CCNN is that our algorithm adds more than one node to each new added hidden layer.

The steps of CCG-DLNN algorithm are:

1. Beginning with a simple neural network with input and output layers only.
2. Training the network and calculating the loss function $L(\phi_t)$.
3. If $L(\phi_t) > DE$, then DE is the desired error. So, we need to do one of the following two options:
 - (a) Adding a new neuron to the last hidden layer.
 - (b) Adding a new hidden layer with one neuron.
5. Repeat steps from 2 to 4 until $L(\phi_t) < DE$.

3.4 CT scan COVID-19 Classification System

In Figure 6, we performed the CT scan COVID-19

classification system using the CCG-DLNN algorithm and Xception Architecture [13].

The Xception architecture is a Convolutional Neural Network (CNN) architecture. This architecture is based on separating convolution layers. The Xception architecture extract features the convolutional layers. This convolutional layer consists of 36 layers sorted by 14 modules which connects linearly except the first and last modules. The Xception architecture is a depth wise linear stack based on separate convolutional layers.

The resulting images from Xception model is the input layer of the CCG-DLNN algorithm.

4 Experimental Results

In this section we will run our proposed classification system and compare the results with [36] model and Xception model on the same dataset COVID-CTset.

We performed all models by Python 3.7, 253 Core i7 with CPU 3.60GHZ, NVIDIA GeForce RTX 2070 GPU and RAM size 32.0 GB. We ran the deep network by Keras library and Tensorflow backend. We used CT scan images dataset that were introduced by [36].

We converted all images to TIFF format and with 32-bit float to visualize them easily. We used the same characteristics as [36] for a fair comparison.

We divided the dataset into 5 folds and divided each fold into 3 sets which were training, validation, and testing sets [36]. The number of images at each fold and for the training and test sets shown in Table 3 (this distribution made by [36]).

We used the same parameters used in [36] to train the dataset. We trained the dataset using the CCG-DLNN algorithm based on Xception model, [36] model, and Xception model only (Table 4).

We evaluated the CCG-DLNN algorithm based on Xception, [36], and Xception models using the accuracy metric during the training process. Then we divided the images at the CT scan lung dataset into four parts:

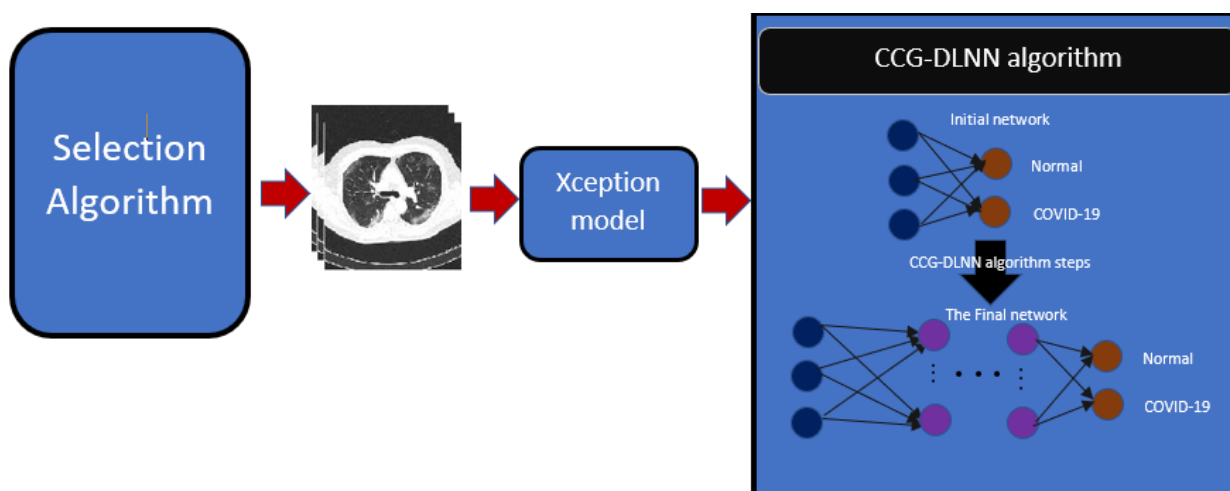


Figure 6: CT scan COVID-19 classification system

1. True Positive (TP): The correct classified images.
2. False Positive (FP): The wrong classified images.
3. False Negative (FN): The images with a wrong class label and are not classified to this wrong class.
4. True Negative (TN): The images with a wrong class label and are classified to this wrong class.

So, we can calculate the accuracy of equation (2), specificity in equation (3), sensitivity in equation (4) and precision in equation (5) using the following equations:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (3)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

The results of the accuracy for each model and each fold are shown in Table 5. Table 6 shows the evaluating results for the 5 folds and the three models. Figure 7 shows the training accuracy and loss in 50 epochs for the three models. The speed of each model is in Table 7 which shows the training time of each model.

5 Conclusion and Future work

In this paper, we used CCG-DLNN algorithm that we previously developed at [29] for diagnosis COVID-19 cases from the CT scan lung images. We used the Xception model as the backbone of our system. The dataset that we used was COVID-CTset1 dataset that was developed by [36]. This dataset contains 63,849 images divided into 15,589 COVID-19 images for 95 COVID-19 patients, and 48,260 normal images. Our system firstly, performed a selection algorithm that [36] developed. This selection algorithm selects the open lung images from the CT scan lung image sequences, and it removes unclear images that have a closing lung and hard to detect COVID 19 from them. The selection algorithm speeds up the training processes at the next phase. The second phase of our system is to make a classification process by CCG-DLNN algorithm based on Xception model. CCG-DLNN algorithm is a constructive algorithm that begins with only an input and output layers. Then the algorithm adds new neurons or new hidden layers gradually during the training process. It uses the same technique as Cascade Correlation Neural Network (CCNN). The difference between CCG-DLNN algorithm and CCNN is that our algorithm adds more than one node to each new added hidden layer. When we compared our proposed system with [36] and Xception model using the same dataset, the accuracy of our system was the highest at 5 folds with 99.2%, 98.6%, 98.2%, 98.8%, and 99.6% overall accuracy.

Table 3: Number of COVID-19 and normal images in training and testing sets [36]

	Training set		Testing set	
	COVID-19	Normal	COVID-19	Normal
Fold1	1820	1916	462	7860
Fold2	1817	1898	465	7878
Fold3	1836	1893	446	7883
Fold4	1823	1920	459	7856
Fold5	1832	1921	450	7785

Table 4: The Training parameters

Training Parameters	CCG-DLNN + Xception model	(96) model	Xception model
Learning Rate	1e-4	1e-4	1e-4
Batch size	14	14	14
Optimizer	Nadam	Nadam	Nadam
Loss function	Categorical Cross Entropy	Categorical Cross Entropy	Categorical Cross Entropy
Epochs	50	50	50
Horizontal/vertical flipping	Yes	Yes	Yes
Zoom range	5%	5%	5%
Rotation range	0-360 degree	0-360 degree	0-360 degree
Width/height shifting	5%	5%	5%
Shift range	5%	5%	5%

Table 5: The resulted accuracy for the three models

Folds	Network	Overall accuracy	COVID19 accuracy	Normal accuracy
1	CCG-DLNN+Xception	0.992	0.992	0.992
	(96) model	0.987	0.987	0.987
	Xception	0.9811	0.9811	0.9811
2	CCG-DLNN+Xception	0.986	0.986	0.986
	(96) model	0.9847	0.9847	0.9847
	Xception	0.9494	0.9494	0.9494
3	CCG-DLNN+Xception	0.982	0.982	0.982
	(96) model	0.9777	0.9777	0.9777
	Xception	0.9741	0.9741	0.9741
4	CCG-DLNN+Xception	0.988	0.988	0.988
	(96) model	0.9868	0.9868	0.9868
	Xception	0.9446	0.9446	0.9446
5	CCG-DLNN+Xception	0.996	0.996	0.996
	(96) model	0.9886	0.9886	0.9886
	Xception	0.9785	0.9785	0.9785

Table 6: The evaluation results of the three models

Fold	Network	COVID19 sensitivity	Normal sensitivity	COVID19 specificity	Normal specificity	COVID19 precision	Normal precision
1	CCG-DLNN and Xception	0.98	0.97	0.97	0.98	0.92	0.989
	(96) model	0.9437	0.9896	0.9896	0.9437	0.8417	0.9967
	Xception	0.987	0.9808	0.9808	0.987	0.7512	0.9992
2	CCG-DLNN and Xception	0.98	0.992	0.992	0.98	0.752	0.992
	(96) model	0.9527	0.9865	0.9865	0.9527	0.8069	0.9972
	Xception	0.9849	0.9473	0.9473	0.9849	0.5246	0.9991
3	CCG-DLNN and Xception	0.99	0.997	0.997	0.99	0.86	0.9995
	(96) model	0.9574	0.9788	0.9788	0.9574	0.7189	0.9975
	Xception	0.9731	0.9741	0.9741	0.9731	0.6803	0.9984
4	CCG-DLNN and Xception	0.989	0.989	0.989	0.989	0.92	0.9995
	(96) model	0.963	0.9882	0.9882	0.963	0.8262	0.9978
	Xception	0.9782	0.9426	0.9426	0.9782	0.4989	0.9987
5	CCG-DLNN and Xception	0.985	0.981	0.981	0.985	0.893	0.9996
	(96) model	0.9311	0.9919	0.9919	0.9311	0.8693	0.996
	Xception	0.9778	0.9785	0.9785	0.9778	0.7249	0.9987

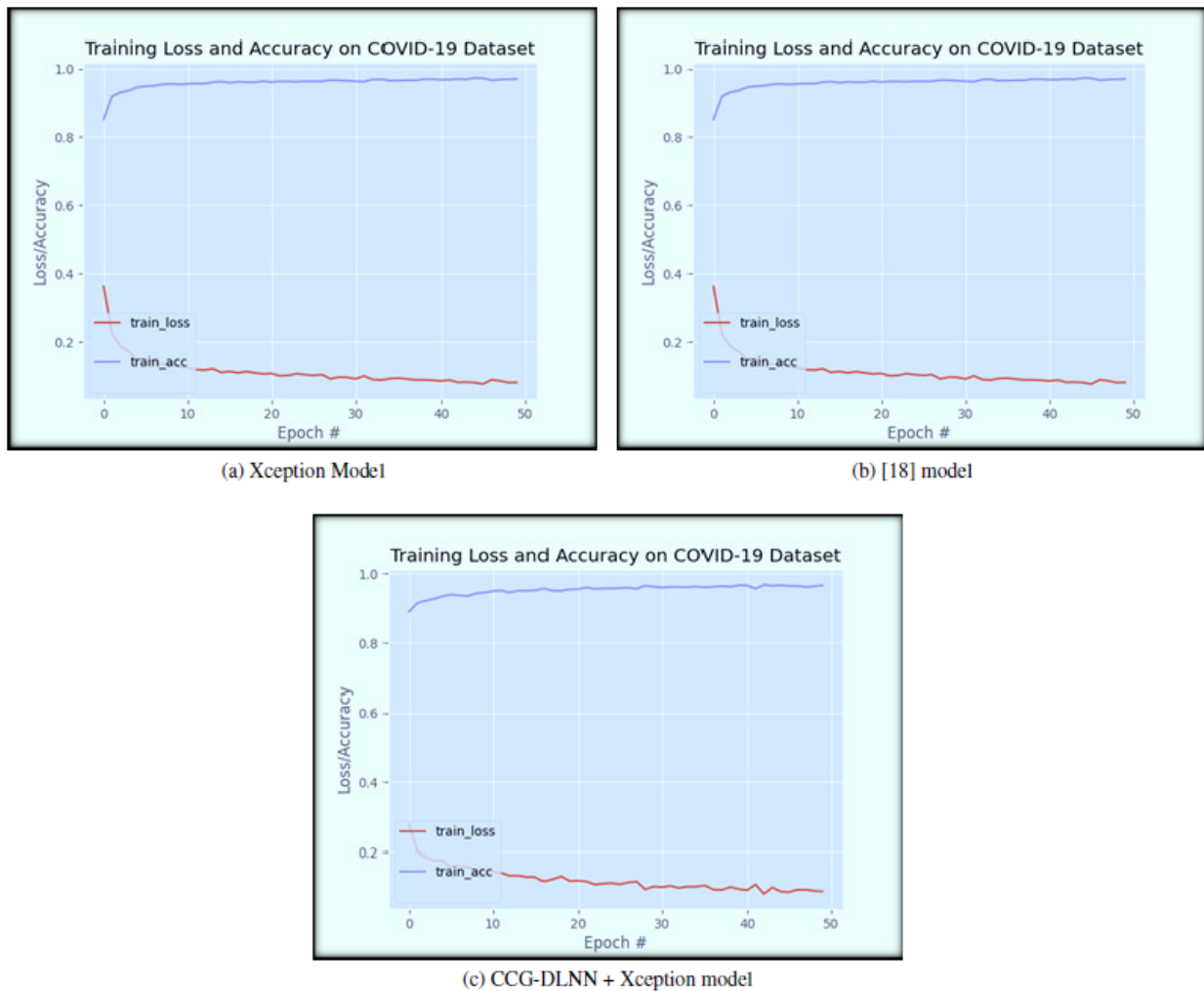


Figure 7: The training loss and accuracy in 50 epochs for the three models (a) Xception model (b) [36] model (c) CCG-DLNN +Xception model

Table 7: The training time in minutes for the three models on NVIDIA GeForce RTX 2070 GPU

Model	Training Time of each Epoch (m)
CCG-DLNN+Xception model	5 m
(96) model	3 m
Xception model	4 m

From all the previous results, we can observe that our system improved the detection of COVID 19 from CT scan lung images.

References

- [1] A. A. Abdulmunem, Z. A. Abutiheen, and H. J. Aleqabie, "Recognition of Corona Virus Disease (COVID-19) using Deep Learning Network," *International Journal of Electrical and Computer Engineering (IJECE)*, 11(1):365–374, 2021.
- [2] ACR, "ACR Recommendations for the Use of Chest Radiography and Computed Tomography (CT) for Suspected COVID-19 Infection — American College of Radiology," 2020 05, <https://www.acr.org/Advocacy-and-Economics/ACR-Position-Statements/Recommendations-for-Chest-Radiography-and-CT-for-Suspected-COVID19-Infection>, Online: accessed 23.06.21, 2020.
- [3] N. C. D. Adhikari, "Infection Severity Detection of

- COVID-19 from X-rays and CT Scans using Artificial Intelligence,” *International Journal of Computer (IJC)*, 38(1):73-92, 2020.
- [4] P. Afshar, S. Heidarian, F. Naderkhani, A. Oikonomou, K. N. Plataniotis, and A. Mohammadi, “Covid-caps: A Capsule Network-based Framework for Identification of COVID-19 Cases from X-ray Images,” *Pattern Recognition Letters*, 138:638-643, 2020.
- [5] T. Ai, Z. Yang, H. Hou, C. Zhan, C. Chen, W. Lv, Q. Tao, Z. Sun, and L. Xia, “Correlation of Chest CT and RT-PCR Testing for Coronavirus Disease 2019 (COVID-19) in China: A Report of 1014 Cases,” *Radiology*, 296(2):E32–E40, 2020.
- [6] A. M. Alqudah, S. Qazan, and A. Alqudah, “Automated Systems for Detection of COVID-19 using Chest X-ray Images and Lightweight Convolutional Neural Networks,” *Research Square*, 1:1-26, 2020.
- [7] P. Angelov and E. Almeida Soares, “SARS-CoV-2 CT-Scan Dataset: A Large Dataset of Real Patients CT Scans for SARS-CoV-2 Identification,” *medRxiv*, 2020.
- [8] I. D. Apostolopoulos, S. I. Aznaouridis, and M. A. Tzani, “Extracting Possibly Representative COVID-19 Biomarkers from X-ray Images with Deep Learning Approach and Image Data Related to Pulmonary Diseases,” *Journal of Medical and Biological Engineering*, 40:462–469, 2020.
- [9] I. D. Apostolopoulos and T. A. Mpesiana, “Covid-19: Automatic Detection from X-ray Images Utilizing Transfer Learning with Convolutional Neural Networks,” *Physical and Engineering Sciences in Medicine*, 43(2):635-640, 2020.
- [10] M. Barstugan, U. Özkaya, and S. Öztürk, “Coronavirus (COVID-19) Classification using CT Images by Machine Learning Methods,” *arXiv preprint arXiv:2003.09424*, 2020.
- [11] X. Chen, L. Yao, and Y. Zhang, “Residual Attention U-net for Automated Multi-class Segmentation of COVID-19 Chest CT Images,” *arXiv preprint arXiv:2004.05645*, 2020.
- [12] N. Chen, M. Zhou, X. Dong, J. Qu, F. Gong, Y. Han, Y. Qiu, J. Wang, Y. Liu, Y. Wei, et al., “Epidemiological and Clinical Characteristics of 99 Cases of 2019 Novel Coronavirus Pneumonia in Wuhan, China: A Descriptive Study,” *The Lancet*, 395(10223):507-513, 2020.
- [13] F. Chollet, “Xception: Deep Learning with Depth Wise Separable Convolutions,” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1251-1258, 2017.
- [14] Y. Fang, H. Zhang, J. Xie, M. Lin, L. Ying, P. Pang, and W. Ji, “Sensitivity of Chest CT for COVID-19: Comparison to RT-PCR,” *Radiology*, 296(2):E115–E117, 2020.
- [15] Genetic Education, “Reverse Transcription PCR: Principle, Procedure, Application, Advantages and Disadvantages,” 2020, <https://geneticeducation.co.in/reverse-transcription-pcr-principle-procedure-applications-advantages-and-disadvantages/#Disadvantages>, Online; accessed 23.06.21.
- [16] I. Ghinai, T. D. McPherson, J. C. Hunter, H. L. Kirking, D. Christiansen, K. Joshi, R. Rubin, S. Morales-Estrada, S. R. Black, M. Pacilli, et al., “First Known Person-to-Person Transmission of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-COV-2) in the USA,” *The Lancet*, 395(10230):1137-1144, 2020.
- [17] B. Ghoshal and A. Tucker, “Estimating Uncertainty and Interpretability in Deep Learning for Coronavirus (COVID-19) Detection,” *arXiv preprint arXiv:2003.10769*, 2020.
- [18] G. P. Green, J. C. Bean, and D. J. Peterson, “Deep Learning in Intermediate Microeconomics: Using Scaffolding Assignments to Teach Theory and Promote Transfer.” *The Journal of Economic Education*, 44(2):142-157, 2013.
- [19] K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image Recognition,” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770-778, 2016.
- [20] E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, “COVIDX-NET: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-ray Images,” *arXiv preprint arXiv:2003.11055*, 2020.
- [21] A. Huemer, D. Elizondo, and M. Gongora, “A Constructive Neural Network for Evolving a Machine Controller in Real Time,” *Constructive Neural Networks*, Springer, pp. 225-242, 2009.
- [22] A. Jaiswal, N. Gianchandani, D. Singh, V. Kumar, and M. Kaur, “Classification of the COVID-19 Infected Patients using DenseNet201 based Deep Transfer Learning,” *Journal of Biomolecular Structure and Dynamics*, 39:1-8, 2020.
- [23] T. Javaheri, M. Homayounfar, Z. Amoozgar, R. Reiazi, F. Homayounieh, E. Abbas, A. Laali, A. R. Radmard, M. H. Gharib, S. A. J. Mousavi, et al., “COVIDCTNET: An Open-Source Deep Learning Approach to Identify COVID-19 using CT Image,” *arXiv Preprint arXiv:2005.03059*, 2020.
- [24] A. I. Khan, J. L. Shah, and M. M. Bhat, “Coronet: A Deep Neural Network for Detection and Diagnosis of COVID-19 from Chest X-ray Images,” *Computer Methods and Programs in Biomedicine*, 196:105581, 2020.
- [25] L. Li, L. Qin, Z. Xu, Y. Yin, X. Wang, B. Kong, J. Bai, Y. Lu, Z. Fang, Q. Song, et al., “Artificial Intelligence Distinguishes COVID-19 from Community Acquired Pneumonia on Chest CT,” *Radiology*, 2020.
- [26] X. Li, W. Zeng, X. Li, H. Chen, L. Shi, X. Li, H. Xiang, Y. Cao, H. Chen, C. Liu, et al., “Ct Imaging Changes of Corona Virus Disease 2019 (Covid-19): A Multi-Center Study in Southwest China,” *Journal of Translational Medicine*, 18:1-8, 2020.
- [27] J. Liu, X. Liao, S. Qian, J. Yuan, F. Wang, Y. Liu, Z.

- Wang, F.-S. Wang, L. Liu, and Z. Zhang, "Community Transmission of Severe Acute Respiratory Syndrome Coronavirus 2, Shenzhen, China, 2020," *Emerging Infectious Diseases*, 26(6):1320, 2020.
- [28] Krishore Medhi, Md Jamil and Md Iftekhar. Hussain, "Automatic Detection of COVID-19 Infection from Chest X-ray using Deep Learning," medRxiv, 2020.
- [29] S. A. E.-M. Mohamed, M. H. Mohamed, and M. F. Farghally, "A New Cascade-Correlation Growing Deep Learning Neural Network Algorithm," *Algorithms*, 14(5):158, 2021.
- [30] A. Narin, C. Kaya, and Z. Pamuk, "Automatic Detection of Coronavirus Disease (COVID-19) using X-ray Images and Deep Convolutional Neural Networks," *Pattern Analysis and Applications*, pp. 1-14, 2021.
- [31] U. Özkaya, S. Öztürk, and M. Barstuğan, *Coronavirus (COVID-19) Classification using Deep Features Fusion and Ranking Technique*, "Big Data Analytics and Artificial Intelligence Against COVID-19: Innovation Vision and Approach, Springer, pp. 281-295, 2020.
- [32] S. Öztürk, U. Özkaya, and M. Barstuğan, "Classification of Coronavirus (COVID-19) from X-ray and CT Images using Shrunk Features," *International Journal of Imaging Systems and Technology*, 31:5-15, 2020.
- [33] N. S. Punn and S. Agarwal, "Automated Diagnosis of COVID-19 with Limited Posteroanterior Chest X-ray Images using Fine-tuned Deep Neural Networks," *Applied Intelligence*, 51(5):2689-2702, 2021.
- [34] M. Rahimzadeh and A. Attar, "A Modified Deep Convolutional Neural Network for Detecting COVID-19 and Pneumonia from Chest X-ray Images Based on the Concatenation of Xception and Resnet50v2," *Informatics in Medicine Unlocked*, 19:100360, 2020.
- [35] M. Rahimzadeh and A. Attar, "Detecting and Counting Pistachios Based on Deep Learning," *Iran Journal of Computer Science*, 5:1-13, 2021.
- [36] M. Rahimzadeh, A. Attar, and S. M. Sakhaei, "A Fully Automated Deep Learning-Based Network for Detecting COVID-19 from a New and Large Lung CT Scan Dataset," *Biomedical Signal Processing and Control*, 68:102588, 2021.
- [37] P. Saha, M. S. Sadi, and M. M. Islam, "Emcnet: Automated COVID-19 Diagnosis from X-ray Images using Convolutional Neural Network and Ensemble of Machine Learning Classifiers," *Informatics in Medicine Unlocked*, 22:100505, 2021.
- [38] K. Sahinbas and F. O. Catak, "Transfer Learning-based Convolutional Neural Network for COVID-19 Detection with X-ray Images," *Data Science for COVID-19*, Elsevier, pp. 451-466, 2021.
- [39] K. Santosh, "Ai-Driven Tools for Coronavirus Outbreak: Need of Active Learning and Cross-Population Train/Test Models on Multitudinal/Multimodal Data," *Journal of Medical Systems*, 44(5):1-5, 2020.
- [40] S. K. Sharma and P. Chandra, "Constructive Neural Networks: A Review," *International Journal of Engineering Science and Technology*, 2(12):7847-7855, 2010.
- [41] D. Shen, G. Wu, and H.-I. Suk, "Deep Learning in Medical Image Analysis," *Annual Review of Biomedical Engineering*, 19:221-248, 2017.
- [42] Dilbag Singh, Vijay Kumar and Manjit Kaur, "Classification of COVID-19 Patients from Chest CT Images using Multi Objective Differential Evolution-based Convolutional Neural Networks," *European Journal of Clinical Microbiology & Infectious Diseases*, 39(7):1379-1389, 2020.
- [43] F. Ucar and D. Korkmaz, "Covidagnosis-net: Deep Bayes Squeeze Net based Diagnosis of the Coronavirus Disease 2019 (COVID-19) from X-ray Images," *Medical Hypotheses*, 140:109761, 2020.
- [44] A. Voulodimos, E. Protopapadakis, I. Katsamenis, A. Doulamis, and N. Doulamis, "Deep Learning Models for COVID-19 Infected Area Segmentation in CT Images," medRxiv, 2020.
- [45] L. Wang, Z. Q. Lin, and A. Wong, "COVID-NET: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-ray Images," *Scientific Reports*, 10(1):1-12, 2020.
- [46] S. Wang, Y. Zha, W. Li, Q. Wu, X. Li, M. Niu, M. Wang, X. Qiu, H. Li, H. Yu, et al., "A Fully Automatic Deep Learning System for COVID-19 Diagnostic and Prognostic Analysis," *European Respiratory Journal*, 56(2):1-11, 2020.
- [47] Wikipedia, COVID-19 Testing – Wikipedia, https://en.wikipedia.org/wiki/COVID-19_testing, 2020.
- [48] X. Xie, Z. Zhong, W. Zhao, C. Zheng, F. Wang, and J. Liu, "Chest CT for Typical Coronavirus Disease 2019 (COVID-19) Pneumonia: Relationship to Negative RT-PCR Testing," *Radiology*, 296(2):E41-E45, 2020.
- [49] J. Zhang, Y. Xie, Y. Li, C. Shen, and Y. Xia, "COVID-19 Screening on Chest X-ray Images using Deep Learning based Anomaly Detection," arXiv preprint arXiv:2003.12338, 2020.



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