

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 8, August 2021 DOI 10.17148/IJARCCE.2021.10811

Distributed Convolutional Neural Network (CNN) for COVID-19 Detection

Digambar Dhanagar¹, Vinay Kumar K Deshpande², Rakshitha Murali³, Sahana Lokesh⁴

Student, BE, Department of Medical Electronics, Dr AIT, Bangalore, India ^{1, 2, 3, 4}

Abstract: Data Analytics of COVID-19 is not just enough for curbing down this deadly disease which now has become a pandemic. The detection of Severe Acute Respiratory Syndrome corona virus 2 (SARS cov-2), which is responsible for corona virus disease 2019 (COVID-19), using chest X-ray images has life- saving importance for both patients and doctors. [1] X-rays are cost-effective and widely available at public health facilities and hospital emergency rooms, they could be used for rapid detection of possible COVID-19-induced lung infections. Therefore, towards automating the COVID-19 detection, in this paper, we propose a viable and efficient Deep Learning Based Chest Radiograph Classification (DL-CRC) framework to distinguish the COVID-19 cases with high accuracy from other abnormal and normal cases. A unique dataset is prepared from four publicly available sources containing the chest view of X-ray data for COVID-19, pneumonia, and normal cases. Our system consists of Convolution Neural Network (CNN) architecture capable of detecting masked and unmasked faces also which will be dealt with in the next paper. The encouragingly high classification accuracy of our proposal implies that it can efficiently automate COVID-19 detection from radiograph images to provide a fast and reliable evidence of COVID-19 infection in the lung that can complement existing COVID-19 diagnostics modalities.

Keywords: Convolution Neural Network (CNN) architecture, COVID-19, Severe Acute Respiratory Syndrome corona virus 2 (SARS cov-2), deep learning based chest radiograph classification (DL-CRC) and radiography images.

I.INTRODUCTION

The general symptoms of COVID-19 patients are flu-like such as fever, cough, dyspnoea, breathing problem, and viral pneumonia. But these symptoms alone are not significant. There are many cases where individuals are asymptomatic but their chest CT scan and the pathogenic test were COVID-19 positive. So, along with symptoms, positive pathogenic testing and positive CT images/X-Rays of the chest are being used to diagnose the disease. For pathological testing, Real- time PCR is being used as a standard diagnostic tool. Healthcare systems around the world are attempting to expand testing facilities for COVID-19. More and more testing will lead to the identification and isolation of infected persons, thereby reducing the spread among the community. But availability does not ensure reliability. The major concern for the governments at this stage is the false negative test results – the test results are negative for the infected individual. Such individuals may unknowingly transmit the virus to others. False test results thus have a negative effect on the efforts to curb the spread of the virus. The impact of this concern on the safety of public and health workers can't be determined as there are no clear or consistent reports on these test performance characteristics. The sensitivity of these tests is largely unknown.[2][3]

II. OBJECTIVES

- i. To accomplish the classification of images as normal or COVID positive.
- ii. To minimize the noise in the images by preprocessing techniques.
- iii. To implement a software web application to view the data/ image sets and results.
- iv. Design and implementation of CNN model.

III. LITERATURE SURVEY

[1] Title: Imaging Modalities for Covid-19 Detection Authors: Di dong, Zencho Tang, Shuowang, Homengliao, Fan Yang, Published Year: 2020

Findings: Most nations had to take measures to react to the sudden and rapid outbreak of COVID-19 within a relatively short period of time. According to, radiology departments have started to focus more on preparedness rather than diagnostic capability, after sufficient knowledge was gathered regarding COVID-19. The study in stated the resemblance of COVID-19 with other diseases caused by other corona virus variants such as the severe acute respiratory syndrome (SARS) and the Middle East respiratory syndrome (MERS). The importance of a tracking the lung condition of a recovering corona virus patient using CT scans was also mentioned in the study. Chest imaging techniques were highlighted to be a crucial technique for detecting COVID-19 by capturing the bilateral nodular and peripheral ground glass opacities in the lung radiograph images.



International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 8, August 2021

DOI 10.17148/IJARCCE.2021.10811

[2] Title: Clinical features of patients infected with 2019 novel corona virus in Wuhan, China Authors: Prof Chaloin Huang, Yeming Wang, Prof Xingwang Li, Published Year: 2020

Findings: All patients with suspected 2019-nCoV were admitted to a designated hospital in Wuhan. We prospectively collected and analysed data on patients with laboratory-confirmed 2019-nCoV infection by real-time RT-PCR and next-generation sequencing. Data were obtained with standardised data collection forms shared by WHO and the International Severe Acute Respiratory and Emerging Infection Consortium from electronic medical records. Researchers also directly communicated with patients or their families to ascertain epidemiological and symptom data. Outcomes were also compared between patients who had been admitted to the intensive care unit (ICU) and those who had not. The 2019-nCoV infection caused clusters of severe respiratory illness similar to severe acute respiratory syndrome corona virus and was associated with ICU admission and high mortality. Major gaps in our knowledge of the origin, epidemiology, duration of human transmission, and clinical spectrum of disease need fulfilment by future studies. Following the pneumonia cases of unknown cause reported in Wuhan and considering the shared history of exposure to Wuhan seafood market across the patients, an epidemiological alert was released by the local health authority on Dec 31, 2019, and the market was shut down on Jan 1, 2020. Meanwhile, 59 suspected cases with fever and dry cough were transferred to a designated hospital starting from Dec 31, 2019. An expert team of physicians, epidemiologists, virologists, and government officials was soon formed after the alert.

[3] Title: COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 In X-Ray Iamges. Authors: Ezz El-Din Hemdan, Marwa A. Shouman, Mohamed Esmail Karar, Published Year: 2020

Findings: The aim of this article is to introduce a new deep learning framework; namely COVIDX-Net to assist radiologists to automatically diagnose COVID-19 in X-ray images. Materials and Methods: Due to the lack of public COVID-19 datasets, the study is validated on 50 Chest Xray images with 25 confirmed positive COVID-19 cases. The COVIDX-Net includes seven different architectures of deep convolutional neural network models, such as modified Visual Geometry Group Network (VGG19) and the second version of Google MobileNet. Each deep neural network model is able to analyze the normalized intensities of the X-ray image to classify the patient status either negative or positive COVID-19 case. Results: Experiments and evaluation of the COVIDX-Net have been successfully done based on 80-20% of X-ray images for the model training and testing phases, respectively. The VGG19 and Dense Convolutional Network (DenseNet) models showed a good and similar performance of automated COVID19 classification with f1-scores of 0.89 and 0.91 for normal and COVID-19, respectively. This study demonstrated the useful application of deep learning models to classify COVID-19 in Xray images based on the proposed COVIDX-Net framework. Clinical studies are the next milestone of this research work.

[4] Title: Pneumonia Detection In Covid-19 Patients Using CNN Algorithm Authors: Vishesh S, Nishanth, Bharath, Amith, Published Year: 2020

Findings: The outbreak of corona virus disease in December 2019 in China spread rapidly across all parts of the world by January 2020. The World Health Organization (WHO) termed it as COVID19 and declared it a pandemic on January 30, 2020. Till June 8th, 2020, the number of confirmed cases is around 7 million globally, and the global fatality rate is around 3-4%. Since it is a highly contagious disease and is spreading rapidly; governments of almost all of the affected countries are taking it on priority to isolate infected individuals as early as possible. The general symptoms of COVID19 patients are flu-like such as fever, cough, dyspnea, breathing problem, and viral pneumonia. But these symptoms alone are not significant. There are many cases where individuals are asymptomatic but their chest CT scan and the pathogenic test were COVID-19 positive. So, along with symptoms, positive pathogenic testing and positive CT images/X-Rays of the chest are being used to diagnose the disease. Deep Learning (DL) techniques specifically Convolutional Neural Networks (CNN) has proven successful in medical imaging classification. Four different deep CNN architectures were investigated on images of chest X-Rays for diagnosis of COVID-19. These models have been pre-trained on the train/test database thereby reducing the need for large training sets as they have pre-trained weights. It was observed that CNN based architectures have the potential for diagnosis of COVID-19 disease.

IV. PROBLEM STATEMENT AND PROPOSED SOLUTION

Real-time PCR is a standard diagnostic tool being used for pathological testing. But the increasing number of false test results has opened the path for exploration of alternative testing tools. Chest X-Rays of COVID-19 patients have proved to be an important alternative indicator of COVID- 19 screening -A diagnosis recommender system that can assist the doctor to examine the lung images of the patients will reduce the diagnostic burden of the doctor. In order to control the spread of COVID-19, a large number of suspected cases need to be screened for proper isolation and treatment. Pathogenic research facility testing is the indicative best quality level however it is tedious with noteworthy bogus negative outcomes. Quick and precise analytic strategies are desperately expected to battle the sickness. In light of COVID-19 radiographical changes in X-ray pictures, we meant to build a deep learning method that could extract

IJARCCE



International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 8, August 2021

DOI 10.17148/IJARCCE.2021.10811

COVID-19's graphical features so as to give a clinical analysis in front of the pathogenic test, thus saving critical time for disease control. In this paper, CNN, a machine learning classification technique is used to classify the Chest X-ray images. As accuracy is the most significant factor in this issue, by taking a more prominent number of pictures for training the network and by increasing the number of iterations, the CNN accuracy can be improved.

V. SYSTEM ARCHITECTURE

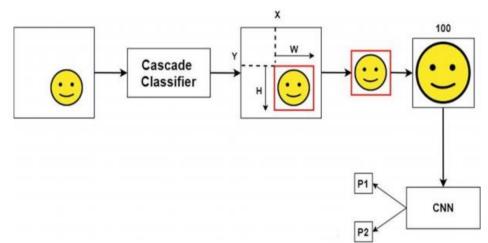


Figure 1 shows the system architecture of the proposed system using CNN and Cascade Classifier method.

Figure 1 shows the system architecture. As shown in the figure there are various components which are involved in the working model for the project. These components are as follows:

RGBtoGray Converter- The images acquired will [4][5] contain RGB components which need to be converted to gray scale for processing. To get started, we need to import the **cv2** module, which will make available the functionalities needed to read the original image and to convert it to gray scale. Next, we need to convert the image to gray scale. To do it, we need to call the "cvtColor" function, which allows converting the image from a colour space to another.

Normalization: The pixel values in images must be scaled prior to providing the images as input to a deep learning neural network model during the training or evaluation of the model. Traditionally, the images would have to be scaled prior to the development of the model and stored in memory or on disk in the scaled format. An alternative approach is to scale the images using a preferred scaling technique just-in-time during the training or model evaluation process. Keras supports this type of data preparation for image data via the "ImageDataGenerator" class and API.

Cascade Classifier: Cascading classifiers are trained with several hundred positive sample views of a particular object and arbitrary negative images of the same size. After the classifier is trained it can be applied to a region of an image and detect the object in question. To search for the object in the entire frame, the search window can be moved across the image and check every location for the classifier. This process is most commonly used in image processing for object detection and tracking.

CNN: We need to train a deep learning model which can take advantage of the robust dataset obtained from our proposed algorithm. Since the problem can be regarded as a classification task of normal, COVID-19, and other abnormal cases (e.g., pneumonia), we investigate the contemporary deep learning architectures suited for classification. In contrast with other variants of deep learning architectures [6] (i.e., longshort term memory (LSTM), deep belief networks, and so forth) and extreme learning machines, CNNs are regarded as the most powerful deep learning architecture for image classification. Therefore, we explore the robust CNN models recently employed to gain reasonable classification accuracy with chest X-ray data.[7][8] By applying the contemporary CNN models on the latest dataset compiled from public repositories, we realize that their reported performances are constrained by overfitting and influenced by biased test data. To address this issue, we propose a two-dimensional (2-D), custom CNN model for classifying X-ray images to predict COVID-19 cases. The 2-D CNN structure is utilized to learn the discriminating patterns automatically from the radiograph images. Figure 2 shows the code of the CNN model. Figure 3 shows the binary classification as COVID negative (P1) or COVID positive (P2).[9][10]

Data Layer: The data layer is responsible for storage of information related to registered users, admin, doctors. The data layer will also be able to store answers of users, appointment information as well as the classification information.

IJARCCE



International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 8, August 2021

DOI 10.17148/IJARCCE.2021.10811

Authentication Layer: The users request is validated and after it is being checked whether the request contains valid application id and also has a valid session. User will be thrown out if the session is invalid.

model=Sequential() model.add(Conv2D(200,(3,3),input shape=data.shape[1:])) model.add(Activation('relu')) model.add(MaxPooling2D(pool size=(2,2))) #The first CNN layer followed by Relu and MaxPooling layers model.add(Conv2D(100,(3,3))) model.add(Activation('relu')) model.add(MaxPooling2D(pool_size=(2,2))) #The second convolution layer followed by Relu and MaxPooling layers model.add(Flatten()) model.add(Dropout(0.5)) #Flatten layer to stack the output convolutions from second convolution layer model.add(Dense(50,activation='relu')) #Dense layer of 64 neurons model.add(Dense(2,activation='softmax')) Figure 2 shows the code of the CNN model.

model.add(Dense(2,activation='softmax'))

#The Final layer with two outputs for two categories

model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])

Figure 3 shows the binary classification as P1 or P2.

VI. RESULTS

Real-time images are fed to the system and now the trained system takes decisions that are based on the historical image set. As shown in figure 4 training is done on 1057 samples which are obtained randomly by train test split. Validation is carried out on 265 samples. Epoch is fixed to 10 and 1057 samples are evaluated epoch number of times and average training time noted on each step. Validation and Train accuracy measured at each step and a line plot generated as shown in figure 5. Figure 6 shows the classification of the fed image as COVID POSITIVE on percentage scale.

Epoch 1/10 1857/1857 [************************************	Train on 1	057 samples, validate on 265 sa	nples									
<pre>y: 0.6520 Epoch 2/10 1057/1857 [====================================</pre>	Epoch 1/16	1										
Epoch 2/10 1057/1057 [=======] - 1295 122ms/step - loss: 0.3260 - accuracy: 0.8581 - val_loss: 0.1913 - val_ec poch 3/10 1057/1057 [======] - 1385 122ms/step - loss: 0.2052 - accuracy: 0.9243 - val_loss: 0.2020 - val_ec poch 4/10 1057/1057 [======] - 1265 119ms/step - loss: 0.1585 - accuracy: 0.9357 - val_loss: 0.2055 - val_ec poch 4/10 1057/1057 [======] - 1325 125ms/step - loss: 0.2076 - accuracy: 0.9262 - val_loss: 0.1677 - val_ec poch 6/10 1057/1057 [======] - 1195 113ms/step - loss: 0.1335 - accuracy: 0.9527 - val_loss: 0.1052 - val_ec poch 6/10 1057/1057 [=======] - 1185 111ms/step - loss: 0.1055 - accuracy: 0.9527 - val_loss: 0.0983 - val_ec poch 7/10 1057/1057 [=======] - 1185 111ms/step - loss: 0.1055 - accuracy: 0.9787 - val_loss: 0.0983 - val_ec poch 7/10 1057/1057 [=======] - 1185 112ms/step - loss: 0.2055 - accuracy: 0.9787 - val_loss: 0.1018 - val_ec poch 7/10 1057/1057 [=======] - 1185 112ms/step - loss: 0.2055 - accuracy: 0.9787 - val_loss: 0.1018 - val_ec poch 7/10 1057/1057 [=======] - 1185 112ms/step - loss: 0.2055 - accuracy: 0.9787 - val_loss: 0.1018 - val_ec poch 7/10 1057/1057 [=======] - 1185 112ms/step - loss: 0.2055 - accuracy: 0.9787 - val_loss: 0.1018 - val_ec poch 7/10 1057/1057 [=======] - 1185 112ms/step - loss: 0.2055 - accuracy: 0.9787 - val_loss: 0.1018 - val_ec poch 7/10 1057/1057 [=======] - 1185 112ms/step - loss: 0.2055 - accuracy: 0.9787 - val_loss: 0.2058 - val_ec poch 10/10	1057/1057	[- 1385	131ms/step	- loss:	0.6428		accuracy:	0.6443	- val_loss:	0.6038	- val_acci
1057/1057 [====================================	y: 0.6528											
y: 0.9221 Epoch 5/10 1057/1057 [======] - 1305 123ms/step - loss: 0.2052 - accuracy: 0.9243 - val_loss: 0.2020 - val_acc y: 0.9132 Epoch 4/10 1057/1057 [=======] - 1255 119ms/step - loss: 0.1585 - accuracy: 0.9357 - val_loss: 0.2055 - val_acc Epoch 5/10 1057/1057 [========] - 1255 125ms/step - loss: 0.2076 - accuracy: 0.9262 - val_loss: 0.1677 - val_acc Epoch 6/10 1057/1057 [========] - 1195 113ms/step - loss: 0.1335 - accuracy: 0.9527 - val_loss: 0.1052 - val_acc Epoch 6/10 1057/1057 [========] - 1195 113ms/step - loss: 0.1065 - accuracy: 0.9540 - val_loss: 0.1052 - val_acc Epoch 6/10 1057/1057 [========] - 1195 112ms/step - loss: 0.0255 - accuracy: 0.9540 - val_loss: 0.0983 - val_acc y: 0.5858 Epoch 6/10 1057/1057 [========] - 1195 112ms/step - loss: 0.0255 - accuracy: 0.9707 - val_loss: 0.1018 - val_acc y: 0.5858 Epoch 6/10 1057/1057 [========] - 1195 112ms/step - loss: 0.1263 - accuracy: 0.9536 - val_loss: 0.0984 - val_acc y: 0.5858 Epoch 6/10 1057/1057 [=======] - 1185 112ms/step - loss: 0.1263 - accuracy: 0.9536 - val_loss: 0.0984 - val_acc y: 0.5858 Epoch 6/10 1057/1057 [=======] - 1185 112ms/step - loss: 0.1263 - accuracy: 0.9536 - val_loss: 0.0984 - val_acc Epoch 10/10	Epoch 2/14											
Epoch 3/10 1857/1857 [====================================	1057/1057	[======================================	- 1295	122ms/step	- loss:	0.3260		accuracy:	0.8581	- val_loss:	0.1913	- val_acci
1957/1957 [====================================	y: 0.9321											
y: 0.9132 Epoch 4/10 1857/1857 [====================================												
<pre></pre>	1057/1057	[] - 130s	123ms/step	- loss:	0.2052		accuracy:	0.9243	- val_loss:	0.2020	- val_acci
<pre>1057/1057 [====================================</pre>	y: 0.9132											
<pre>y: 0.8755 Epoch 5/10 1857/1857 [====================================</pre>												
Epoch 5/10 1057/1057 [======] 1057/1057 [=====] 1057/1057 [=====] 1057/1057 [=====] 1057/1057 [=====] 1057/1057 [=====] 1057/1057 [=====] 1057/1057 [=====] 1057/1057 [======] 1057/1057 [=====] 1057/1057 [=====] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [======] 1057/1057 [=======] 1057/1057 [=======] 1055 1057/1057 [========] 1057/1057 [=========] 1057/1057 [=========] 1057/1057 [===========] 10583 1057/1057	1057/1057	[- 1265	119ms/step	- loss:	0.1585		accuracy:	0.9357	- val_loss:	0.2855	- val_accu
<pre>1957/1957 [====================================</pre>	y: 0.8755											
<pre>y: 0.9283 Bpoch 6/10 1857/1857 [====================================</pre>												
\$poch 6/10 1057/1057 [*************************] - 1195 113ms/step - loss: 0.1335 - accuracy: 0.9527 - val_loss: 0.1052 - val_acc \$poch 7/10 1057/1057 [********************************] - 1185 111ms/step - loss: 0.1065 - accuracy: 0.9640 - val_loss: 0.0983 - val_acc \$poch 6/10 1057/1057 [************************************		[***********************************	- 1325	125ms/step	- loss:	0.2076		accuracy:	0.9262	- val_loss:	0.1677	- val_acci
1057/1057 [************************************												
y: 0.5555 Epoch 7/10 1857/1057 [====================================												
Epoch 7/10 10857/1487			- 1195	113ms/step	- loss:	0.1335		accuracy:	0.9527	- val_loss:	0.1052	- val_accu
1057/1057 [====================================												
y: 0.9698 Spoch 0/10 1057/1057 [====================================												
Epoch 8/10 1857/1857 [====================================		[*****************************	- 1185	111ms/step	- loss:	0.1065	•	accuracy:	0.9640	- val_loss:	0.0983	- val_accu
1057/1057 [====================================												
y: 0.9698 Epoch 9/10 1057/1057 [====================================												
<pre>Epoch 9/10 1857/1857 [*************************] - 118s 112ms/step - loss: 0.1263 - accuracy: 0.9536 - val_loss: 0.0904 - val_ac y: 0.9585 Epoch 10/10</pre>		[************************	- 1195	112ms/step	- 1055:	0.0925		accuracy:	0.9707	- val_loss:	0.1018	- val_acci
1057/1057 [====================================												
y: 0.9585 Epoch 10/10					-							
Epoch 10/10		[*****************************	- 1185	112ms/step	- 105S:	0.1263	•	accuracy:	0.9536	- val_loss:	0.0904	- val_accu
											12-1222	
105//105/ [====================================		[==============================	- 1185	111ms/step	- 1055:	0.0655	•	accuracy:	0.9801	- val_loss:	0.0852	- Val_acci

Figure 4 shows the process of training on the samples after train test split.

IJARCCE



International Journal of Advanced Research in Computer and Communication Engineering

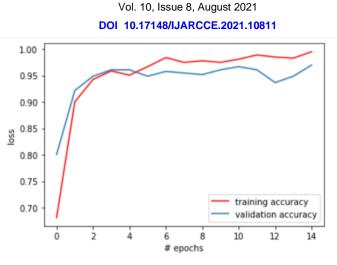


Figure 5 shows the accuracy measure of the model after execution.

```
print(model.evaluate(test_data,test_target))
```

```
147/147 [========================] - 2s 13ms/step
[0.30164477452128924, 0.9319728016853333]
```

Figure 6 shows the classification of the input image as COVID POSITIVE.

VII. CONCLUSIONS AND FUTURE SCOPE

COVID-19 is affecting the health of the global population at an alarming rate. Testing of large numbers of individuals is crucial to curb the spread of disease. Real-time PCR is a gold standard pathological test for the diagnosis of this disease. But the increasing number of negative false reporting has led to the use of Chest X-rays as an alternative for diagnosis of COVID-19. Deep learning based recommender systems can be of great help in this scenario when the volume of patients is very high and required radiological expertise is low. We have presented results on detecting COVID-19 positive cases from chest X-Rays using a deep-learning model. The results look promising, though the size of the publicly available dataset is small. The results suggest that CNN based architectures have the potential for the correct diagnosis of COVID19 disease. In future, fine tuning of these models may further improve the accuracy. We may further validate our approach using larger COVID-19 X-ray image datasets and clinical trials. Other methods can be discovered to get more precise results.

REFERENCES

[1] P. Chatterjee et al., "The 2019 novel coronavirus disease (Covid-19) pandemic: A review of the current evidence," Indian Journal of Medical Research, Supplement, vol. 151, no. 2–3. Indian Council of Medical Research, pp. 147–159, 2020, doi: 10.4103/ijmr.IJMR_519_20.

[2] G. Pascarella et al., "COVID-19 diagnosis and management: a comprehensive review," Journal of Internal Medicine, 2020, doi: 10.1111/joim.13091.

[3] C. P. West, V. M. Montori, and P. Sampathkumar, "COVID-19 Testing: The Threat of False- Negative Results," Mayo Clinic Proceedings. Elsevier Ltd, 2020, doi: 10.1016/j.mayocp.2020.04.004.

[4] D. Wang et al., "Clinical Characteristics of 138 Hospitalized Patients with 2019 Novel Coronavirus-Infected Pneumonia in Wuhan, China," JAMA - Journal of the American Medical Association, vol. 323, no. 11, pp. 1061–1069, Mar. 2020, doi: 10.1001/jama.2020.1585.

[5] C. Huang et al., "Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China," The Lancet, vol. 395, no. 10223, pp. 497– 506, Feb. 2020, doi: 10.1016/S0140- 6736(20)30183-5.

[6] M. Anthimopoulos, S. Christodoulidis, L. Ebner, A. Christe, and S. Mougiakakou, "Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network," IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1207–1216, May 2016, doi: 10.1109/TMI.2016.2535865.

[7] P. Rajpurkar et al., "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning," Nov. 2017, [Online]. Available: http://arxiv.org/abs/1711.05225.

[8] E. Luz, P. L. Silva, R. Silva, L. Silva, G. Moreira, and D. Menotti, "Towards an Effective and Efficient Deep Learning Model for COVID-19 Patterns Detection in X-ray Images," Apr. 2020, [Online]. Available: http://arxiv.org/abs/2004.05717.

[9] F. Shan et al., "Lung Infection Quantification of COVID-19 in CT Images with Deep Learning Author list."

[10] E. El-Din Hemdan, M. A. Shouman, and M. E. Karar, "COVIDXNet: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-Ray Images," arXiv preprint arXiv: 2003.11055, 2020