COVRAID: COVID-19 Rapid Artificial Intelligence Based Detection

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***Abstract*— World has experienced a new potent challenge in the shape of Coronavirus disease 2019 (COVID-19). Rapid screening and detection of infected patients is important step in fighting against this disease, so that proper measures can be taken to stop it from further spreading. Majority of the countries who have been successful in controlling the disease, have done it through effective early detection. The same factor is very evident in the countries where COVID-19 has gone out of control that they were or are not successful in early detection of suspected patients. This paper presents an artificial intelligence-based approach to provide new screening approach to detect COVID-19 from X-ray images. More than thirty-five thousand local/international negative and positive corona X-ray images were obtained to train VGG-16 model. Proposed method has two classifiers, first classifier distinguishes between negative cases and other infected cases, second classifier identifies pneumonia and other infected cases. These other infected cases will be recognized as COVID-19. Experimental evaluation on different X-ray imaging were conducted where this method classified positive and negative cases very effectively. A comparative study with publicly available network such as COVID-NET is also carried out. Proposed method outperformed COVID-NET in all three major areas such as overall accuracy, sensitivity and specificity. Overall accuracy for our technique is 95.08%, while sensitivity and specificity values are 100% and 93.15% respectively, while overall accuracy, sensitivity, specificity values for COVID-NET are 52.36%, 86.79% and 27.39% respectively.**

I. INTRODUCTION

Coronavirus disease 2019 (COVID-19) is an pandemic disease caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). The case of coronavirus was first identified in December 2019 in Wuhan, the capital of China's Hubei province, and has since spread across the world, resulting in the ongoing 2019–20 coronavirus pandemic. Dealing with COVID-19 is major challenge now a days and most effective approach can be its early detection and cost-effective screening. The standard method for COVID- 19 screening is Real-Time Reverse Transcription Polymerase Chain Reaction (rRT-PCR), which can detect SARS-CoV-2 RNA from respiratory specimens (which can be found in nasopharyngeal or oropharyngeal swabs) . One of the major benefit of this approach is its standardization, that's why it is used worldwide. The main drawback in this approach is its expensiveness and considerable time requirement to identify patients. Additionally, the sensitivity of RT-PCR testing is varying and its results aren't clear and consistent to date, and initial findings in China has shown relatively poor sensitivity[1].

Another popular method is human eye-based screening, in which a chest X-ray (CXR) image or computed topography images are analyzed by radiologists to find ground-glass opacities, bilateral and interstitial abnormalities to identify COVID-19 positive patients [2]. This approach is widely used to identify other diseases too, for example pneumonia, tuberculosis etc. It is very conventional approach in disease diagnosis and is not effective as human error involved plus it is quite difficult for a radiologist to handle high number of patients at a time.

Figure 1 shows X-ray images of corona positive, corona negative merged together while figure 2 depicts pneumonia positive and tuberculosis positive images merged. These

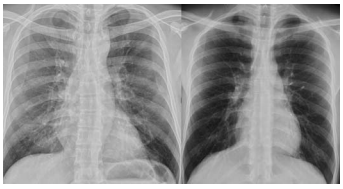


Fig. 1: COVID-19 Positive (left) and Negative Image (right)

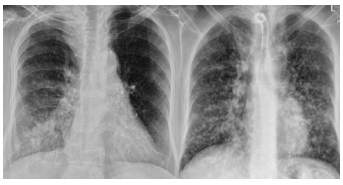


Fig. 2: Pneumonia (left) and Tuberculosis Image (right)

scenarios motivated researchers to develop AI based solution which can identify COVID-19 by looking abnormalities in x-ray images. Number of benefits are associated with proposed scheme, some of them are as under;

- **Rapid Screening:** X-ray based coronavirus detection technique is quite fast as compared to standard methods and can be used in assisting radiologists.
- **Cost Effectiveness:** This approach is very affordable for general public specifically residing in developing and poor countries as X-ray imaging is many times cheaper than PCR test.

- **Pain-Free:** Nasal swabbing process during PCR testing is quite painful procedure for many people, but X-ray based technique is painless as compared to that.
- **Availability and Accessibility:** Chest X-ray imagery is most readily available technology in most healthcare systems, that's why it is easily accessible in many testing areas and imaging centers. If talk specifically, X-ray imagery is comparatively has higher available than CT scan imagery, especially in developing countries where CT scanners are not cost effective due to expensive machine and its maintenance cost [1].
- **Portability:** With the availability of portable Chest X-ray allows to perform imaging process within the isolation wards, thus greatly reducing the risk of COVID-19 transmission, which mostly occurs when patients gather around or go to sites, where fixed imaging facility is available [3].

Inspired by above mentioned benefits, a new screening approach is developed, known as COV-RAID. COV-RAID is a software based on Artificial Intelligence to predict Covid-19 in suspected individuals.

II. Related Work

Since coronavirus emergence, researchers started developing solutions to rapidly screen it. Drop weights based Bayesian Convolutional Neural Networks (BCNN) is presented in [4], which has the ability to estimate uncertainty in Deep Learning algorithms and subsequently improve the performance of diagnosis of the man-machine combination using dataset which publicly available of chest X-rays infected with COVID-19 and show that the uncertainty in prediction is strongly correlated with the accuracy of the prediction. In [5], three different convolutional neural network-based models (ResNet50, InceptionV3 and Inception-ResNetV2) have been proposed for the detection of coronavirus pneumonia infected patient using chest X-ray radio graphs. Differentiation of pneumonia caused by virus from the pneumonia not caused by virus and healthy controls into a one-class classification-based anomaly detection problem is described in [6], and the confidence-aware anomaly detection (CAAD) model is proposed, which has three modules first one is the shared feature extractor, the second module detects the anomalies, and the last module predicts the confidence. Pneumonia chest x-ray detection based on generative adversarial networks (GAN) with a fine-tuned deep transfer learning for a limited dataset is shown in [7]. [8] presents an alternative modeling framework based on Capsule Networks, referred to as the COVID-CAPS, being capable of handling small datasets, which is important due to sudden and rapid emergence of COVID-19. In [9] well-known CheXNet model is utilized to develop COVID-CXNet. This powerful model can detect the novel coronavirus pneumonia based on relevant and meaningful features with precise localization. [10] has presented three ResNet-based models, retrained to classify X-rays in a one-against-all basis from (a) normal or diseased, (b) pneumonia or non-pneumonia, and (c) COVID-19 or non-COVID individuals.

III. Methodology

In this research, transfer learning-based technique is applied on VGG-16 model. Publicly and locally available X-ray images of Covid-19, negative and pneumonia patients were used to train, test and validate. Here we will elaborate procedure of dataset creation and cleansing, VGG-16 model and its features, modified principled architecture.

A. Dataset Creation:

Performance of any AI network is (mostly) directly proportional to availability of correct training data. Local hospitals and publicly available datasets were used to train, test and validate model. In given scenario, the available dataset for training is limited. Hierarchical approach is adopted to overcome this issue. The indigenous algorithm work in a step wise mode, where in first step normal patients are segregated from pneumonia like patients. As data for normal and pneumonia patients is available in quite a big amount, 1st network can segregate the normal patients quite well. In second step, the output of 1st network is fed into 2nd network which is trained to separate COVID patients from pneumonia like patients. This way, by selecting a hierarchical approach, we have improved our results by a big margin. Data augmentation techniques (scale adjustment for zoom in and zoom out, translation shift, rotation for $\pm$ 5 degrees etc...) were utilized to make best use of data. There were more than 35000 X-ray images available after data augmentation. Data division for first and second classifier is shown in figure [3] and figure [4]. 70:20:10 ratio was used for training, testing and validation dataset preparation.

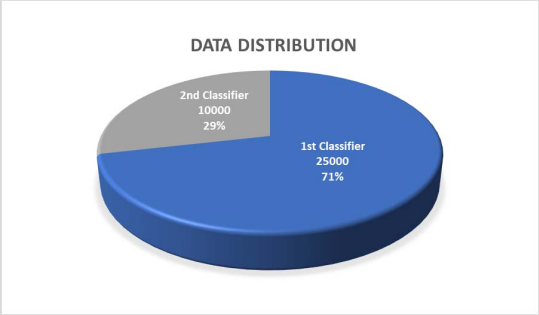


Fig. 3: Data Division for 1st and 2nd Classifier

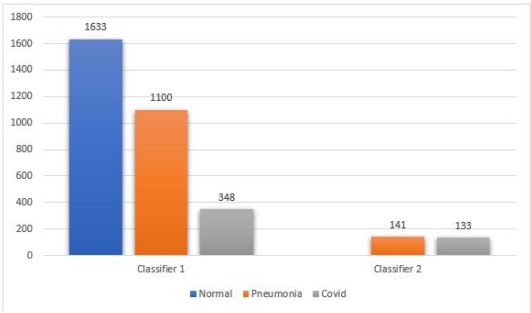


Fig. 4: Data Division without Data Augmentation

B. Data Cleansing Procedure:

As data was gathered from many different resources, there were many artifacts, brightness/contrast problems. These problems were solved by image segmentation and manual adjustment of brightness/contrast of images.

1) Image Segmentation: Image segmentation is very important because it allows CNN model to focus on main features rather than on background. Image was cropped manually in such a way that only X-ray's lungs section is left out.

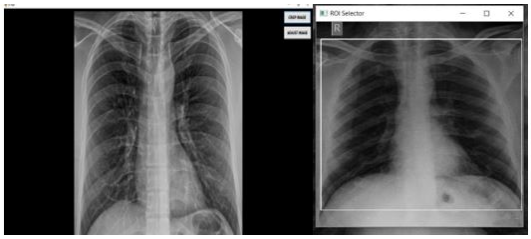


Fig. 5: Image Segmentation Process

2) Image Brightness Correction: Image brightness correction is one of important task. It mostly occurs due to bad illumination or sensitivity settings of X-ray machine. As X-rays are taken from multiple sources, that's why there is no general value for brightness/contrast. It was adjusted manually in such a way that X-ray image features are prominent and image illuminance is at decent level.

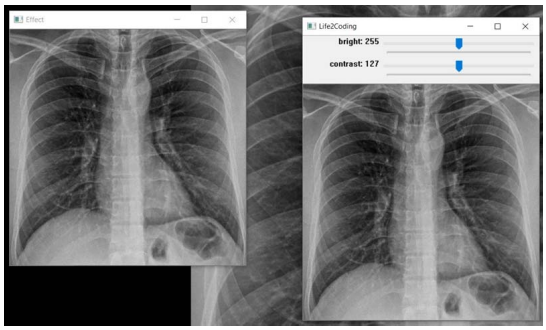


Fig. 6: Image Brightness Process

C. Software Design

A front end software has been prepared which is currently deployed in many hospitals. Overall working algorithm for COV-RAID via usage of front end software is displayed in figure 7.

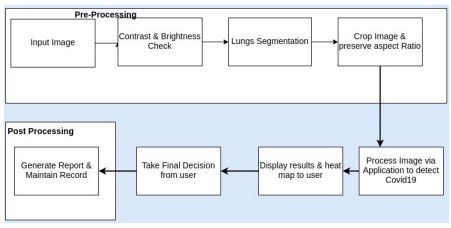


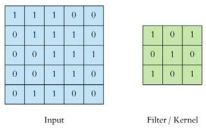
Fig. 7: Workflow Chart for COV-RAID

D. VGG-16 Model and Its Features:

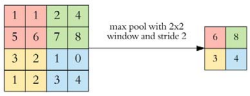
"Very Deep Convolutional Networks for Large-Scale Image Recognition" is a paper by K. Simonyan and A. Zisserman from the University of Oxford in which VGG16 was proposed which is a convolutional neural network. The model has achieved 92.7% on the top-5 test accuracy on ImageNet, which is a dataset that consists of 14 million images and it has 1000 classes. It was one of the famous models submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 33 kernel-sized filters. [11]

E. Modified Principled Architecture

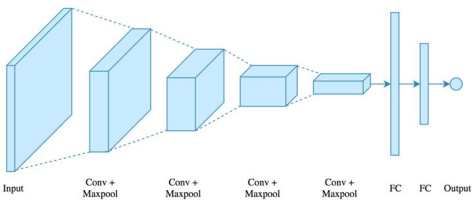
VGG-16 model was modified according to requirements and was trained for couple of days using NVIDIA Titan Black GPU's. Modified model is depicted in figure 8 and figure 9. It shall resize any input image to 512*512 pixels. Input shall be fed to the input layer. Filter shall be applied on the input matrix. Activation function shall be applied on



each neuron output. Pooling layer will be used to lower the dimensions of the input layer while retaining the critical information. The Deeper the network goes the information about the image decreases in the feature map and the information about the class of the image increases. They still encode useful features, but they are less interpretable by us visually. Multiple layers shall be used while processing.



The Model shall use two classifiers which shall classify between Healthy and Covid-19 patients. If an individual X-Ray feature scores matches to healthy person, then the 1st classifier shall be used. Otherwise feature scores of the last layer (of 1st classifier) shall be fed into the input of the first layer (of 2nd classifier). The 2nd classifier shall use multiple layers to predict if an individual has Covid-19 or not. The last layer of a classifier is a fully connected layer. It has logit scores which relate to probability of the input image. Activation function i.e. "Softmax" is used to convert logit score to predicted classifier.



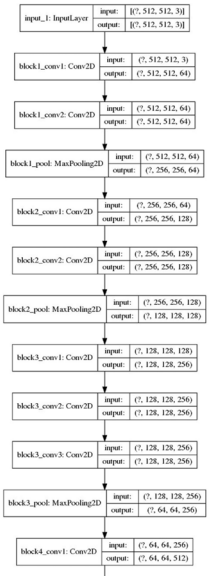


Fig. 8: First Part of Modified Principle Architecture

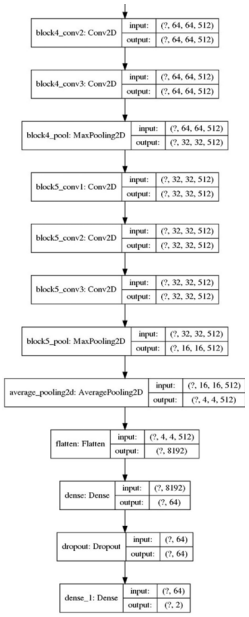


Fig. 9: Second Part of Modified Principle Architecture

F. Training parameters

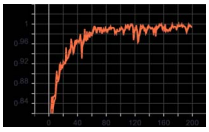
Following parameters were used:

- Number of epochs: 700 for 1st classifier, 200 for 2nd classifier
- Layers of Classifier 1 : 18 layer neural network
- Layers of Classifier 2 : 18 layer neural network
- Type of Activation functions on output: Softmax
- Input Images size: 512*512
- Batch size = 15

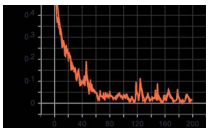
G. ROC and Learning Curves

The learning plot graphs are the visualization of about how better the network is learning from the training dataset provided. These graphs are the quantitative representations of the learning of any neural network.

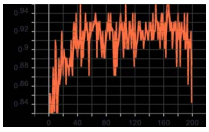
1) Epoch Accuracy Graph: Epoch Accuracy Graph tells how the network improves itself at each epoch over a given dataset. The x-axis here represents epochs while the y-axis represents accuracy of the network during training.



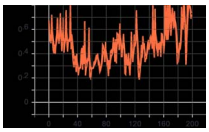
2) Epoch Loss Graph: The Epoch Loss Graph is quantitative representation of the losses over each epoch. Here the x-axis represents number of epochs, and y-axis represents loss of the network during training.



3) Epoch Validation Accuracy: While training, the network validates itself over a set of dataset. The Epoch Validation Accuracy Graph is the quantitative representation of the of the validation accuracy over each epoch. The x-axis here represents epochs and y-axis represents validation accuracy.



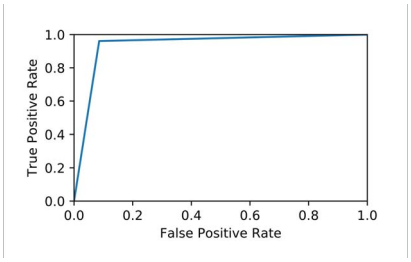
4) Epoch validation loss: The Epoch Validation Loss Graph is quantitative representation of the validation loss over each epoch. The x-axis here represents epochs and y-axis represents validation loss.

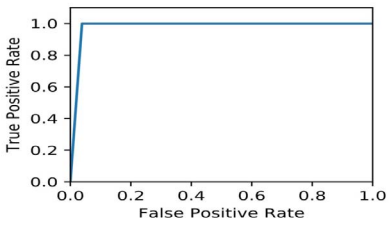


5) Characteristic (ROC) Curves Graphs: The Receiver Operating Characteristic (ROC) curve during the training of the network is vital. It quantitatively visualizes how the network achieves true positives from the false positives. As the model consists of two classifiers (alpha and beta), the ROC of each of the classifier is given below. The first image shows ROC of classifier alpha, and second image shows ROC of classifier beta.

IV. Results

Different internal/external evaluations/validations and comparison with open source models were performed whose detail is as following:





A. *Internal/External Evaluations*

Five different validations' detail is as under;

1) Validation 01: Evaluation details are as under;

Eval-01	**Total X-Rays**	13
	Covid	4
	Non-Covid	9

Confusion Matrix

True Positive	True Negatives	False Positives	False Negatives
TP	**TN**	**FP**	**FN**
SaMD revealed COVID-19 when it was classified as present in test data.	SaMD did not reveal COVID-19 when it was classified as absent in test data.	SaMD revealed COVID-19 when it was classified as absent in test data.	SaMD did not reveal COVID-19 when it was classified as present in test data.
4	**3**	**6**	**0**

Standard Set of Diagnostic Metrics

For software version '0.2'

ID	Metric	Description	Formula	Minimum Acceptable Value*	Value Obtained
SDM1	Sensitivity (True Positive Rate)	The probability that the test is positive when the COVID-19 is present.	TP/(TP + FN)	0.81	1.00
SDM2	Specificity (True Negative Rate)	The probability that the test is negative when COVID-19 is not present.	TN/(TN + FP)	0.81	0.333
SDM3	Accuracy	Level of correspondence of the test to actual results.	(TP + TN)/(TP + TN + FP + FN)	0.81	0.5385

2) Validation 02: Evaluation output results are as under, which shows COV-RAID's sensitivity and other important parameters;

3) Validation 03: Evaluation result details are as under, important parameters such as sensitivity, accuracy and specificity can be seen from it;

Eval-02	**Total X-Rays**	41
	Covid	7
	Non-Covid	34

Confusion Matrix

True Positive	True Negatives	False Positives	False Negatives
TP	**TN**	**FP**	**FN**
SaMD reveled COVID-19 when it was classified as present in test data.	SaMD did not reveal COVID-19 when it was classified as absent in test data.	SaMD revealed COVID-19 when it was classified as absent in test data.	SaMD did not reveal COVID-19 when it was classified as present in test data.
7	**29**	**5**	**0**

Standard Set of Diagnostic Metrics:

For software version '0.4'

ID	Metric	Description	Formula	Minimum Acceptable Value by PEC	Value Obtained
SDM1	Sensitivity (True Positive Rate)	The probability that the test is positive when the COVID-19 is present.	TP/(TP + FN)	0.81	1.00
SDM2	Specificity (True Negative Rate)	The probability that the test is negative when COVID-19 is not present.	TN/(TN + FP)	0.81	0.8529
SDM3	Accuracy	Level of correspondence of the test to actual results.	(TP + TN)/(TP + TN + FP + FN)	0.81	0.878

Eval-03	**Total X-Rays**	21
	Covid	3
	Non-Covid	18

Confusion Matrix

True Positive	True Negatives	False Positives	False Negatives
TP	**TN**	**FP**	**FN**
SaMD revealed COVID-19 when it was classified as present in test data.	SaMD did not reveal COVID-19 when it was classified as absent in test data.	SaMD revealed COVID-19 when it was classified as absent in test data.	SaMD did not reveal COVID-19 when it was classified as present in test data.
3	**17**	**1**	**0**

Standard Set of Diagnostic Metrics

For software version '0.5'

ID	Metric	Description	Formula	Minimum Acceptable Value*	Value Obtained
SDM1	Sensitivity (True Positive Rate)	The probability that the test is positive when the COVID-19 is present.	TP/(TP + FN)	0.81	1.0
SDM2	Specificity (True Negative Rate)	The probability that the test is negative when COVID-19 is not present.	TN/(TN + FP)	0.81	0.9444
SDM3	Accuracy	Level of correspondence of the test to actual results.	(TP + TN)/(TP + TN + FP + FN)	0.81	0.9524

4) Validation 04: Evaluation results are as under, false positives, false negatives and true positives, true negatives are there, which shows true picture;

5) Validation 05: Evaluation results are shown below;

B. *Comparison With Other Models:*

Comparison with publicly available network such as COVID-NET [12] has been conducted and COV-RAID outperformed in all three major areas such as sensitivity,

Eval-04	Total X-Rays	48
	Covid	15
	Non-Covid	33

Confusion Matrix

True Positive	True Negatives	False Positives	False Negatives
TP	TN	FP	FN
SaMD revealed COVID-19 when it was classified as present in test data.	SaMD did not reveal COVID-19 when it was classified as absent in test data.	SaMD revealed COVID-19 when it was classified as absent in test data.	SaMD did not reveal COVID-19 when it was classified as present in test data.
15	31	2	0

Standard Set of Diagnostic Metrics
For software version '0.5'

ID	Metric	Description	Formula	Minimum Acceptable Value*	Value Obtained
SDM1	Sensitivity (True Positive Rate)	The probability that the test is positive when the COVID-19 is present.	TP/(TP + FN)	0.81	1.0
SDM2	Specificity (True Negative Rate)	The probability that the test is negative when COVID-19 is not present.	TN/(TN + FP)	0.81	0.9394
SDM3	Accuracy	Level of correspondence of the test to actual results.	(TP + TN)/(TP + TN + FP + FN)	0.81	0.9583

Eval-05	Total X-Rays	122
	Covid	49
	Non-Covid	73

Confusion Matrix

True Positive	True Negatives	False Positives	False Negatives
TP	TN	FP	FN
SaMD revealed COVID-19 when it was classified as present in test data.	SaMD did not reveal COVID-19 when it was classified as absent in test data.	SaMD revealed COVID-19 when it was classified as absent in test data.	SaMD did not reveal COVID-19 when it was classified as present in test data.
48	68	5	1

Standard Set of Diagnostic Metrics
For software version '1' (Latest version)

ID	Metric	Description	Formula	Minimum Acceptable Value*	Value Obtained
SDM1	Sensitivity (True Positive Rate)	The probability that the test is positive when the COVID-19 is present.	TP/(TP + FN)	0.81	0.9796
SDM2	Specificity (True Negative Rate)	The probability that the test is negative when COVID-19 is not present.	TN/(TN + FP)	0.81	0.9315
SDM3	Accuracy	Level of correspondence of the test to actual results.	(TP + TN)/(TP + TN + FP + FN)	0.81	0.9508

specificity and accuracy. Comparison table is shown below in table 1. Claimed accuracy for COVID-NET is 93.3 %,

Model	Accuracy Value	Sensitivity	Specificity
COV-RAID	95.08 %	100 %	93.15 %
COVID-NET	52.36 %	86.79 %	27.39 %

TABLE I: Comparison with COVID-NET and COV-RAID

and on proposed research data, it was 52.36 %. It is not perfoming well, because it was trained on specific type of data while COV-RAID's dataset is very diversified, which gives it an edge over COVID-NET.

V. Discussion:

COV-RAID was designed to highly impact screening system in Pakistan. A desktop and web-based screening tools has been created, which are deployed and practiced in many public and private sector hospitals. This approach has resulted in successful early detection of COVID-19. COV-RAID had been approved by medical licensing authorities and came up as blessing for developing country like Pakistan. This approach can further be extended to diagnose other severe diseases such as diabetes, cancer etc.

VI. CONCLUSION

Corona Virus is one of most challenging problem of this time and it is impacting lives of many people. To overcome this problem to some extent, an early detection/screening technique based on CNN model has been designed. VGG-16 based model has been trained for publicly and locally available chest X-rays to distinguish between Covid and normal patients. This approach is more accurate and sensitive as compared to other open source available solutions such as COVID-NET. Proposed method outperformed COVID-NET in all three major areas such as overall accuracy, sensitivity and specificity.

References

[1] Linda Wang, Alexander Wong (2020) COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images

[2] Jacobi, A., Chung, M., Bernheim, A., Eber, C. (2020). Portable chest X-ray in coronavirus disease-19 (COVID-19): A pictorial review. Clinical imaging, 64, 35–42. https://doi.org/10.1016/j.clinimag.2020.04.001

[3] Rubin, G. D. et al. The role of chest imaging in patient management during the COVID-19 pandemic: A multinational consensus statement from the fleischner society. Radiology (2020).

[4] Biraja Ghoshal and Allan Tucker(2020) Estimating Uncertainty and Interpretability in Deep Learning for Coronavirus (COVID-19) Detection

[5] Ali Narin, Ceren Kaya and Ziynet Pamuk (2020), Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks

[6] Jianpeng Zhang, Yutong Xie, Guansong Pang, Zhibin Liao, Johan Verjans, Wenxin Li, Zongji Sun, Jian He, Yi Li, Chunhua Shen, Yong Xia (2020), Viral Pneumonia Screening on Chest X-ray Images Using Confidence-Aware Anomaly Detection

[7] Nour Eldeen M. Khalifa, Mohamed Hamed N. Taha, Aboul Ella Hassanien and Sally Elghamrawy (2020), Detection of Coronavirus (COVID-19) Associated Pneumonia based on Generative Adversarial Networks and a Fine-Tuned Deep Transfer Learning Model using Chest X-ray Dataset

[8] Parnian Afshar, Shahin Heidarian, Farnoosh Naderkhani, Anastasia Oikonomou, Konstantinos

N. Plataniotis, Arash Mohammadi,(2020), COVID-CAPS: A capsule network-based framework for identification of COVID-19 cases from X-ray images

[9] Arman Haghanifar,Mahdiyar Molahasani Majdabadi, Younhee Choi, S. Deivalakshmi and Seokbum Ko (2020), COVID-CXNet: Detecting COVID-19 in Frontal Chest X-ray Images using Deep Learning

[10] Sampa Misra,Seungwan Jeon,Seiyon Lee,Ravi Managuli,In-Su Jang, and Chulhong Kim, (2020), Multi-Channel Transfer Learning of Chest X-ray Images for Screening of COVID-19

[11] Karen Simonyan,(2015),Very Deep Convolutional Networks for Large-Scale Image Recognition