COVID-19 detection from chest x-rays using deep learning methods

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***Abstract*—The first case of the COVID 19 Pandemic was confirmed in Wuhan, China on December 31st. Since then, it has drastically affected the course of this world. The healthcare systems were pushed to their limits since more and more people required screening. Reverse Transcription Polymerase chain reaction (RT-PCR) was the definitive test for the detection of the virus, but the need for better and faster results was increasing, and therefore medical advancement in COVID 19 Testing was required. Chest X-ray based disease classification has emerged as an alternative method to help diagnosis of COVID 19. In this paper, a model is trained that is able to classify between a COVID-19 infected and a Normal CXR. The family of ResNets, and its variants which are convolutional neural networks were trained using transfer learning on the dataset and the experimental results were compared. The maximum accuracy achieved was 88.43% on the ResNet-50 model.**

***Index Terms*—Convolutional neural networks, transfer learning, CXR, COVID-19, disease classification**

I. Introduction

The first case of COVID 19 was confirmed in December 2019. Within months, the virus was declared as a global pandemic. As the pandemic progressed, the number of cases increased, and so the workload in hospitals. There were just not enough resources to accommodate all the patients, so crucial life decisions needed to be made by clinicians and doctors.

Limited number of detection methods of COVID 19 were available, and unfortunately were not available to everyone. Some of the tools for detection of COVID 19 [2] are described below:

A. RT-PCR

Reverse-Transcription Polymerase Chain Reaction, also called RT-PCR test, is the most common COVID-19 test used across the globe. It is considered as the gold standard for viral testing, with almost all hospitals using it for COVID detection [1]. Despite being the universal standard, RT-PCR has many major drawbacks. It is an expensive test which requires a lot of resources and trained staff to carry out, which is also the reason why it is not available in many poor countries. The results take a lot of time, sometimes days to come back. It also puts the health workers in direct contact with the coronavirus. Hence, in some cases it can be quite inconvenient.

B. Lateral Flow Tests

LFTs are very similar to RT-PCR tests, requiring a nose swab sample. The only feature that differentiates them is that it indicates the with a colored line on the test sample if there COVID-19 present. This way, the results come in within 30-40 minutes without the need of sending the sample to the laboratory. The drawbacks of these tests are inaccuracies or low diagnostic sensitivity. The reason for this is that LFT requires 10,000 particles per mL which is high for early stage detection as compared to 300 particles per mL for RT-PCR [22]. A research conducted by scientists at University of Liverpool showed that LFTs were able to detect only 48.89% COVID-19 infected patients. Therefore, using LFTs for COVID tests are very inconvenient.

TABLE I
TABLE 1: COMPARING SOME COMMON COVID 19 DIAGNOSTIC TOOLS.

RT-PCR	LFT
Gold standard for COVID-19 testing	A rapid testing solution. Needs to be confirmed by RT-PCR.
Samples sent to laboratory for results	Samples are not sent to the laboratory.
Results can take days.	Results are available in 30-40 minutes
High diagnostic sensitivity	Low diagnostic sensitivity
300 particles per mL for early stage detection	10000 particles per mL for early stage detection
Requires skilled staff to carry out procedures	Can be done patients themselves
Drawbacks: Expensive, requires resources and equipment	Drawbacks: Inaccurate

Tests such as RT-PCR required trained medical staff and expensive resources which was not feasible to accommodate the huge demand of tests due to the rising number of cases. A quicker and more reliable detection method was required to fill the huge inefficiency gap. Researchers and data scientists around the world started testing deep learning techniques to produce algorithms that can easily detect COVID 19 from images such as Chest X-rays of the patient.

Deep learning is a branch of machine learning that allows computational models, or algorithms that are composed of multiple processing layers to learn the representation of data with multiple layers of abstraction. [3]

Deep learning helped overcome several factors which were slowing down the workflow in hospitals, thus improving hospital management. Deep learning techniques were used for quicker and more accurate diagnosis of COVID 19 using radiography images such as Chest X-rays (CXR) and Computed Tomography Scan (CT Scan), which means that the doctors were able to start the treatment at an early stage. Aid of deep learning means that resources such as medical staff spending hours for medical diagnosis to arrive at the right conclusion, can be saved to decrease the huge inefficiency gap.

Simple Chest X-ray and CT Scans play a key role in the diagnosis of COVID-19 pneumonia. Practically X-rays and CT scans are both viable imaging techniques for detecting COVID-19 in a patient but X-Rays are always preferred. One of the reasons is that it enables rapid triaging. Not all the patients that come with symptoms of COVID-19 have COVID-19 due to the similarity of COVID-19 symptoms with pneumonia symptoms. Hence, improper diagnosis will lead to lack of hospital resources for people who genuinely need it. It will also result in congestion in hospitals around the globe.

Chest X-ray imaging is readily available in every hospital. It is a primary piece of equipment that must be present in every hospital and clinic. CT scanner on the other hand is not available everywhere since it consists of heavy and costly equipment that every hospital cannot afford. The CT scanner is also not portable. It takes up an entire room of equipment and is fixed. X-Ray machine is a portable machine which can be transported to isolation rooms for diagnosis which means that patients will not have to leave their rooms and contain the virus, preventing it from transmission.

Also, a Chest X-ray is a part of a standard procedure which is carried out if a patient comes with a respiratory complaint. Therefore, if somebody shows up in a hospital with tightening in his chest or shortness of breath which are symptoms of COVID-19 [17], chest X-ray will be carried out without doubt. Therefore, using CXR to detect COVID-19 will be much more convenient.

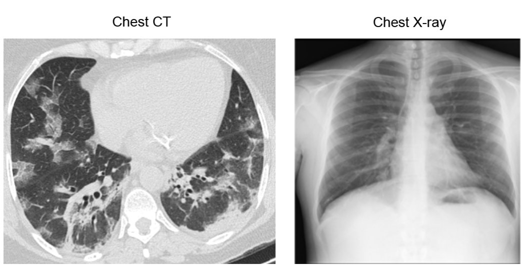

Fig. 1. A chest CT scan [18] of a COVID 19 infected patient and a Chest X-ray [9] [19] of a COVID-19 infected patient

A person with a COVID-19 is likely to show abnormalities in a CXR. In the paper [6], studies were conducted which shows that patients with COVID 19 showed abnormalities in their Chest X Rays. Hence, radiography images such as CXRs (Chest X Rays) can be used to identify the presence of Coronavirus infection in a patient [7]. Some of the recent studies have identified the features that indicate that the person has COVID-19. The main radiological characteristic is ground-glass opacities and areas of bilateral lung consolidation. They may also develop pulmonary fibrosis. These features are observed in all the coronaviruses such as SARS-CoV-2, SARS-CoV, and MERS-CoV [20].

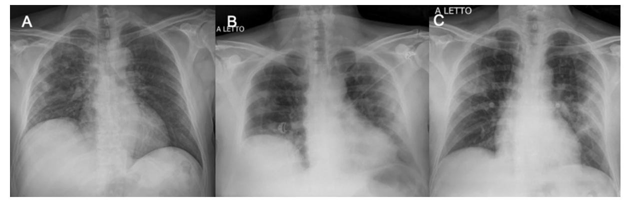

Fig. 2. Chest X-rays of 3 male patients showing bilateral lung consolidation. [21]

Many scientists around the globe have successfully built models that detect COVID-19 in patients with high accuracies. The work illustrated in this paper will show how a model was built using the convolutional neural network and the techniques that were adopted to make the model more accurate for a successful detection and diagnosis of COVID-19.

II. Literature Review

To date, researchers have been successful in detecting COVID 19 from Chest X Rays using various methods of deep learning. Kubra et al. [8] used SqueezeNet which is a CNN to classify between normal and abnormal CXRs and detect COVID 19 with an accuracy of 90.95%. M. E. H. Chowdhury et al. [9] used transfer learning to train several pre-trained models with and without data augmentation for detection of COVID 19 in CXRs. The highest accuracy achieved was with DenseNet-201 with an accuracy of 98.80%. K. Biçakci and V. Tunali [10] used some very popular pre-trained DenseNet, Inception-v3, Inception-ResNet-v2, ResNet, VGG, and Xception models. They also ensembled three popular pre-trained architectures: DenseNet201, Inception-ResNet-v2, and Xception to make an ensemble model which achieved the highest F1 Score of 99%. S. R. Abdani et al. [11] proposed a lightweight 14-layer convolutional neural network with a modified spatial pooling module, SPP-COVID-Net to detect COVID 19 from CXRs. They deployed the model in mobile phones and tablets which used less than 4 Megabytes of memory. Their method managed to achieve a best mean accuracy of 0.946. Amel et al. [12] used fine-tuned ResNet-101, ResNet-50, and ResNet-34 pre-trained on ImageNet weights for COVID-19 detection on CXRs. The highest accuracy level was reached with ResNet-34 of 98.34%. Neha et al. [13] used a different way to detect COVID-19 from CXRs. They decomposed the Chest X-ray into seven modes which were inputs to a multi-scale convolutional neural network [14] into three classes: pneumonia, no-finding, and COVID-19 infected. With 5-fold cross validation scheme, the model obtained a maximum accuracy of 96%, and 100% on dataset A, and dataset B respectively. Other than X-Rays, researchers around the world also used other imaging techniques as well. A. Kaya et al. used CT scans instead of CXRs to detect COVID-19 in a patient. They used data-augmentation [15] to increase the size of their dataset due to lack of clean datasets for training. The classification was done using pre-trained CNN networks. The highest accuracies obtained were for VGG-16 and Efficient-NetB3 of 96.5%, and 97.9% respectively. Vipul et al. [16] used CT scans for COVID-19 detection. They fine-tuned the architecture of pre-trained MobileNet-V2 and made an optimized version for it to be compatible with mobile and edge devices. They achieved a classification accuracy of 96.4%.

III. Dataset used

To make a model that differentiates between COVID-19 CXR, and Normal CXR, a dataset must be compiled that will be used for the training of the model. The dataset that was used in this study is the COVID-19 Chest Radiography dataset which was compiled by researchers around Qatar, Bangladesh, Pakistan and Malaysia [23] [24]. The dataset is also the winner of the COVID-19 dataset award by Kaggle Community.

The dataset was last updated in March 2022. It contains a total of 21165 images which consists of 3616 COVID-19 CXRs, 10192 Normal CXRs, 6012 Lung Opacity (Lung infection) CXRs, and 1345 Viral pneumonia CXRs. The classification in this paper is only limited to COVID-19 and normal CXRs, therefore, the viral pneumonia and lung opacity CXRs were not used.

The images in the dataset are all labeled with a resolution of 299 x 299, with 3 channels (RGB). The dataset can be reached at the following link: https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database

Figure 3 shows some examples from the COVID-19 Chest Radiography dataset.

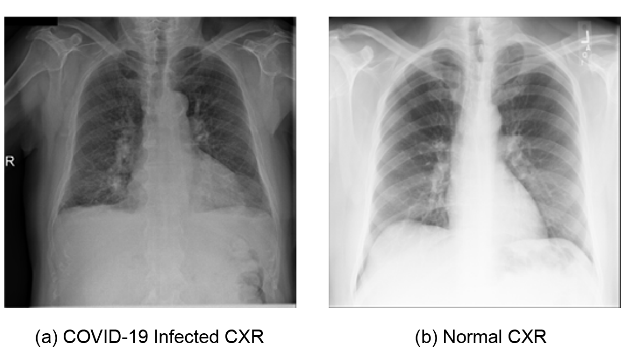

Fig. 3. Sample images from each class in the COVID-19 Chest Radiography dataset

IV. Methods

In order to take full advantage of the Chest X-rays, image pre-processing of images is done so that the images which are input to the CNN must be as clean as possible. There are several problems that unclean dataset can give rise to. Images may have different contrast or brightness based on the shape of the patient's body and the x-ray dose which he was provided. This gives a wide variation in the contrast and brightness of the images. To counter this effect, Histogram Equalization (HE) and contrast Limited Adaptive Histogram Equalization (CLAHE) techniques were used. HE and CLAHE are discussed in detail in the next subsection.

The Google Collaboratory environment which is a cloud-based platform was used for building and training the model. Model was trained using Intel(R) Xeon(R) CPU @ 2.00 GHz, NVIDIA Tesla T4 70W.

A. Preprocessing

First, the reshape process was applied to all the images. The original images were in a resolution of 299 x 299. ResNet50, which is one of the models used in the classification process uses a resolution of 224 X 224. Hence, a reshape algorithm was used to reshape all the images in the dataset.

After reshaping, histogram equalization was applied to all the images. Histogram equalization is a tool that is used to enhance the contrast of images. A histogram of an image is a plot of number of pixels against intensity where the number of pixels at a specific intensity is plotted. In a grayscale image, the intensity varies from 0 to 255. Histogram equalization stretches the dynamic range of the image's histogram resulting in overall contrast improvement [25]. It means that the pixel levels are then spread evenly between 0 and 255.

To further improve the contrast around the different zones, CLAHE was applied. Contrast limited adaptive histogram equalization, or CLAHE has produced good results on medical images [26]. CLAHE is a variant of adaptive histogram equalization, which operates histogram equalization in small patches rather than on the whole image. It also restricts contrast amplification. The reason for this is because histogram equalization cannot be implemented in images with very large intensity variation [27]. Hence, CLAHE can be used to increase the contrast of different zones in X-rays such as consolidation zones, ribs, spine, collar bones, and heart [28].

Figure 4 shows the comparison between the three images, the original image, and the images processed after Histogram Equalization, and CLAHE.

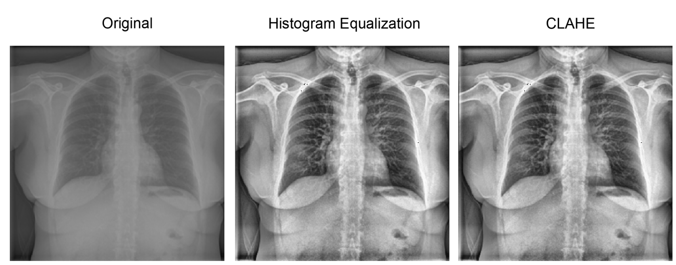

Fig. 4. The outputs of HE, and CLAHE are shown along with the original image. It can be seen how much the contrast has improved when compared with the original image

The stages which the images were run through can be seen in figure 5.

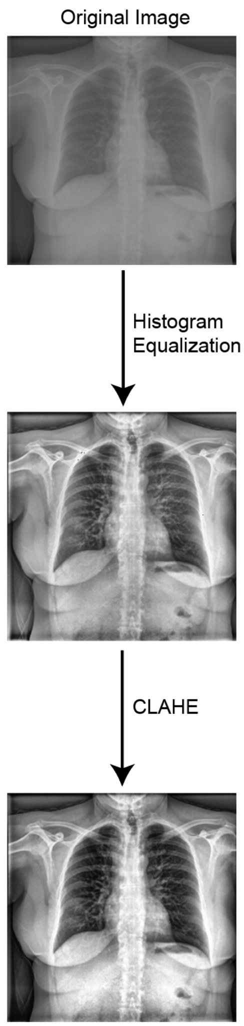

Fig. 5. The image at each stage of pre-processing is displayed

Image augmentation is a very useful technique especially for scarce datasets. It expands the training dataset artificially using rotation, shear, cropping, and a number of preprocessing functions. The problem with small datasets is that after training with less number of images the model is not able to generalize to the validation and test dataset. Thus, it decreases the model's accuracy, and they suffer from the problem of overfitting. To reduce overfitting, several methods were discussed in the paper by Wang et al. [29]. One of the methods is image augmentation. Using image augmentation, overfitting can be minimized, and the accuracy of the model can be increased [30].

B. Classification of Chest X-Rays

In this paper, the family of ResNet architectures were used to classify Chest X-ray images into COVID-19 and non-COVID-19. ResNet made its entry in 2015 and sent a wide wave across the computer vision market. Many researchers have looked into the secrets of this architecture, and refined it to make models which perform even better.

As networks were becoming more deeper, they were becoming harder to train. That is because the gradient was becoming smaller and smaller. This leads to the network saturating its performance and starts degrading quickly.

The basic idea of ResNet is to introduce a skip connection or a residual (RESidual) connection that skips one more layer to counter the problem of small gradients. They learn residual functions with reference to the layer, instead of learning the unreferenced layers. Therefore, the residual mapping is easier to optimize rather than the original unreferenced mapping [31].

Since the introduction of ResNet, many variants of the architecture have come out. Some models have different numbers of layers such as ResNet-50, ResNet-101, and ResNet-200.

In this study, we have trained different models on our dataset such as ResNet-50, ResNet-101, ResNet-152, and ResNet-200.

C. Training

To train these models, transfer learning was used. Transfer learning is a very popular approach in machine learning where pre-trained models such as ResNets as discussed above are used as a starting point for new different problems. Since a vast amount of resources and time is required to train those models, it is not feasible to repeat all the steps for a new problem. Therefore, the knowledge or weights from pre-trained models are transferred, and the models adapt to the target problem, which is detection of COVID-19 and non-COVID-19 in this case.

The input images were all in the RGB format which were converted to grayscale in the pre-processing of the images. The preprocessed dataset which was done in the previous section is then used as the input to the ResNet architecture. All the 13822 images were then split into train dataset, test dataset, and validation dataset.

20% of the 13822 images were randomly split into the test dataset. The remaining 80% were then randomly split into validation dataset and train dataset into a ratio of 0.15 and 0.85 respectively. Therefore, the total number of images in each category is shown in Table 2.

TABLE II
THE NUMBER OF COVID AND NORMAL IMAGES IN EACH CATEGORY FOR TRAINING THE MODEL

	Total Images	Images (COVID)	Images (Normal)
Train	9398	2463	6935
Test	2765	733	2032
Validation	1659	430	1229

The loss function used was Binary Crossentropy. The optimizer that was used to compile the model was the Adam optimizer. The default parameters, $\beta_1 = 0.9$, and $\beta_2 = 0.999$ were used. The learning rate was set to 0.001, and the numerical stability constant was set to the default value of

$\epsilon = 0.0000001$. The method of training was transfer learning as discussed in the above sections with a batch size of 32. A summary of the operation is shown on Figure 7.

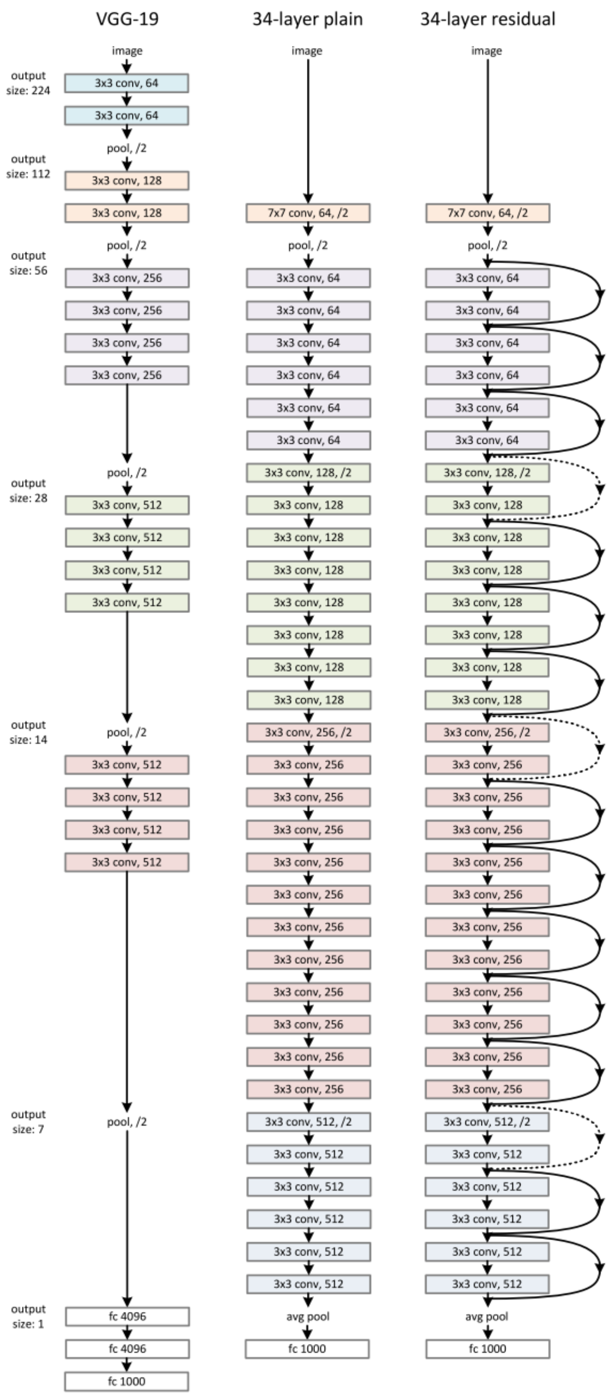

Fig. 6. Comparing the different models with ResNet-34. [31]

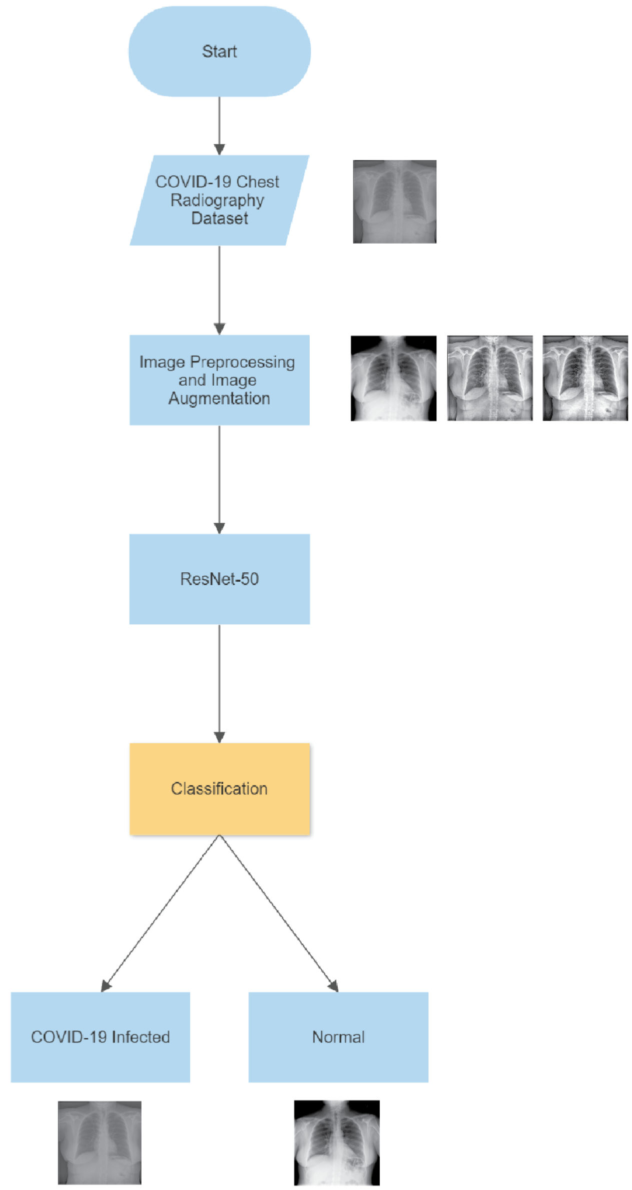

Fig. 7. The operation of classification with all the blocks shown

The ResNet-50 model was then fitted on the train and validation dataset with 10 number of epochs. The experimental results after training are discussed in the next section.

V. Experimental Results

As the result of ResNet-50 model's training was carried out, the classification of COVIS-19 infected CXRs, and Normal CXRs achieved a maximum validation accuracy of 88.43% with 10 number of epochs. The train gloss decreases as the number of epochs increases, and the validation loss decreases overall, with an increasing number of epochs as seen on Figure 8.

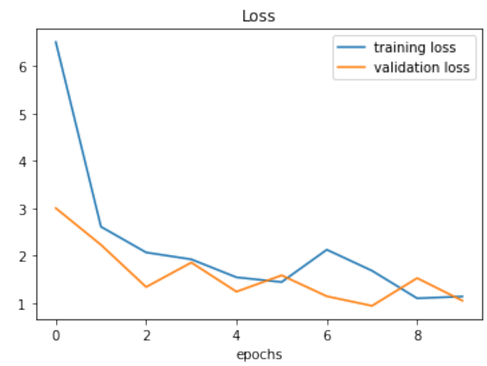

Fig. 8. The loss curve for the training of ResNet-50

In a similar fashion, the training curve is shown on Figure 9. It can be seen that there is an overall increase in the training curve. The reason for this fluctuation in the curves is the non-uniform number of samples in the batch size. Due to less number of COVID-19 CXRs, and very large number of normal CXRs, the samples in each batch size are not the same. This creates uneven batches because of which there is so much fluctuation in the curves.

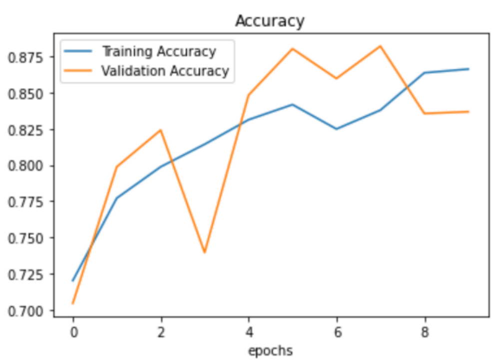

Fig. 9. The training curve for ResNet-50 architecture

Similarly, other models were also trained and evaluated. The validation accuracy of all the architectures trained in this study are shown in Table 3.

TABLE III
THE SUMMARY OF VALIDATION ACCURACIES OF ALL THE ARCHITECTURES USED

Model	Validation Accuracy
ResNet-50	88.43%
ResNet-101	78.30%
ResNet-152	85.47%
ResNet-200	75.83%

Among the tested models, ResNet-50, and ResNet-152 performed well. The highest accuracy achieved among these models was by ResNet-50 of 88.43%. The testing of this model was done using the test set that contained a total of 2765 images (733 COVID-19, 2032 Normal). The confusion matrix after the testing of ResNet-50 is shown in Figure 10.

TABLE IV
EVALUATION METRICS OF RESNET-50

Evaluation Metrics	Value
Precision	0.85
Recall	0.85
F1-Score	0.85

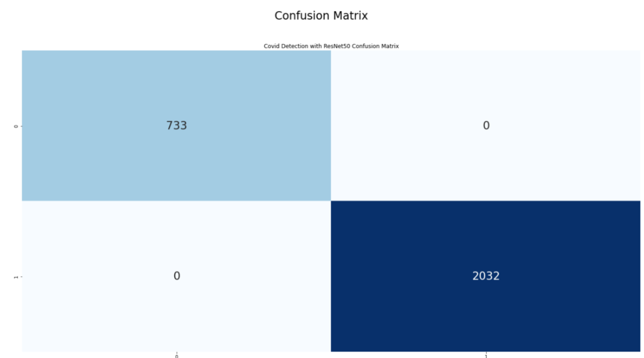

Fig. 10. onfusion Matrix of the test data with ResNet-50

The evaluation metrics of the ResNet-50 is shown in Table 4.

In Figure 11, the left CXR was predicted to be a Normal CXR (Actual Class: Normal) by the model with a probability of 98.51%. The right CXR was predicted to COVID-19 infected (Actual Class: COVID) by the model with a probability of 97.2%.

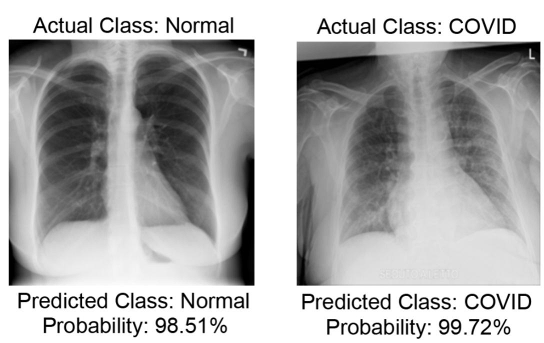

Fig. 11. Two examples chosen randomly after the classification of ResNet-50

VI. CONCLUSION

The COVID-19 pandemic was a calamity that united people. This pandemic should be seen as an opportunity to advance technical solutions that can handle the torrents of cases efficiently. This pandemic introduced the power of deep learning to the medical industry which showed that the two combined can make a team that can handle the magnitude of a pandemic.

In this study, using a dataset of Chest X-rays, we trained the family of ResNets so that they are able to classify between an COVID-19 infected CXR, and a normal CXR. A high accuracy of 88.43% was achieved by ResNet-50.

The high accuracy results open the door to developing mobile and easy-to-use apps that increase diagnosis accuracy, reduce burden for overworked health providers, and improve healthcare access in understaffed/underequipped locations. This area, as well as the creation and evaluation of multiclass classification models, will be the focus of future research.

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