

# Detecting Covid-19 In Chest X-ray Images Using Neural Networks

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**Abstract** – In this paper we study the applications of Artificial Intelligence, particularly, neural networks in predicting whether a patient is inflicted with Covid-19, the illness caused by the SARS-CoV-2 virus. Convolutional Neural Networks (CNN), a subtype of deep neural networks are the most suitable for image analysis. In this study, the Convolutional neural network algorithm is applied to chest X-ray images of patients afflicted with various respiratory pathologies to determine if they are suffering from Covid-19. Another key aspect is differentiating between Covid-19 and other lung illnesses like viral pneumonia.

**Key Words:** Neural Networks, COVID-19, Convolution, X-ray, Image Analysis

## 1. INTRODUCTION

With a shortage of testing kits and healthcare infrastructure in many countries overwhelmed, new, accurate and automated methods to detect Covid-19 infections are the need of the hour. Modern A.I. (Artificial Intelligence) techniques can be effective to detect COVID-19 in medical images, particularly when radiologists are not available [1].

Covid-19 produces ground glass and consolidative opacities with a bilateral, peripheral, and lower lung distribution [2]. We aim to detect these lung opacities using Convolutional Neural Networks and help identify Covid-19 in the medical images of patients.

### 1.1 Existing Models

Detection of Covid-19 in CT Scan images using deep anomaly detection algorithms can also be performed. Jianpeng Zhang et al. reported a 96.0% accuracy in detecting Covid-19 by using such techniques [3]. Ordinary deep neural networks have also been applied to this task but do not yield optimal performance. Thus, we shall turn to Convolutional Neural Networks to perform this classification.

### 1.2 Need For New Detection Approaches

The Covid-19 pandemic has consumed the world, with 192 countries affected and global cases nearing 150 million. The widely used reverse transcriptase polymerase chain reaction (RT-PCR) test can have a false negative rate from 67% to 21% [4]. As radiologists are not always available to analyse data from CT Scans and X-ray images,

a system which can perform this task automatically greatly aids the medical fraternity.

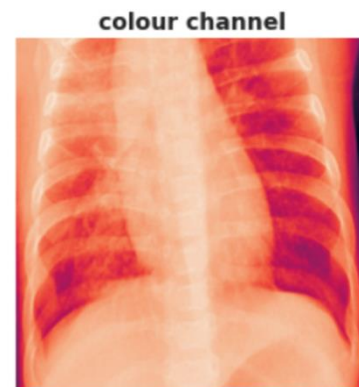
## 2. DATA COLLECTION AND ANALYSIS

The dataset on Covid-19 radiography images was created by researchers from the Qatar University in Doha, Qatar and the University of Dhaka in Dhaka, Bangladesh [5,6] along with other collaborators. Total number of images is 21,165. An overview of the dataset is presented in Table-1.

**Table -1:** Covid-19 Radiography Dataset Overview

Covid-19 Radiography Data		
Image Class	Percent	Number of Images
Healthy	48.2%	10,192
Lung Opacity	28.4%	6,012
Covid-19	17.1%	3,616
Viral Pneumonia	6.4%	1,345

Even though the images are greyscale they are composed of 3 channels- Red, Green, and Blue (RGB). However, all the colour channels have the same value. A single channel of a sample image is shown in Fig- 1. The images are an array of numbers where each dimension represents Height, Width, and Channel. The size of each image is thus 299x299x3. Asymptomatic or minimally symptomatic patients may have positive chest radiographs after 14 days of quarantine, even with no RT-PCR testing for COVID-19 [7] (sensitivity reported to be 59% by Ai et al [8]).



**Fig -1:** Image After Selection of One Colour Channel

Fig- 2 below shows 5 sample images from each of the classes: Covid-19, Lung Opacity, Normal, and Viral pneumonia in row-wise order. The pixel values in the array of an image can range from 0 to 255.

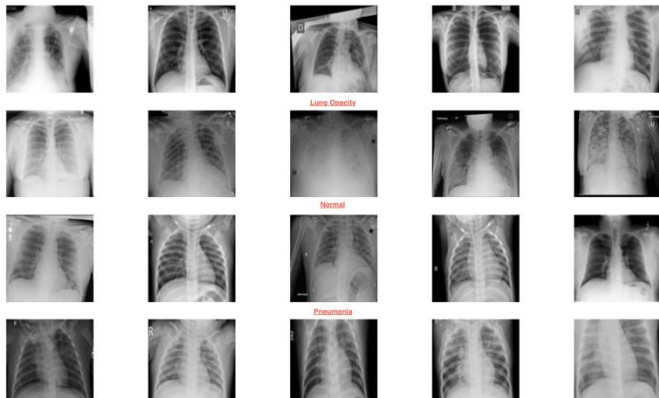


Fig -2: Samples from each Image Class

Our goal is to train a Convolutional Neural Network on this dataset using standard training algorithms and evaluate its performance on the testing set.

### 3. NEURAL NETWORK ARCHITECTURE

For the purpose of classifying chest X-ray images, we shall deploy a Convolutional Neural Network. Images in the real world often have a hierarchical structure, that is, they are composed of motifs that are repeated across images. These features are captured in the form of filters, and convolution is the process in which the filter is moved across the image and a high amplitude hotspot is obtained when the filter matches a region of the image. A sample CNN architecture is shown in Fig- 3.

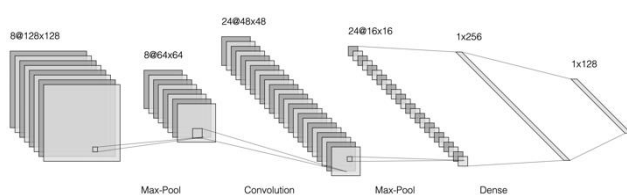


Fig -3: Example Of A CNN

The output of the convolution process is summarized by the equation below,

$$C(I, W) = \sum_i \sum_j I_{ij} W_{ij} \dots \dots \dots (1)$$

I = Input Image  
 W = Filter  
 C = Convolved Output

Each convolution layer in the network uses the ReLU (Rectified Linear Unit) [9] activation function defined as:

$$ReLU(a) = \begin{cases} 0 & \text{for } a < 0 \\ a & \text{for } a \geq 0 \end{cases} \dots \dots \dots (2)$$

The average pooling layers reduce the size of the input passed to the subsequent layer by taking the average of the pixel values of a certain part of the image. The architecture of the model used in this study is summarized in Fig- 4.

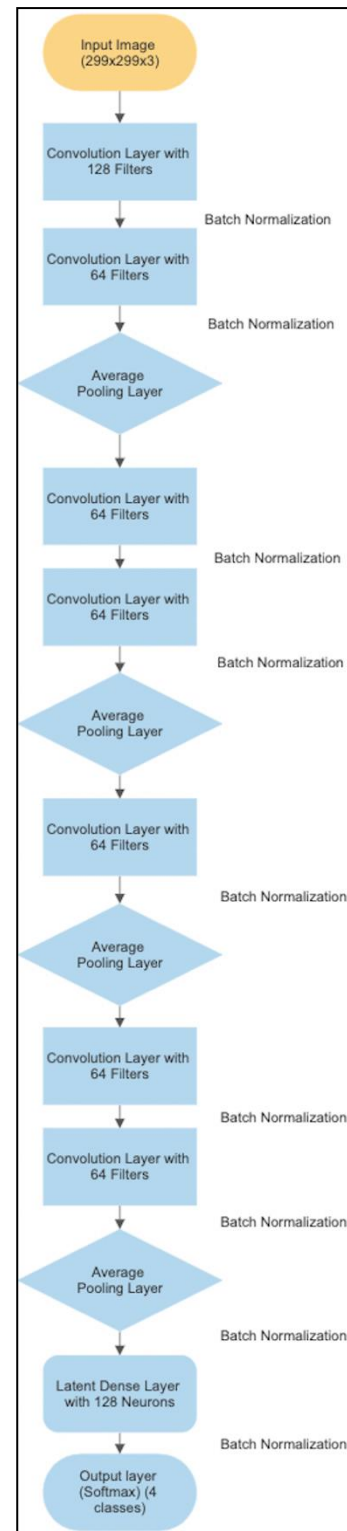


Fig -4: Network Architecture

### 3.1 Optimization

For optimization we use the Adam optimization algorithm. It combines the AdaGrad and RMSProp algorithms. Adam can solve deep learning problems more efficiently than other methods like Stochastic Gradient Descent, Root Mean Square Propagation, Adaptive Gradient Descent (AdaGrad), and others [10].

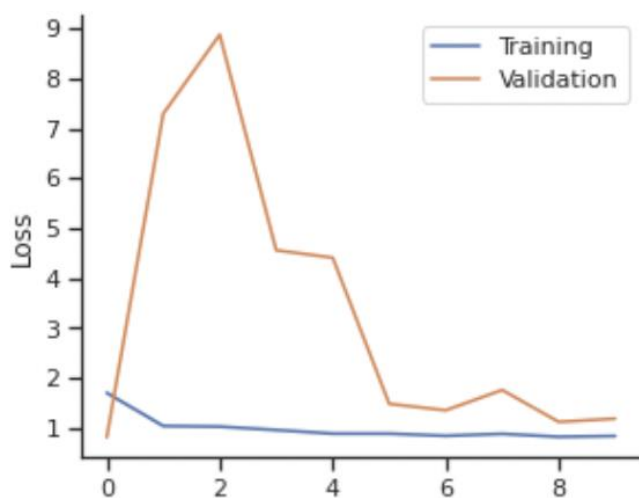
### 4. MODEL TRAINING AND EVALUATION

For the purpose of training the model, the whole data set was divided into two parts. We used 80.0% of the data (16,933 images) for training the model and the remaining 20.0% (4,232 images) as the test set for validating the model. We deployed Learning Rate Reduction and Early Stopping to train the model as effectively as possible. The summary of various runs is given in Table-2.

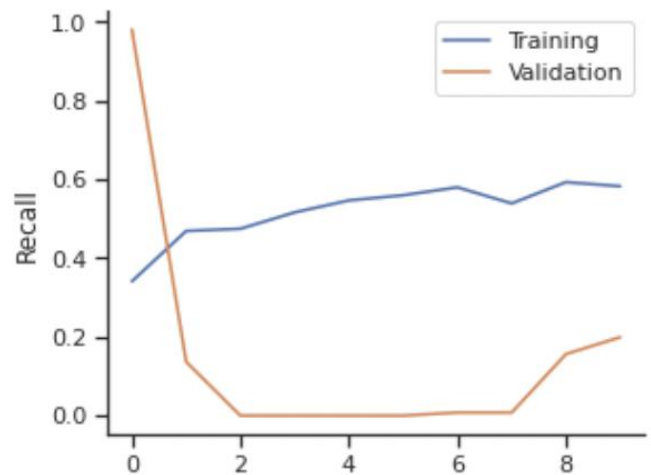
**Table -2:** CNN Performance Summary

Model Performance		
Batch Size	Epochs	Classification Accuracy
16	10	38.45%
16	100	79.77%
32	10	79.91%
32	100	80.1%

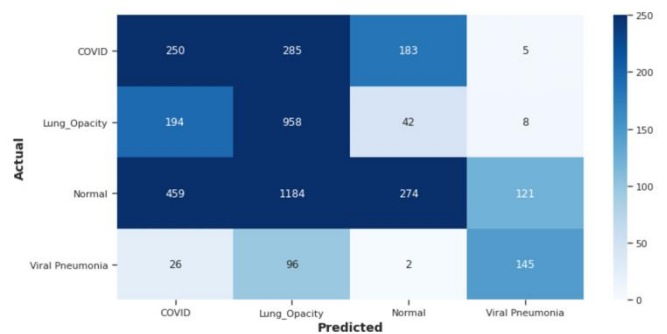
First, the model was trained for 10 epochs with a batch size of 16.



**Chart -1:** Loss For 10 Epochs, 16 Images Per Batch

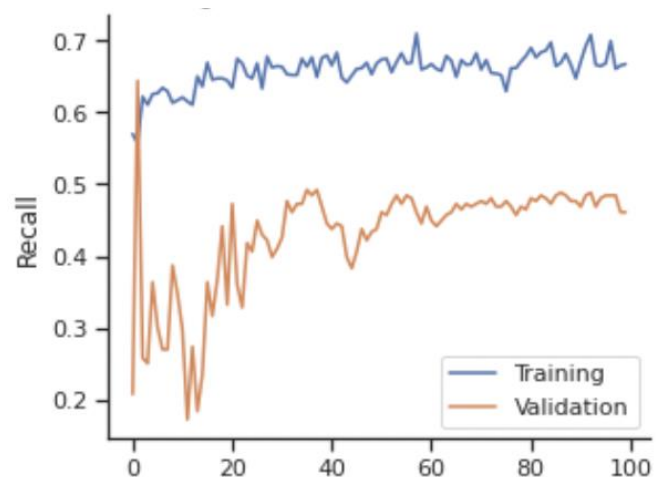


**Chart -2:** Metric Recall For 10 Epochs, 16 Images Per Batch



**Fig-5:** Confusion Matrix For 10 Epochs, 16 Images Per Batch

Then, the model was trained for 100 epochs with a batch size of 16.



**Chart -3:** Metric Recall For 100 Epochs, 16 Images Per Batch

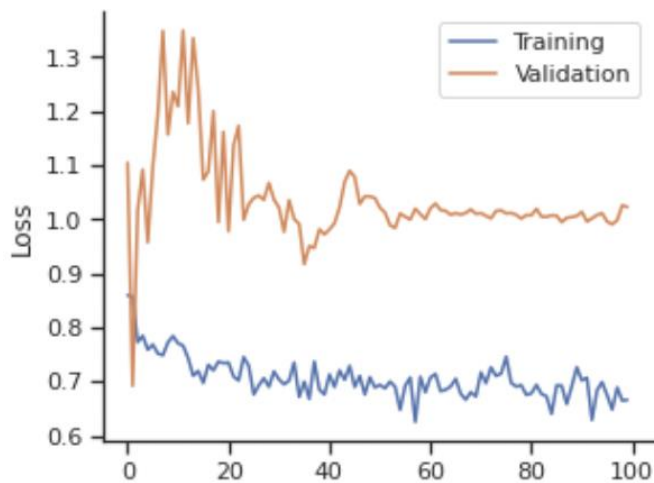


Chart -4: Loss For 100 Epochs, 16 Images Per Batch

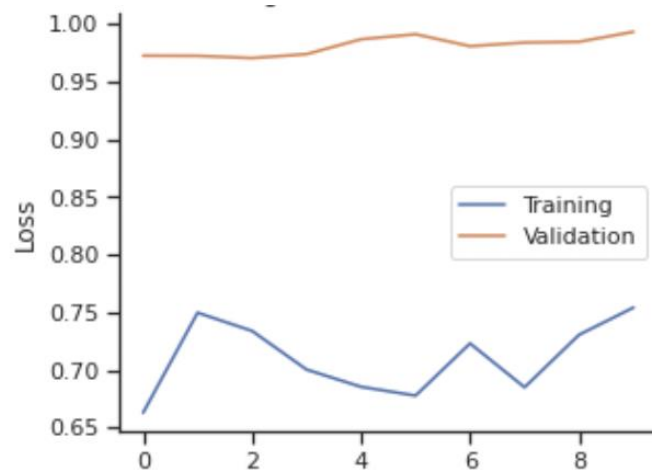


Chart -6: Loss For 10 Epochs, 32 Images Per Batch

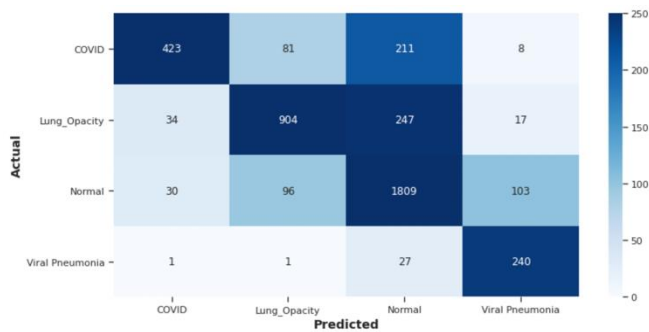


Fig-6: Confusion Matrix For 100 Epochs, 16 Images Per Batch

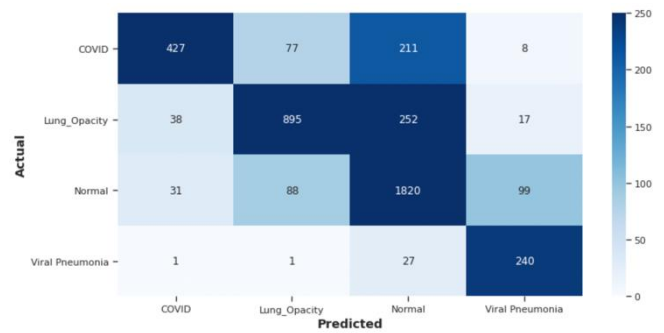


Fig-7: Confusion Matrix For 10 Epochs, 32 Images Per Batch

Then we trained the model with a batch size of 32 for 10 epochs.

Finally, the model was trained for 100 epochs with a batch size of 32.

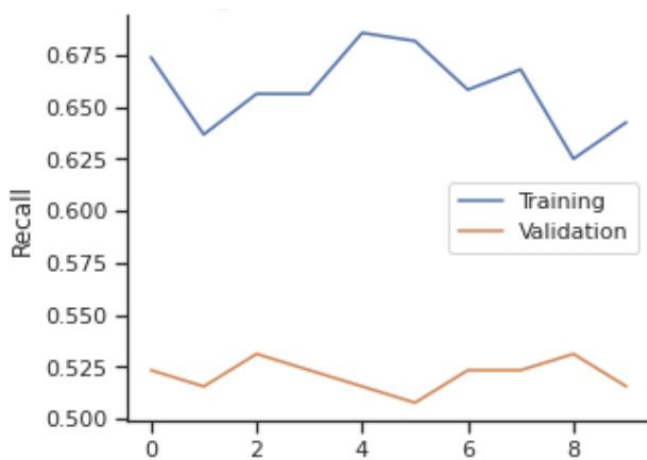


Chart -5: Metric Recall For 10 Epochs, 32 Images Per Batch

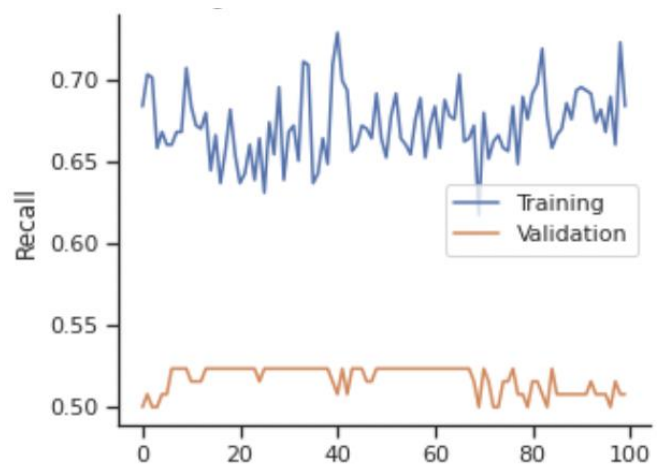


Chart -7: Metric Recall For 100 Epochs, 32 Images Per Batch





Chart -8: Loss For 100 Epochs, 32 Images Per Batch

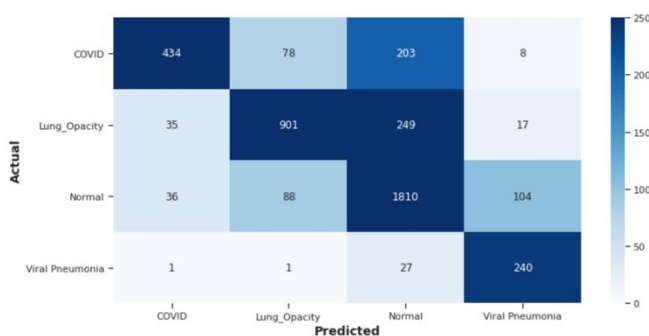


Fig-8: Confusion Matrix For 100 Epochs, 32 Images Per Batch

## 5. CONCLUSIONS

From the data and performance metrics presented above, it can be seen that the best performing model is the CNN trained for 100 epochs with a batch size of 32 with an average accuracy of about 80% across the 4 classes: Covid-19, Lung Opacity, Normal, and Viral Pneumonia. Even though the model does not classify all Covid-19 samples correctly, its accuracy matches that of radiologists.

It is seen that larger batch sizes yield similar accuracy, irrespective of number of epochs. We did not make use of hyperparameter tuning but a learning rate of 0.01 provided good performance. The number of wrongly classified Covid-19 samples may have to be reduced before field deployment. Performance of CNNs can be improved by applying a Min-Max objective layer below the output layer [11].

Such CNN models have applications beyond detecting Covid-19 as well. For example, using transfer learning this model can be applied to detect lung tumors and other ailments associated with respiration. It may also be useful to account for medical history and data of patients like age, gender, medication use, etc.

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