COVID-19 DETECTION WITH RADIOGRAPHY IMAGES

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THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF BACHELOR'S IN COMPUTER SCIENCE (ARTIFICIAL INTELLIGENCE)

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ABSTRACT

In the beginning of year 2020, the whole world faced a difficult challenge which is the wide spread of COVID-19 disease. A usual method to diagnose the disease is through the use of laboratory testing kit. The testing kit often requires 3 to 48 hours to produce results. Moreover, the testing kits are also quite costly. Hence, an alternative method is to use chest radiography images. In this project, we aim to demonstrate the use of deep learning to accurately classify and detect COVID-19 positive chest radiography images from the normal ones. A publicly available dataset from Kaggle is used to train the model in this project which contains 1143 COVID-19 positive images and 1341 normal images. Model architecture chosen is the InceptionV3 model which is pretrained on ImageNet dataset. The final model successfully achieves an accuracy of 98.7% on the test dataset.

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LIST OF SYMBOLS AND ABBREVIATIONS

CDF	:	Cumulative distribution function
CLAHE	:	Contrast Limited Adaptive Histogram Equalization
COVID-19	:	Coronavirus disease 2019
GradCAM	:	Gradient-weighted class activation mapping
PNG	:	Portable Network Graphics
ROC	:	Receiver operating characteristics
SGD	:	Stochastic gradient descent
WHO	:	World Health Organization

INTRODUCTION

1.1 Problem Statement

In the beginning of 2020, World Health Organization (WHO) had declared that a new novel coronavirus has been spreading all around the globe. Humankind was faced with a huge challenge – a global pandemic of severe acute respiratory syndrome coronavirus or more commonly known as coronavirus disease 2019 (COVID-19). At the time of writing (2nd January 2021), there are over 84 million confirmed cases and 1.8 million deaths due to the disease all around the world. Some common symptoms of COVID-19 include fever, dry cough, tiredness, sore throat, and others. To diagnose COVID-19, it requires a long amount of time and high costs of laboratory kits used for diagnosis. COVID-19 tests are usually expected to produce results after 3 to 48 hours. Moreover, many countries in the world might not have access to test kits that give results rapidly. Since there are no effective treatment available, it is important to have fast detection and diagnosis method. Hence, one alternative method is to use chest radiography for patients with COVID-19 to reduce the cost of using laboratory kits. Deep learning can be applied here to automate the process of identifying chest radiography with COVID-19 infection.

1.2 Objectives

The project aims to:

1. To classify whether a given chest radiography image is infected by COVID-19 or is a normal chest radiography image
2. To evaluate the accuracy of COVID-19 classification on chest radiography images

1.3 Dataset Source

The dataset used in this project is created by a team of researchers from Qatar University, Doha, Qatar and the University of Dhaka, Bangladesh along with collaborators from Pakistan and Malaysia. The dataset is released on Kaggle titled "COVID-19 RADIOGRAPHY DATABASE". It contains 1143 COVID-19 positive images, 1341 normal images and 1345 viral pneumonia images (not used in the project). All the images are in Portable Network Graphics (PNG) file format and resolution is both in 1024x1024 and 256x256 pixels. Figure 1 shows a few COVID-19 positive chest radiography images while Figure 2 shows a few normal chest radiography images.

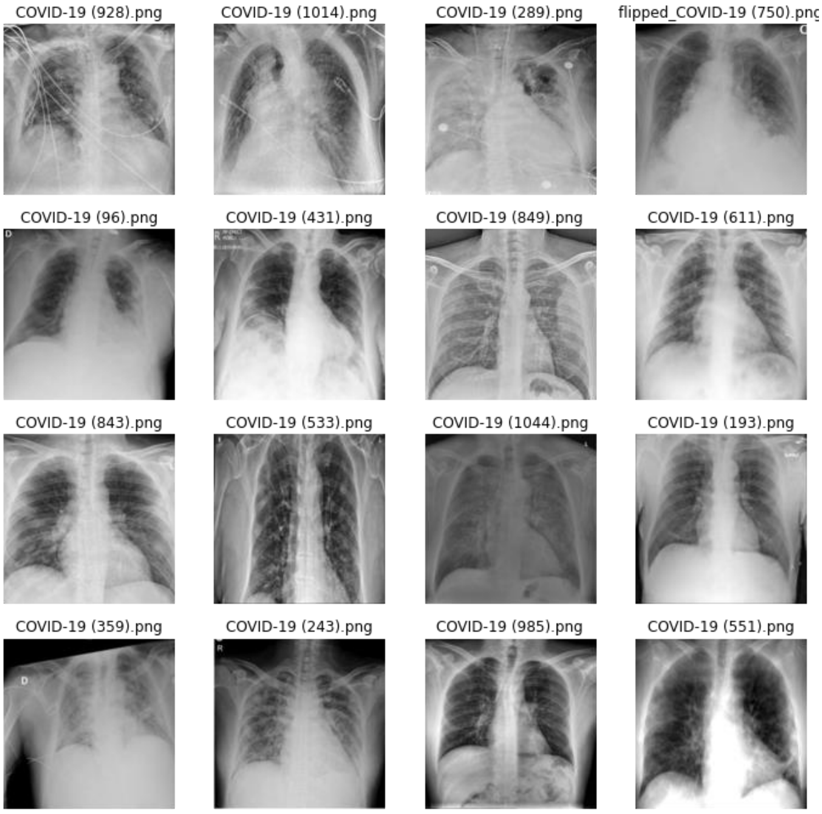

Figure 1: Sample images of COVID-19 positive chest radiography images

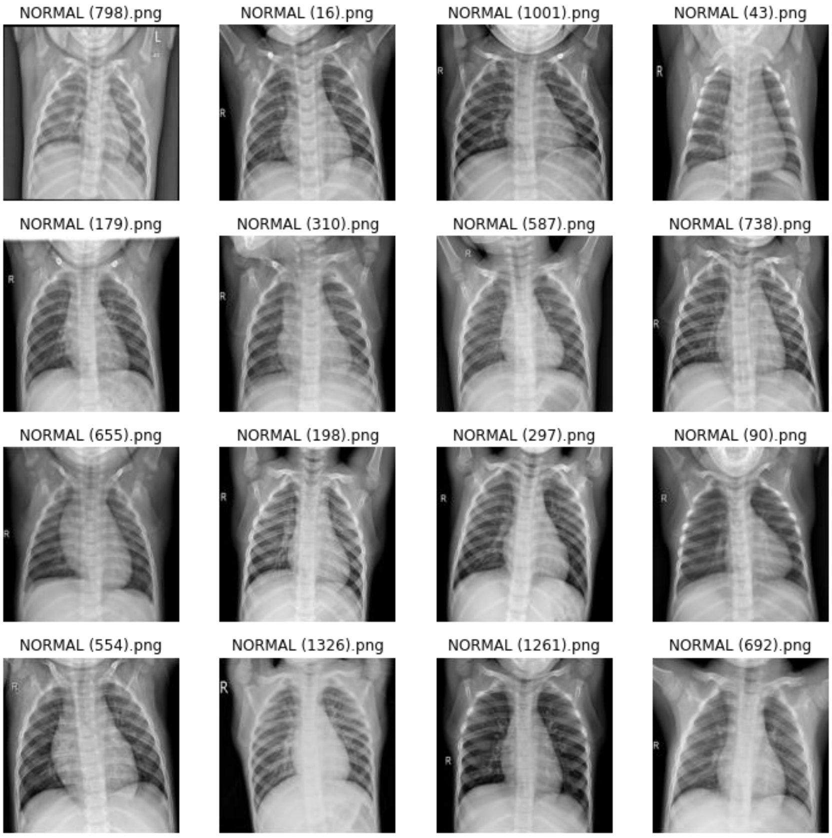

Figure 2: Sample images of normal chest radiography images

CHAPTER 2: ANALYSIS AND DESIGN

2.1 Tools for System Development

The project is developed in Python 3.6 and uses a few public libraries. Tools used includes:

- Python
- Tensorflow 2.4.0 & Keras
- Matplotlib
- Scikit-learn
- OpenCV
- Pillow
- Numpy
- ImageIO

Github link: https://github.com/zhiqin1998/covid19-detection

2.2 Flowchart

Figure 3 depicts the flowchart of the project.

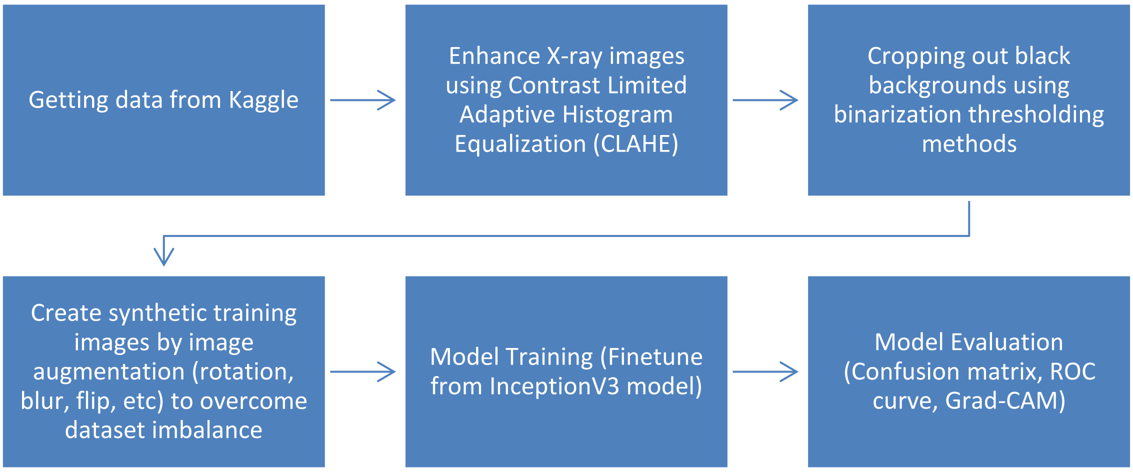

Figure 3: Flowchart of the project

2.3 Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is an image processing method used to improve contrast in images. The technique computes the histogram for the region around each pixel in the image, improving the local contrast and enhancing the edges in each region. CLAHE is a variant of adaptive histogram equalization in which the contrast amplification is limited, to prevent the problem of overamplifying noises in the near-contrast regions. CLAHE limits the amplification by clipping the histogram at a predefined value before computing the cumulative distribution function (CDF). This limits the slope of the CDF and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighbourhood region. Common values limit the resulting amplification to between 3 and 4.

It is advantageous not to discard the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins. Figure 4 shows the process of redistributing the clipped histogram.

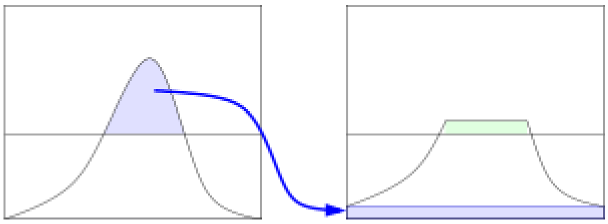

Figure 4: Redistribution of clipped histogram in CLAHE

CLAHE can be applied to enhance radiography images greatly. Figure 5.1 and Figure 5.2 demonstrate the results of CLAHE applied on radiography images.

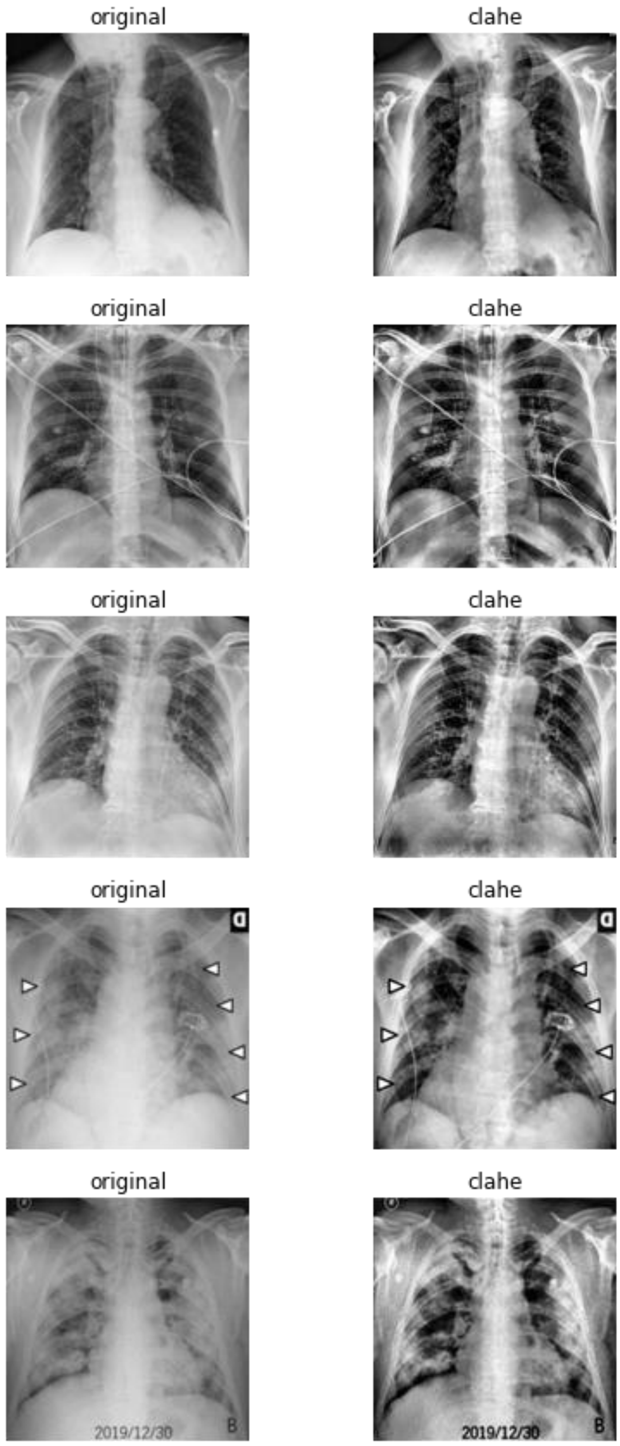

Figure 5.1: Results of CLAHE applied on normal chest radiography images

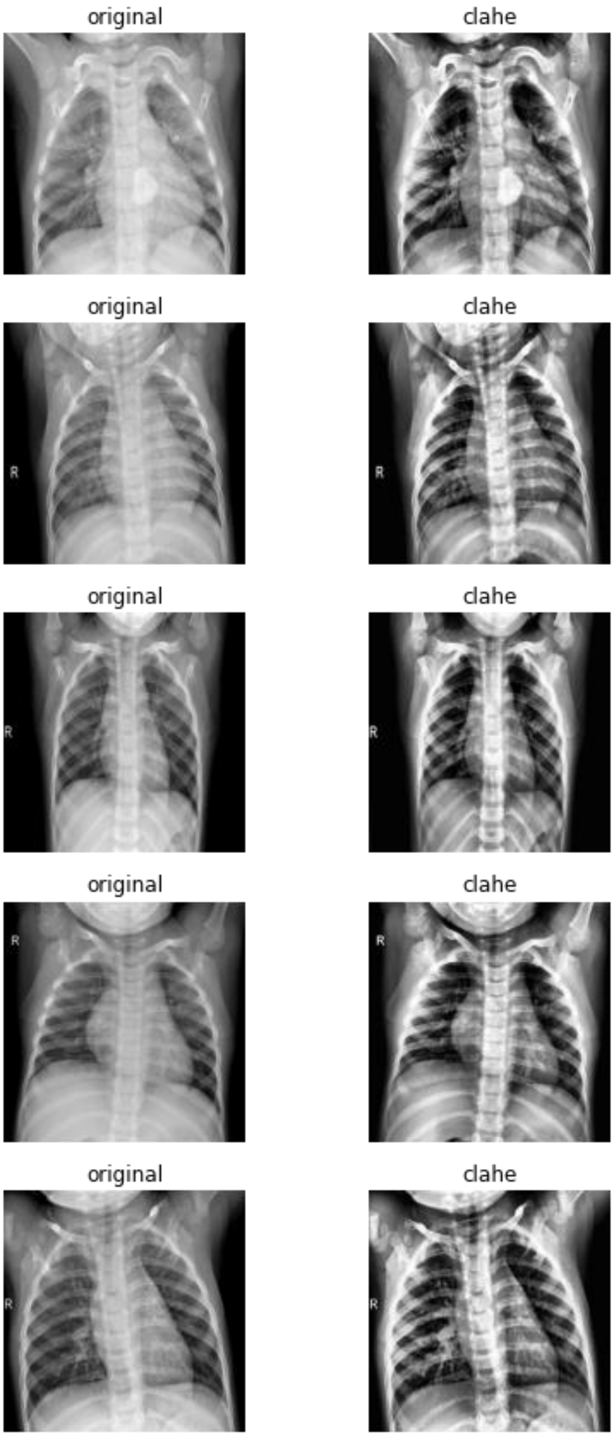

Figure 5.2: Results of CLAHE applied on COVID-19 positive chest radiography images

2.4 Class Imbalance

In the dataset, there are slightly more normal radiography images as compared to COVID-19 positive radiography images as seen in Figure 6. We can observe that the ratio of dataset is slightly imbalanced.

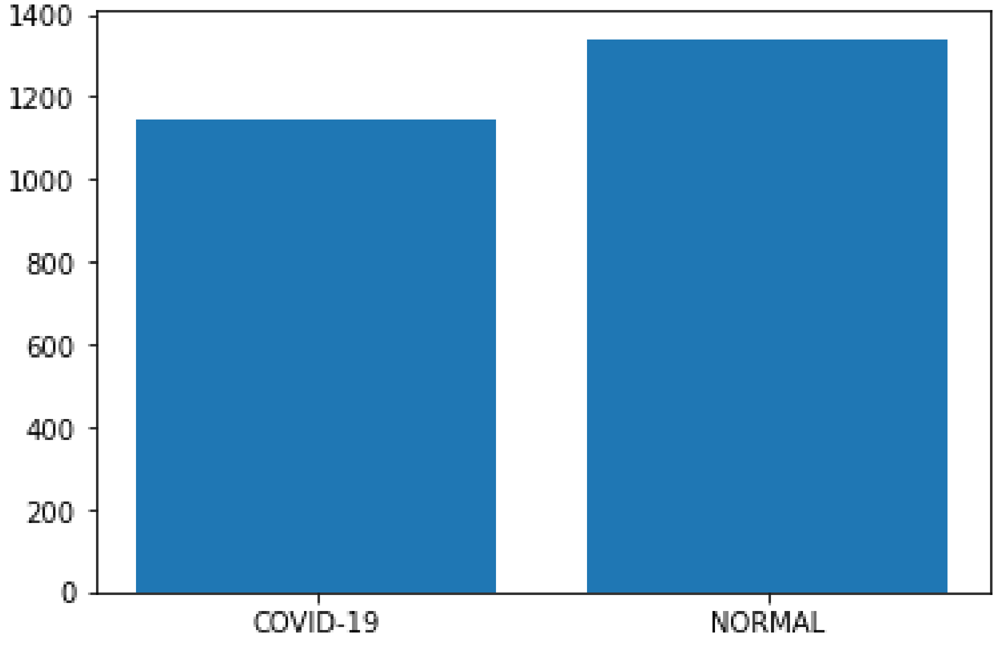

Figure 6: Histogram of number of images in each class

Data augmentation is used to synthesize more images for training. It is done by randomly sampling and flipping images horizontally from the minor class (COVID-19).

CHAPTER 3: EXPERIMENT RESULTS

3.1 Data Augmentation

To prevent overfitting of the model, some image augmentation techniques is applied to the training dataset to help the model generalize better. The images are augmented by randomly shifting, rotating, zooming, flipping horizontally, and changing the brightness of the image. Figure 7 shows a few examples of data augmentation on the training dataset.

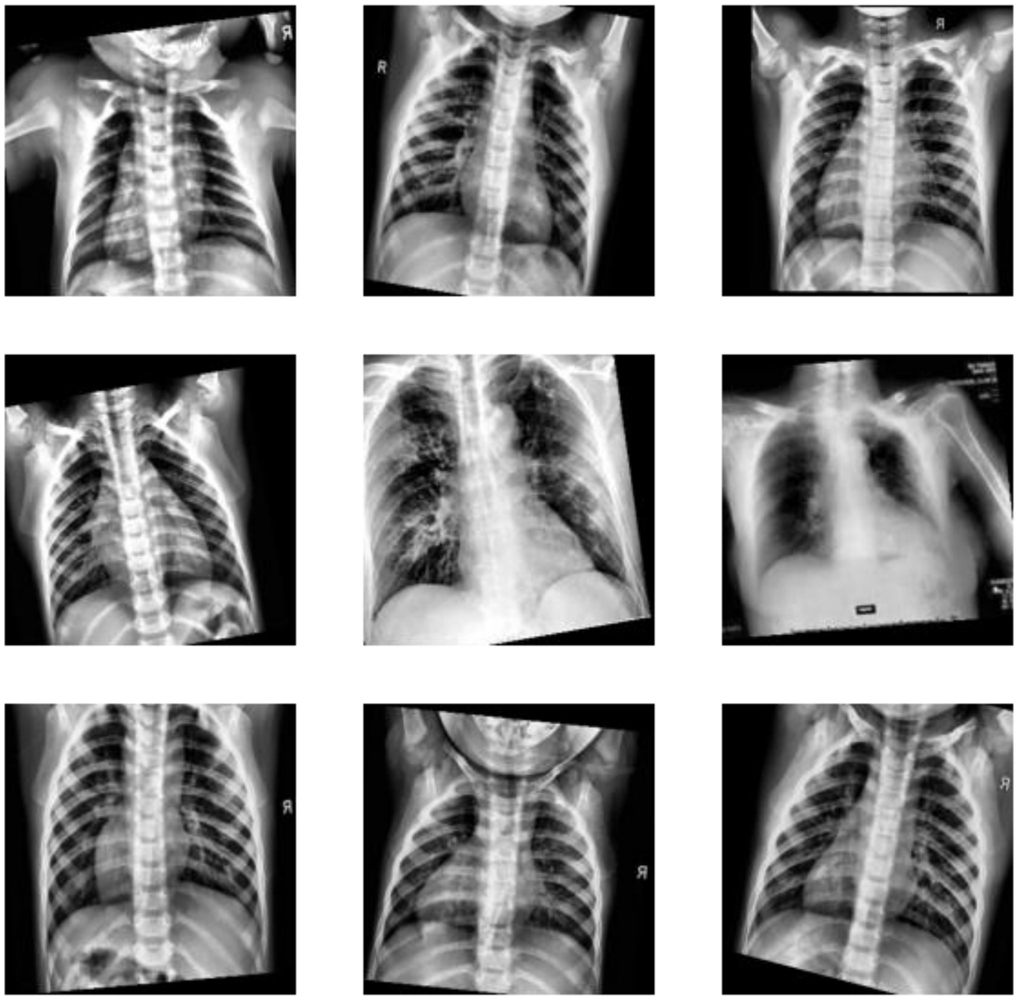

Figure 7: Examples of image augmentation on training dataset

3.2 Training Results

The model training is done using Tensorflow 2.0 and Keras framework. To save time, we will do transfer learning instead of training from scratch. The pretrained model will act as a feature extractor. InceptionV3 model that is previously trained on ImageNet is chosen because it has low number of parameters (24M) while having a high accuracy (78%) on the ImageNet dataset. We use the InceptionV3 base model and add our own classifier dense layer to it to predict our 2 image classes. The model is first trained by training the final classifier dense layer using Adam optimizer. After 3 epochs, we obtain weight value better than the initial random values. Then, we unfreeze a few inception blocks and train the model with stochastic gradient descent (SGD) using a low learning rate (0.0001) until 15 epochs.

3.2.1 Epoch Plots

Overall, the epoch plot looks good with a good fit. (No underfit or overfit). The small spike at epoch 3 is because we unfreeze the last few inception block and the parameters are being retrained. The final validation loss is 0.0258 and the final validation accuracy is 0.9907.

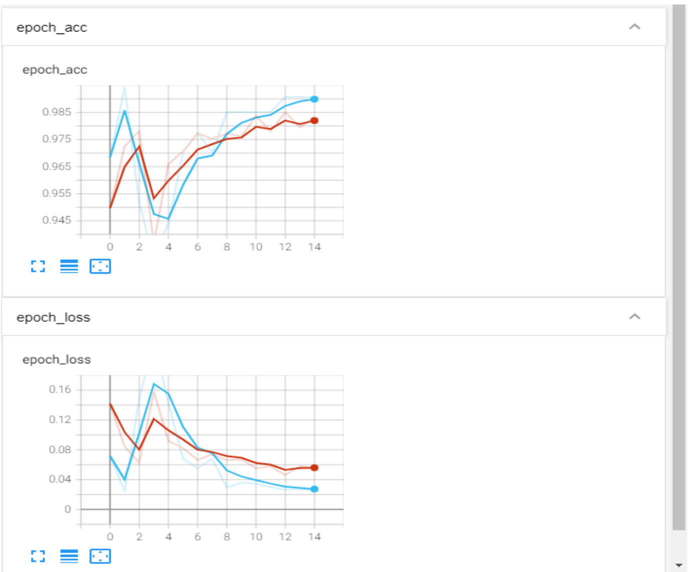

Figure 8: Epoch accuracy and loss plot

3.2.2 Prediction Output

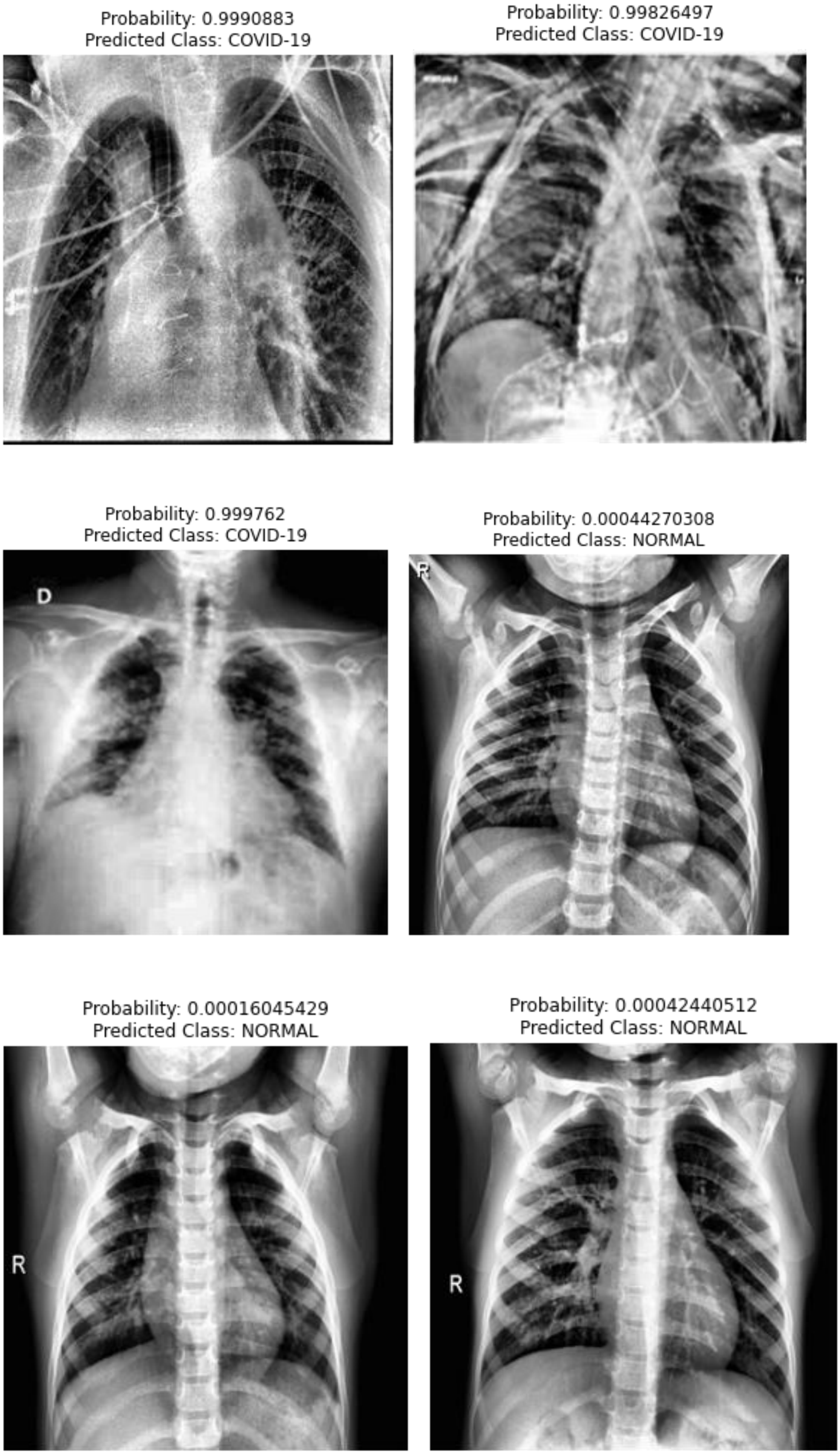

Figure 9: Example prediction of the trained model

3.2.3 Confusion Matrix

From the confusion matrix, we can see that only 2% of the time when our model predicts NORMAL class, it is a wrong prediction. Figure 10 shows the confusion matrix.

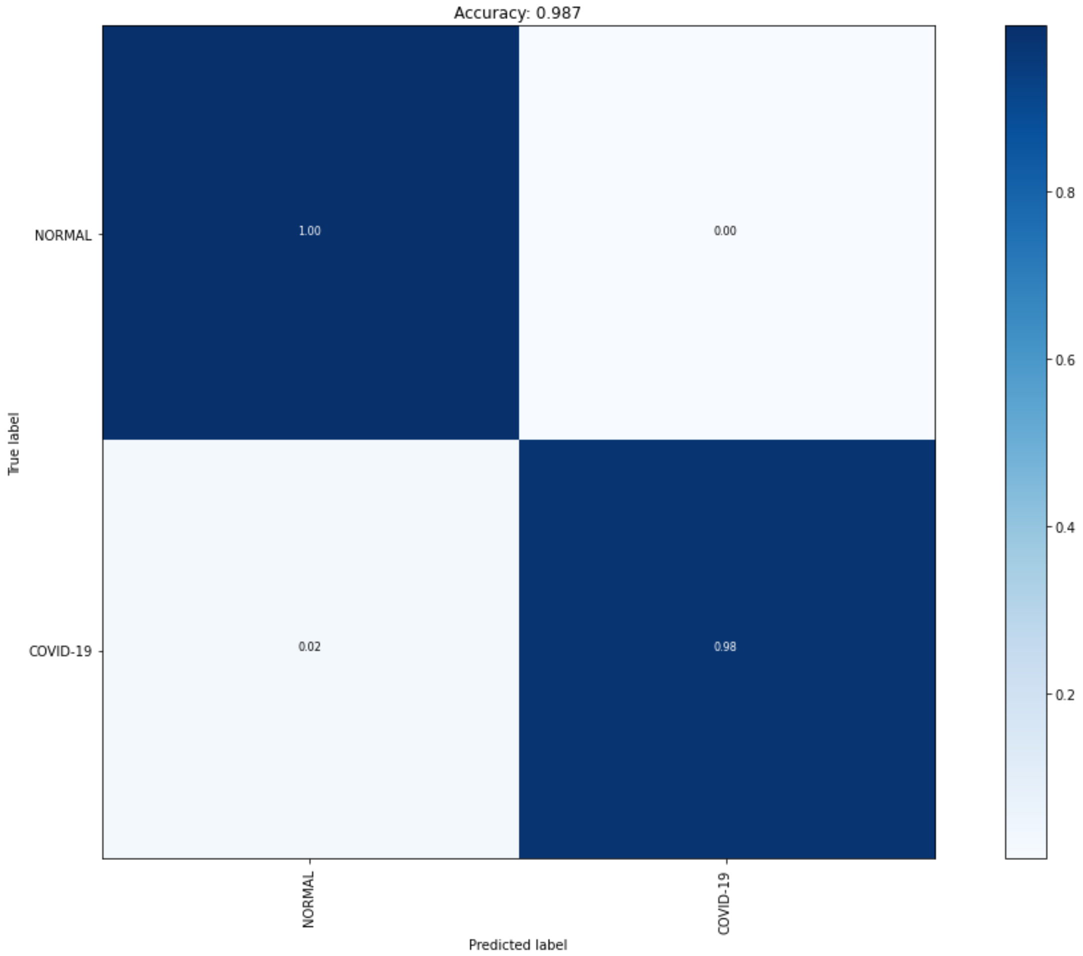

Figure 10: Normalized confusion matrix

3.2.4 Receiver Operating Characteristic (ROC) Curve

To interpret a ROC curve, the curve closer to the top-left corner indicate a better performance, while closer to the diagonal means less accurate model. The graph is expected given the high precision and recall rate of our model. Figure 11 is the ROC curve for the trained model.

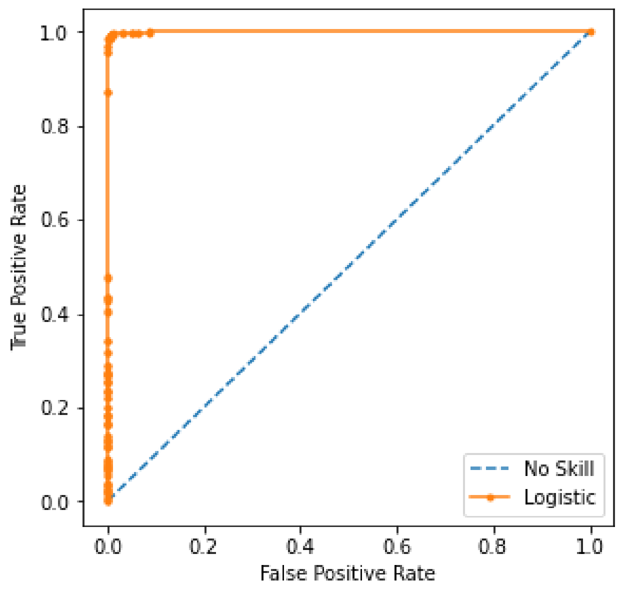

Figure 11: ROC curve

3.2.5 Guided Gradient-Weighted Class Activation Mapping (GradCAM)

Guided gradient-weighted class activation mapping (GradCAM) is a method to visualize region of inputs that are "important" for getting the final class predictions. GradCAM produces a heatmap that indicates important regions while Guided GradCAM combines the heatmap with a saliency map produced by guided backprop.

Figure 12 shows a few examples of GradCAM on the testing dataset. We can observe that some of the COVID-19 images has boxes that indicates the effects of COVID-19 disease (fluid, debris, pneumonia) and our model successfully learnt how to identify those effects.

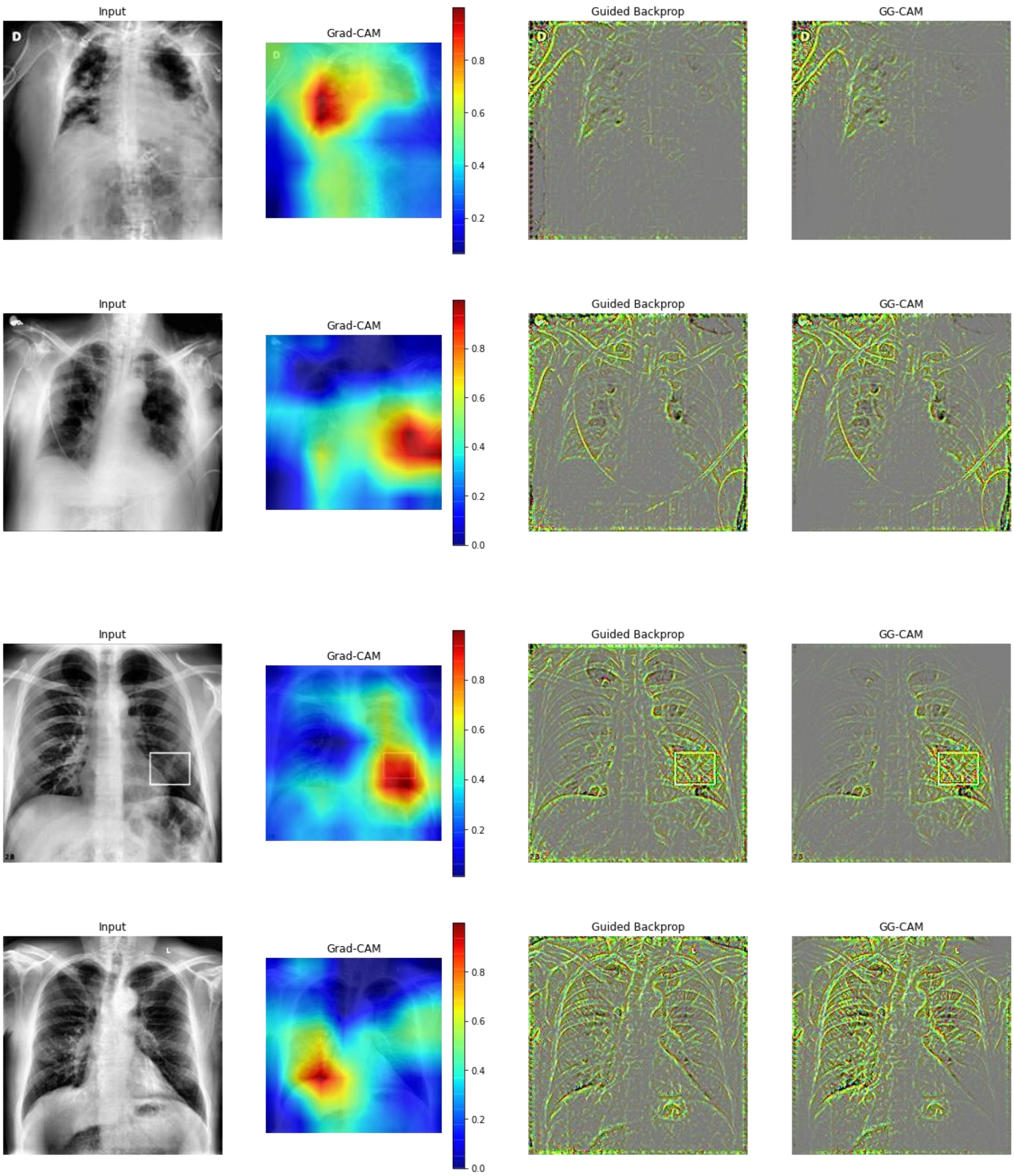

Figure 12: Example of GradCAM on testing dataset

CHAPTER 4: DISCUSSION

4.1 Limitations and Suggestions

Overall, the image classification task is considered not hard as there are only 2 class to predict. However, there are one limitation of the model from the project which is that most of the normal chest radiography images are very similar (refer to sample images from chapter 1). This may be due to the radiography images originating from the same scanner. In my experiments, although all training images is augmented with random rotation, zoom, shear, etc., the model might still learn to predict normal images based on the "similar" features instead of looking at the correct features. Since, deep learning models are a black-box model, there is no easy way to tell whether the model is predicting based on the correct features. We can easily overcome this limitation by getting more training images from various sources.

Another limitation of the project is the small dataset size of radiography images, which may cause the model to be less generalizable and therefore results in biased results. At the time of writing, this dataset is the only publicly available dataset that is reliable. To obtain a more accurate and generalized model, we must collect more radiography images to train the model. As we cannot conclude the robustness of the model, there exists a risk to use it in real-life situation as false positive or false negative prediction can affect the life of the patients.

CHAPTER 5: CONCLUSION

Rapid detection of COVID-19 diseases from chest radiography images is important for doctors and patients in an effort to decrease diagnostic time and reduce financial cost. Deep learning and artificial intelligence are capable of recognizing images classes quickly. In this project, we used InceptionV3 model pretrained on ImageNet dataset as our base model and added our own classifier dense layer to predict whether a radiography image is COVID-19 positive or a normal chest image. The model achieves an accuracy of 98.7% on the testing dataset and is able to successfully identify regions that indicate the effects of COVID-19 as seen from the GradCAM. However, we are unable to conclude with great confidence that the model is generalizing well due to the small size of dataset.

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