CLASSIFICATION OF COVID-19 IMAGES USING ALEXNET TRANSFER LEARNING

A THESIS SUBMITTED TO THE INSTITUTE OF GRADUATE STUDIES

OF

NEAR EAST UNIVERSITY

BY

BETHEL CHUKWUDI OKARA

In Partial Fulfilment of the Requirements for the Degree of Master of Science

in

Electrical and Electronic Engineering

NICOSIA, 2022

CLASSIFICATION OF COVID-19 IMAGES USING ALEXNET TRANSFER LEARNING

A THESIS SUBMITTED TO THE INSTITUTE OF GRADUATE STUDIES

OF

NEAR EAST UNIVERSITY

BY

BETHEL CHUKWUDI OKARA

In Partial Fulfilment of the Requirements for the Degree of Master of Science

in

Electrical and Electronic Engineering

NICOSIA, 2022

APPROVAL

DECLARATION

ACKNOWLEDGEMENT

My sincere gratitude goes to all Near East University lecturers who lectured me, and more especially Assistant Prof. Sertan Serte who is my course adviser and also thesis supervisor.

DEDICATION

To my parents…

ABSTRACT

As the world gradually recovers from one of the worst health crises in human history as a result of the Coronavirus disease 2019 (COVID-19) outbreak, we must never relent in seeking the best method of detecting and treating the infection. The world has made great progress in tackling the infection, but is still nowhere near enough looking at the recurrent rise in the number of COVID-19 cases and complications resulting from the infection that have caused the deaths of many people. In this study, we investigate the ability of deep learning (DL) to differentiate radiographic images of COVID-19 from non-COVID-19. To achieve our goal, we used a deep transfer learning approach with the AlexNet architecture to perform binary classification on COVID-19 and non-COVID-19 CT images, COVID-19 and viral pneumonia X-ray images, and COVID-19 and normal X-ray images. We measured the performance of the model using accuracy, sensitivity and specificity, and determined the effects of varying batch size, learning rate and epoch on the performance. The model performed better on X-ray images than on CT images.

Keyword: COVID-19; Deep Learning; Computed Tomography; X-ray; AlexNet; Transfer Learning

ÖZET

Dünya, 2019 Coronavirus hastalığı (COVID-19) salgınının bir sonucu olarak insanlık tarihinin en kötü sağlık krizlerinden birinden yavaş yavaş kurtulurken, enfeksiyonu tespit etmek ve tedavi etmek için en iyi yöntemi aramaktan asla vazgeçmemeliyiz. Dünya, enfeksiyonla mücadelede büyük ilerleme kaydetti, ancak COVID-19 vakalarının sayısındaki tekrarlayan artışa ve birçok insanın ölümüne neden olan enfeksiyondan kaynaklanan komplikasyonlara bakıldığında hala yeterince yakın değil. Bu çalışmada, derin öğrenmenin (DL) COVID-19'un radyografik görüntülerini COVID-19 olmayanlardan ayırt etme yeteneğini araştırıyoruz. Hedefimize ulaşmak için, COVID-19 ve COVID-19 olmayan CT görüntüleri, COVID-19 ve viral pnömoni X-ray görüntüleri ve COVID-19 ve normal üzerinde ikili sınıflandırma gerçekleştirmek için AlexNet mimarisiyle derin bir transfer öğrenme yaklaşımı kullandık. Röntgen görüntüleri. Modelin performansını doğruluk, duyarlılık ve özgüllük kullanarak ölçtük ve değişen parti boyutunun, öğrenme hızının ve dönemin performans üzerindeki etkilerini belirledik. Model, X-ray görüntülerinde CT görüntülerinden daha iyi performans gösterdi.

Anahtar Kelime: COVID-19; Derin Öğrenme; Bilgisayarlı Tomografi; X-ray; AlexNet; Transfer Öğrenimi

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

2019-nCOV: 2019 Novel Coronavirus

AI: Artificial Intelligence

ANN: Artificial Neural Network

ARDS: Acute Respiratory Distress Syndrome

CNN: Convolutional Neural Network

COVID-19: Coronavirus Disease 2019

CT: Computed Tomography

DNA: Deoxyribonucleic Acid

DNN: Deep Neural Network

FC: Fully Connected

FN: False Negative

FP: False Positive

GPU Graphics Processing Unit

ICTV: International Committee for Taxonomy of Viruses

ILSVRC: ImageNet Large Scale Visual Recognition Competition

MATLAB: MATrix LABoratory

MERS-COV: Middle East Respiratory Syndrome Coronavirus

ML: Machine Learning

NN: Neural Network

ReLU: Rectifier Linear Unit

RGB: Red, Green and Blue

RNA: Ribonucleic Acid

RT-PCR: Reverse Transcriptase –Polymerase Chain Reaction

SARS-COV: Severe Acute respiratory Syndrome Coronavirus

TL: Transfer Learning

TN: True Negative

TP: True Positive

WHO: World Health Organization

CHAPTER 1

INTRODUCTION

1.1 Problem Statement

The outbreak of COVID -19 in 2019, which later became a pandemic in March 2020 and caused morbidity and mortality worldwide, is now one of the worst health crises in human existence. Rapid and accurate detection of the virus and subsequent proper treatment of the infected continue to pose challenges around the world. In 2020, the infection spread like wide fire and healthcare workers were overwhelmed with the influx of infected COVID-19 patients, to the extent many hospitals could not contain patients again. The world breathed a sigh of relief when the some of the vaccines for the infection were approved for use by the end of 2020 and people started getting vaccinated, but that did not actually bring total relief. In 2021, there were COVID-19 infection spikes in various parts of the world, resulting in the infection's second and third waves.

Despite being fully vaccinated, some people with underlying health problems have had complications and some have even died just because of the infection. This is a big challenge before humanity at present and we cannot afford to allow it to continue. There have been challenges before humanity since its inception, and humans have always overcome them. We have no option other than to accept the existence of COVID-19, just like other known viral diseases that have been in existence before COVID-19 (Al-Turjman et al). All we have to do is to accept the infection as a threat to human existence but fight and contain it using artificial intelligence (Al-Turjman et al). This is a challenge to humanity that calls for a quick and accurate detection method for the virus and subsequent proper treatment of any COVID -19 case.

1.2 Aim of this Thesis

The aim of this thesis is to distinguish CT and X-ray images of COVID-19 infections from that of non-COVID-19 infections.

1.3 Motivations

There has been laboratory and radiographic methods of diagnosing COVID-19. These methods have been successful in detecting the infection but they have some drawbacks. The limitations for the laboratory methods include false results, the length of time it takes for test results to be available, low sensitivity, particularly at the early stages of the virus, and the inability of the testing method to determine if the lower respiratory system has been compromised. Traditional radiography in disease diagnosis requires lots of manual labour and time before decisions can be made, due to large volume of COVID-19 cases and scarcity of medical resources in many areas, radiologists were overstretched and unable to meet up with diagnostic results. These are calls to action for a more efficient or supplementary COVID-19 screening method.

To increase the diagnostic rate, improve efficiency, and also reduce the workload on radiologists, computer-aided diagnostic tools has to be employed based on deep learning technique. As an infection that affects the respiratory system, medical imaging is not only vital in its diagnosis but also required for proper treatment. Looking that the constraints of the laboratory methods, availability of radiographic images and advancement of CNN in image classification, we decided to apply deep learning technique of image classification on CT and X-ray images.

1.4 Limitations of this Study

Even though deep learning has been embraced in the health sector because of its lots of benefits, there are challenges at every development and implementation. In the classification of medical images, real images, rather than synthetic images are required, and image clarity and correct labelling are critical in determining reliable results. Also, as a deep learning model becomes more complex, its algorithm becomes more difficult to understand. We were not insulated from the limitations in the course of this work, as we encountered in the area of dataset and explainability. The medical images we used were not collected from the field by us. They are public databases, collected, labelled and made available online for public use by a group of

scholars. If the images were not real, or there were mistakes in their collection and labelling, we can never figure them out. When a complex AI model like deep learning models is used in medicine, the need to understand all the processes and results become very important. Lack of clarity and explainability have been the major shortcomings of AI applications.

1.5 Overview of this Thesis

The aim of this thesis is to distinguish COVID-19 images from that of non-COVID-19. To implement this, we employed a deep learning approach of transfer learning, using AlexNet architecture. We used transfer learning because of the small number of images used in the training and AlexNet because of its excellent performance in image recognition and classification. We collected datasets made available online for public use and designed three binary datasets (A, B and C) from them. With MATLAB R2020a installed on a personal computer, we performed image classifications on the three datasets and generated these results: 93.50% accuracy, 99.73% sensitivity and 87.26% specificity from dataset A, 94.33% accuracy, 100% sensitivity and 88.67% specificity from dataset B, and 99.33% accuracy, 100% sensitivity and 98.86% specificity for dataset C.

1.6 Deep Learning Basics

Deep Learning (DL) is a subset of machine learning (ML) containing algorithms motivated by the structure and operation of human brain or neural networks. It was as a result of its structural makeup and operations that it is referred to as an Artificial Neural Network (ANN). DL is a ML technique that focuses on training systems to learn by examples (Mishra et al, 2021). This is not unlike humans. We learn by examples or from experiences. In teaching a student, an apprentice or a novice, the teacher, the master or the learned uses examples and the more examples used, the more the learner understands. This is why the larger the amount of data on a DL algorithm, the better the performance of the algorithm. As an algorithm based on neural networks architecture, deep learning learn features and task directly from the data with which they are trained, eliminating the need for professionals to manually extract characteristics (Alzubaidi et al, 2021).

We created datasets with labelled sets of images and used the model to classify each image in the dataset as COVID-19, non-COVID-19, Viral Pneumonia, or Normal (healthy lungs). The labelled images were required by the deep learning algorithm because they train the algorithm with the specific features and objects in the images. After that, the algorithm learned how to categorize the input images into the appropriate groups. Deep learning approaches employ neural network designs, and it is because of this that deep learning models are frequently referred to as deep neural networks (DNN) (Kugunavar et al, 2021). The term "deep" refers to the number of hidden layers in ANN. One popular type of DNN is Convolutional Neural Network (CNN) which is best used for image data analysis (Kugunavar et al, 2021).

Why is DL used for this study? The use of this ML technique has surged in recent times and it is one of the most widely used models in AI because; DL models are more accurate than humans in image classification. High-performance computing enabled by GPU enables us to train deep networks in less time. Another reason is that in recent years, the amount of label data required for deep learning has become more readily available. Deep learning approaches have shown to be superior to traditional ML approaches when enough labelled images are available (Abbas et al, 2021). As DL evolves at a rapid pace, image categorization is becoming increasingly important. Data analysis using DL has a bright future ahead of it, and it will undoubtedly have a global impact in the coming years.

1.6.1 Convolutional Neural Networks (CNNs or ConvNets)

As humans, when we look at an animal, we will be able to classify it as a dog or cat from its high-level physical features such as the shape of the head, the ears, eyes, mouth, legs and other parts of the body. However, for a computer, the perception is different. It looks for the small physical attributes like corners and curves, then uses a series of convolutional processes to build up abstract concepts in order to perform classification. A computer uses the extracted low-level physical features to generate high-level physical features that humans see with their eyes to identify the object. This is implemented using CNN. CNN is a network architecture for DL that specializes in image processing and classification (Mishra et al, 2021). It is one of the most widely used and popular DL networks (Dhillon et al, 2020). Nowadays, DL is very

popular as a result of CNN. CNN's main advantage over its predecessors is that it detects significant features automatically without the need for human intervention, making it the most widely used. (Alzubaidi et al, 2021).

CNN consists of layers, where each layer transforms the values that come to it from the previous layer into some complex values, which are then passed on to subsequent layers for further generalization. The network extracts the pixel values of its input images, performs special mathematical operations on the values through a sequence of layers, and outputs a classification for the images (Vinh et al, 2020). It is one of the variants of Neural Networks (NN) in which the hidden layer is consisting of convolutional layers with activation function, pooling layers and fully connected layers. As shown in Figure 1.1, the architecture of CNN is a combination of two main building blocks – the feature extraction block and the classification block (Sumit Saha, 2018). At the feature extraction block, CNN uses a convolution tool and pooling mechanism to separate and identify the various features of an image. At the classification block, the fully connected layer uses the output from the feature extraction block, that is, the extracted features to predict the class of the image (Vinh et al, 2020).

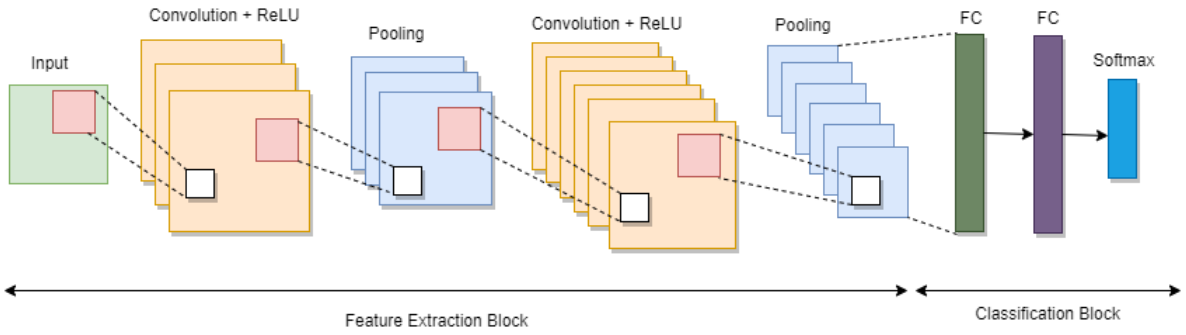

Figure 1.1: The basic CNN architecture (Sumit Saha, 2018)

1.6.1.1 Convolutional Layer

Convolution and activation operations take place at the convolutional layer (Wu, T. et al 2021).

Convolution

It is the linear mathematical operation of applying a filter matrix over the image matrix. The filter slides across the input image, multiplying the filter values with the regions of the input

image that are proportional to the filter's size, that is, the local receptive fields (Yamashita, et al 2018). The multiplications are summed up to produce a single value from each of the local receptive fields, generating an output known as the feature map. This process of convolution is depicted in Figure 1.2

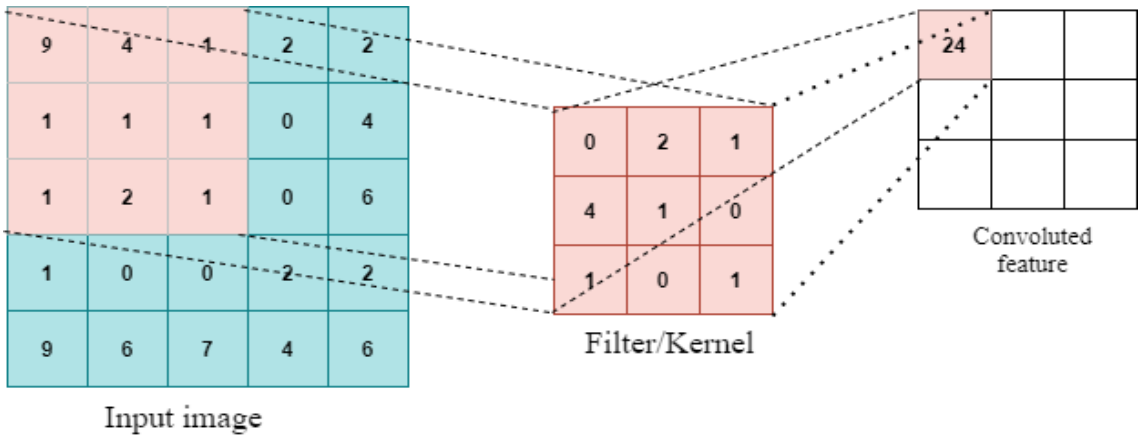

Figure 1.2: Convolution of an input image with a 3×3 kernel (Yamashita, et al 2018)

Activation Function

The activation function transforms the elements of the feature map to the highest positive value or if the element is negative, it translates it to zero. It is diagrammatically explained in Figure 1.3. It adds nonlinearity to the network. Rectifier Linear Unit (ReLU) is a non-linear activation function that is commonly used (Yamashita, et al 2018). The advantage of ReLU over other activation functions is its low computational load (Alzubaidi et al, 2021).

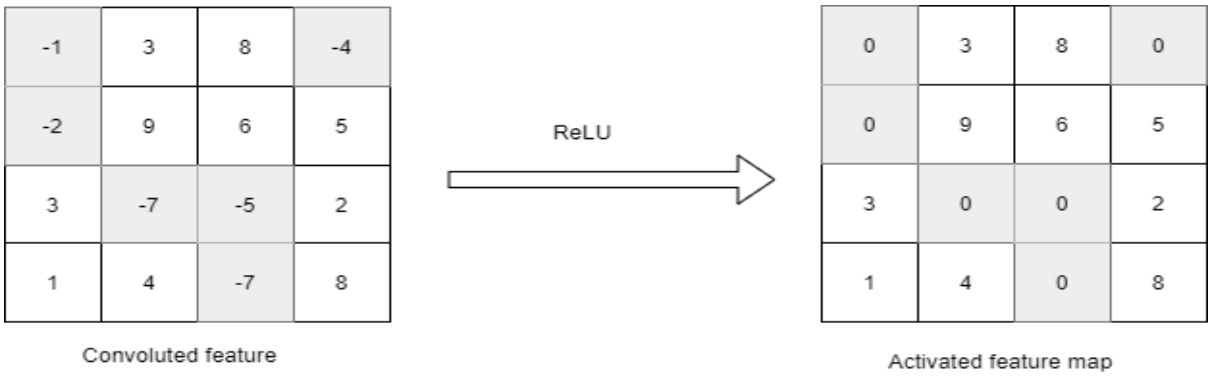

Figure 1.3: Activation operation on the convoluted feature (Rokas Balsys, 2019).

1.6.1.2 Pooling Layer:

The main purpose of the pooling layer is to perform down sampling by reducing the dimension of the convoluted feature map to a single output. (Alzubaidi et al, 2021, Ibrahim et al, 2021). Figure 1.4 illustrates max and average pooling. The advantage of this process is that it reduces the computational cost and still retains the features that define an image. Another plus to pooling is that it helps to minimize over-fitting.

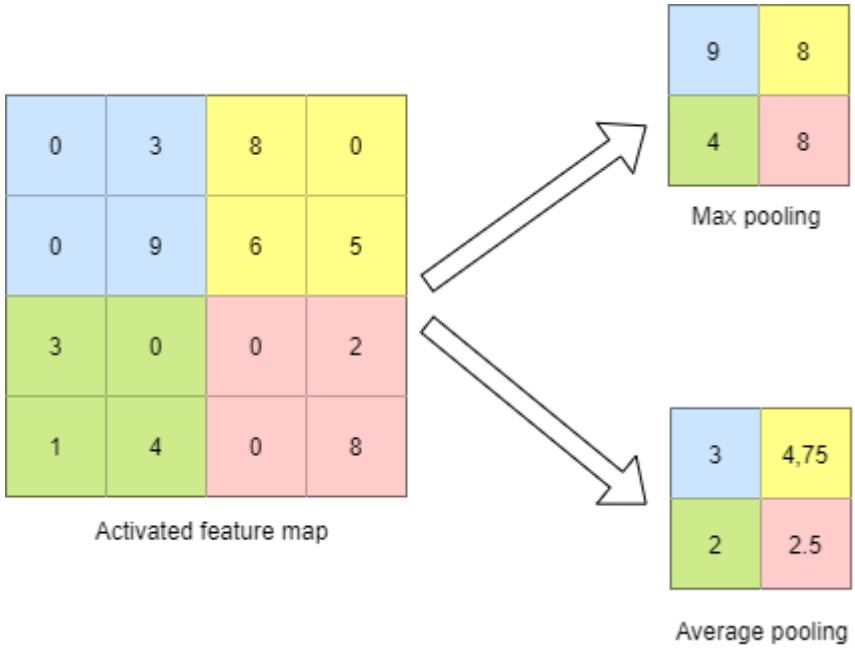

Figure 1.4: Max and average pooling on an activated feature map (Sumit Saha, 2018)

1.6.1.3 Fully Connected Layers

After feature extraction we need to classify the images into various classes, this can be done using fully connected (FC) layers. FC layers are make up the final stage in CNN where classification happens. Feature maps from the pooling layer of the convolution block are converted into a one-dimensional array of numbers and connected to one or more fully connected layers, in which each input is connected to every output by a learnable weight (Yamashita, et al 2018). Figure 1.5 gives a pictorial description of flattening. Without the FC layers, a traditional CNN will not be able to predict classes. Hence, after applying all the convolutional layer operations, the flattened feature map passes through an ANN for

classification. The whole process of using CNN for classification is like adding an ANN to a convolutional layer. Figure 1.6 shows the FC layers. The FC layers receive the whole flattened feature map from the ANN input layer, then the network combines the features into more attributes that better predict the classes after mathematical operations on each of the FC layers. The output layer is where we get the predicted results (Towards data science, 2018).

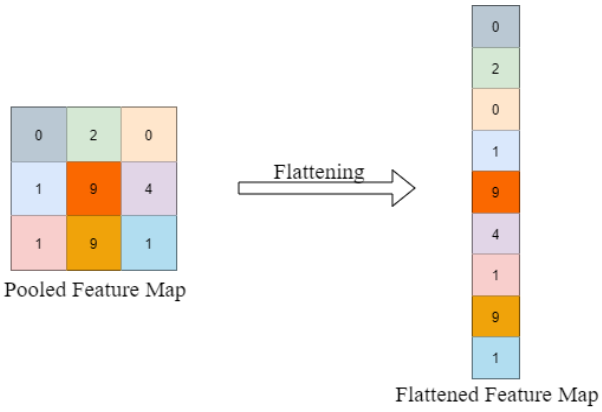

Figure 1.5: Flattening of a 3×3 image matrix to a 9×1 vector (Sumit Saha, 2018).

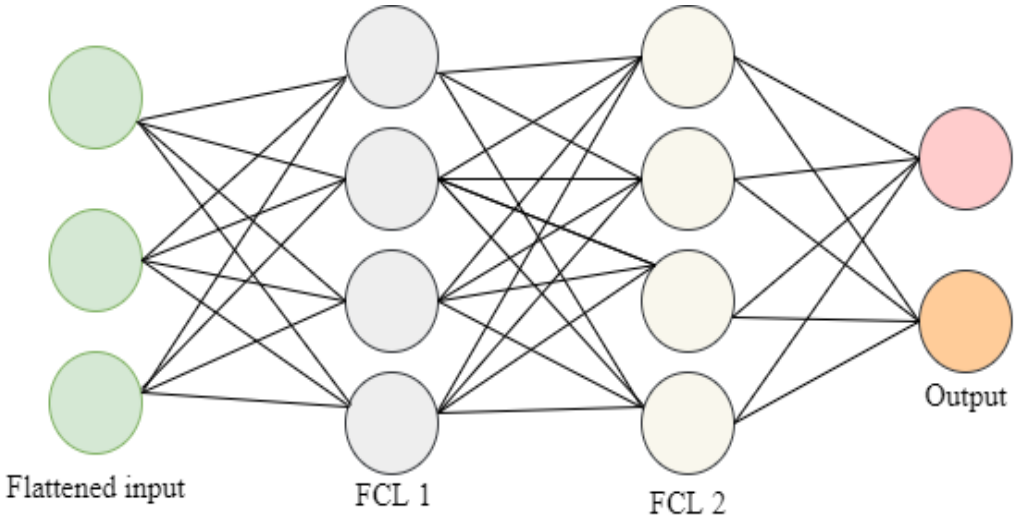

Figure 1.6: The fully connected layers with flattened input (Jiwon Jeong, 2019).

1.6.2 AlexNet and Its Architecture

AlexNet model is a DL model designed based on CNN architecture. Alex Krizhevsky, in collaboration with Ilya Sutskever and Geoffrey Hinton, introduced AlexNet model (Krizhevsky et al, 2017, Ibrahim et al, 2021, Alzubaidi et al, 2021). After winning the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) with an accuracy of 84 percent, the model gained popularity (Krizhevsky et al, 2017, Ibrahim et al, 2021), bringing back CNN, which application before then was only on handwritten digit recognition tasks. AlexNet increased the depth of the network and used several parameter optimization methods to improve CNN learning ability. (Alzubaidi et al, 2021). AlexNet is highly regarded in deep CNN architecture for its innovative results in image recognition and classification (Alzubaidi et al, 2021).

AlexNet has five convolutional layers, three max-pooling layers, two normalization layers, two fully connected layers, and one softmax layer in its architecture. Figure 1.7 is the diagrammatic description of AlexNet architecture. AlexNet model accept image input size of 227×227×3. Each convolutional layer is made up of filters and ReLU, a nonlinear activation function (Yamashita et al, 2018). The first two convolutional layers are composed of three operations: convolution, pooling, and normalization (Ibrahim et al, 2021). The following two convolutional layers (the third and the fourth) perform only convolution with no pooling or normalization. As shown in Figure 1.7, the final convolution layer performs two operations; convolution and pooling with no normalization. The first two fully connected layers are dropout layers, with the primary function of reducing overfitting by reducing the number of neurons. The softmax, which is the classification layer is the final fully connected layer.

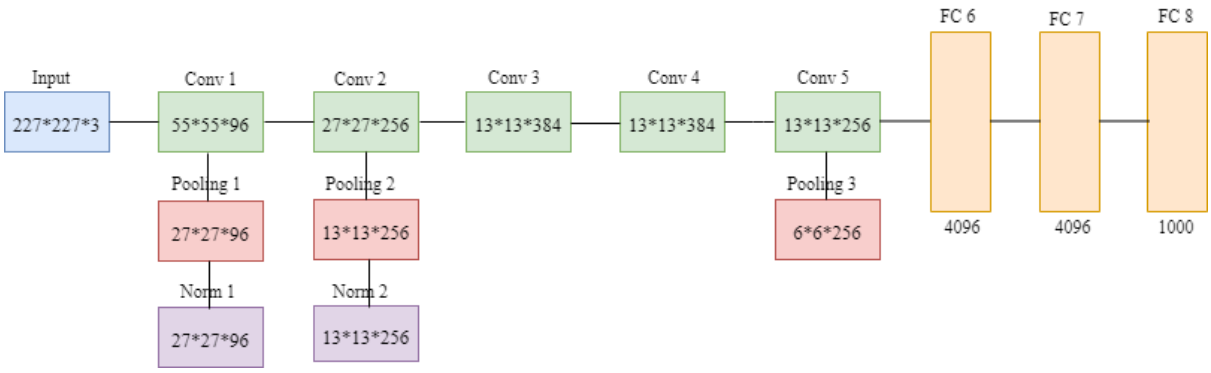

Figure 1.7: AlexNet architecture (Ibrahim et al, 2021)

1.6.3 Transfer Learning

Deep Learning algorithms require a large amount of data to perform well, but the challenge the models are faced with is lack of training data. This challenge is now addressed with transfer learning technique, which is efficient in dealing with limited training data issue. (Alzubaidi et al, 2021). TL can be likened to the relationship between a teacher and a student, where the teacher is the pre-trained model and the student is the novel DL algorithm. The teacher gathers detailed knowledge of a subject and then transfers the acquired knowledge to the student.

Transfer learning is a useful and powerful learning approach employed in deep learning that enables quick and effective training of deep learning algorithms with limited amount of labelled data (Chaddad et al, 2021). The principle of this learning strategy is to leverage on a model previous tasks as starting point to train a model for another similar tasks. TL is preferably used by researchers in medical imaging because it is fast and easy to implement without the need for a large annotated dataset for training, (Abbas et al, 2021). Pre-trained models are commonly used for domain adaptation and improving the accuracy of a model that will be trained on a smaller dataset (Andrea Yoss, 2020). The transfer learning used for this study is the AlexNet pre-trained model.

CHAPTER TWO

LITERATURE REVIEW

As a result of the outbreak of the COVID-19, which later became a pandemic, causing a great negative impact on the world, there have been several kinds of research and papers on how to tackle the infection. Researchers have leveraged the advancement of machine learning in the area of deep learning to classify and analyze medical images of pneumonia infections in other to separate COVID-19 images from that of non-COVID-19. In this section, we reviewed some previous studies on COVID-19, the laboratory and radiographic methods of detecting COVID-19, the application of AI-based models on COVID-19 images from CT scan and X-ray, and supplementary roles of the two diagnostic methods.

2.1 COVID-19 Origin and Nature

COVID-19 is a viral infection that causes symptoms similar to a cold and can lead to complications such as acute respiratory distress syndrome (ARDS). It was first reported to the world in December 2019 as an infectious disease that originated in Wuhan, Hubei Province, China, and was declared a pandemic by the World Health Organization on March 11, 2020. (WHO, March 2020). At the onset of the disease, the infected experience dry cough, fever (pyrexia), loss of smell (anosmia), muscle pain (myalgia), and shortness of breath (dyspnea). The infection can lead to pneumonia and patients who are not well taken care of, risk developing ARDS, a severe form of the infection that can lead to death. Some people who survive ARDS recover completely, while in others the lungs are permanently damaged (Halgurd et al, 2020 and Song et al, 2020). As an infection that affects the lungs and causes respiratory tissue damage in infected individuals, chest imaging is crucial for the infection diagnosis and management (Weinstock et al, 2020).

The virus is related to two zoonotic coronaviruses: SARS-CoV (severe acute respiratory syndrome coronavirus), which was discovered in 2003, and MERS-CoV (Middle East respiratory syndrome coronavirus), which was discovered in 2012. (Ren, et al 2020). At first,

the infection was called 2019-nCOV after the identification of the causative agent as a novel virus that belongs to the family of Coronavirus family (Cascella et al., 2021 and dos Santos, 2020). Because of the virus's genetic relationship to the 2003 SARS outbreak, the International Committee for Taxonomy of Viruses (ICTV) renamed it Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2). (Cascella et al., 2021 and Dos Santos, 2020). The disease was named COVID-19, an abbreviation of Coronavirus Disease 2019, by the WHO Director-General during a media briefing on 2019-nCoV on February 11, 2020. (WHO, Feb. 2020).

2.2 Laboratory Diagnostic Method

Direct detection of viral genetic material in respiratory samples is commonly used to diagnose viral infections like SARS-CoV-2. (IDSA 2021). Reverse transcriptase–polymerase chain reaction (RT–PCR) was the first diagnostic method developed for COVID-19 and was widely used to detect people infected with the virus during the early days of the outbreak (Corman et al., 2020), and it remains the main molecular diagnostic method for COVID-19 diagnosis. SARS-CoV-2 is a ribonucleic acid (RNA) virus that is detected using RNA detection formats, but in order to adapt to the commonly used deoxyribonucleic acid (DNA) detection formats, the genetic material of the virus must be translated into DNA using reverse transcriptase (Vandenberg et al, 2020). The commonly used diagnostic method for COVID-19 has been RT–PCR, but it has some drawbacks (Alam et al, 2021). These drawbacks are false results, the length of time it takes for the test results to be out, less expertise in carrying out the test and low sensitivity, especially at the early stage of the virus. These are calls to action for a more efficient COVID-19 screening method.

Apart from RT-PCR which is a molecular test, other laboratory screening methods are antigen test and antibody test. The molecular test is used to detect the virus (SARS-COV-2). The antigen test is used to determine whether or not the virus antigen is present. The virus antibodies produced by the host immune response against the virus are detected using an antibody test. (FDA, 2021). Each of these test methods has its pitfalls but the most preferred is the molecular test. As at the time of writing this report, RT-PCR is still the widely used molecular test for epidemiological diagnosis of SARS-CoV-2 infection, while immune response techniques are used as complementary methods. But RT-PCR tests can be time-consuming, with many

processes in between sampling and analysis, where errors can occur. These flaws can be improved by the addition of more automation, and this will invariably cut down the errors and also the time. Test results should be well interpreted in the post-analytical phase based on molecular and serological findings (Tang et al, 2020). But can these methods reveal the effects of the infection on the lungs?

2.3 Radiographic Diagnostic Method

As a respiratory infection that affects the lungs and causes tissue damage when not handled properly, it is critical to use radiography in COVID-19 diagnosis and in determining its effects on the human respiratory system. In the introductory part of their paper with the title "COVID-19 Detection from Chest X-ray Images Using Feature Fusion and Deep Learning", Alam et al stated that "The respiratory tract and lungs are the media where the virus can spread easily. As a result, inflammation occurs, and air sacs can be filled with fluid and discharge. The process is responsible for creating an obstacle in oxygen intake" (Alam et al, 2021). The radiographic method, unlike the laboratory testing techniques (molecular, antigen and antibody tests) cannot only detect the infection from the features of a radiographic image but also the extent of harm the virus might have caused the respiratory organs and tissues.

On the clinical application values of CT on COVID-19 diagnosis and management, Jiang et al are of the submission that in addition to assisting in early diagnosis, CT investigation can also be used to evaluate the severity of COVID-19, and during treatment, it can be used to track the progression of the disease and quickly detect lung complications (Jiang et al, 2020). In their work on the use of radiological imaging to detect COVID -19, Emtiaz Hussain and colleagues agreed that computed tomography scans and radiographs play important roles in the early detection and treatment of COVID-19 (Hussain et al, 2020). CT scans of the chest can aid in the diagnosis of COVID-19, particularly in patients who have typical clinical symptoms but negative RT-PCR results. (Kovacs et al, 2020). Also, using chest X-ray to diagnose COVID-19 is a reliable method of predicting mortality and the need for a ventilator. (Balbi et al, 2020).

2.4 Deep Learning Applications in Diagnosis and Treatment

On the application of deep learning on chest X-ray for COVID-19 diagnosis, Borkowski and colleagues affirm that DL algorithms have the capacity of supplementing traditional radiographic interpretation in a variety of ways. These various ways include detecting infection, sorting patients in order of treatment, and speeding up the diagnosis process (Borkowski et al, 2020). To diagnose COVID -19 from medical images, researchers have used DL algorithms to classify and analyze chest images. This method works by extracting features from images using the CNN technique, then applying the extracted features to an ANN to perform classification and detection.

One of the most important considerations in treating a COVID -19 patient is supposed to be the determination of the extent of the infection first. The presence of SARS-COV-2, its antigens or antibodies, as the case may be, can be identified in the laboratory, but the virus's impact on the lungs cannot be determined. An AI-based automated imaging system will determine the severity of COVID -19 in the lungs. According to the introduction section of their review paper, "The Role of Imaging in the Detection and Management of COVID-19", Dong et al believe that the interpretation of typical imaging characteristics of the lung of patients infected with SARS-COV-2 is critical not only in the diagnosis of COVID-19, but also in monitoring disease progression and determining treatment efficacy (Dong et al, 2020). Based on Borkowski et al affirmation on the screening and treatment of COVID -19 patients and Dong et al, AI-based radiology applications can be used in these five clinical processes - early and accurate detection of infection, assessment of infection severity, the prognosis of infection, triaging and monitoring of patients under treatment.

By thoroughly analyzing previous patient data, AI can predict the possibility of death. (Alafif et al, 2021). In a situation where there are many COVID -19 cases, healthcare givers are overwhelmed and hospitals cannot admit more patients, triaging patients will be helpful. The process of sorting patients based on their need for immediate medical treatment can be best

done using a DL-based algorithm in respect to the analyzed images. According to Zhen-zhen Jiang and colleagues' findings on the role of CT in COVID-19 diagnosis, monitoring, and follow-up, COVID -19 manifestations can be classified as early, advanced, critical, or complicated based on lesion extent and severity from CT scan analysis (Jiang et al, 2020). The application of an AI-enabled chest imaging system will track the progression of COVID -19 and rapidly detect pulmonary complications.

2.5 Supplementary Role of Lab Testing and AI-based Imaging

Human interpretations of results from chest X-rays and CT scans cannot accurately distinguish COVID-19 from other respiratory infections, but DL-based algorithms on medical images can. However, they should not be used as the sole form of COVID-19 diagnosis. The augment is this; laboratory testing cannot be put aside during COVID -19 screening because SARS-COV-2 enters the human body through the mouth or nose before reaching the lower respiratory tract.. The samples used for molecular and antigen testing methods are collected from the upper respiratory tract, the gateway for the virus to get to the lungs. Clinical imaging for pneumonia is performed at the lower respiratory section and not at the upper section. On the other hand, molecular and antigen testing methods will not be the best or final screening process because they can only detect the virus but will not reveal the effect of the infection on the respiratory system. Also, one of the challenges in these testing methods is false-negative results, the cause of which may be due to various reasons and human error cannot be ruled out.

The use of chest CT for screening COVD-19 patients with clinical and epidemiological features consistent with infection, especially when RT-PCR tests are negative, is recommended by Fang and his co-authors in their paper - Clinical Characteristics of Coronavirus Disease 2019 (COVID-19): An Updated Systematic Review. (Fang et al, 2020). The combination of radiographic features and laboratory testing results is necessary for early and accurate detection of COVID -19. Combining the results of an AI-based automated imaging analysis with the three laboratory testing methods can help clinicians to understand the infection better and, as a

result, detect or predict the virus's early signs. (Waheed et al., 2020). An AI-based imaging system through DL will be complementary to the shortcomings of the laboratory testing methods and in providing accurate detection and better management of any form of COVID-19 case.

CHAPTER 3

METHODOLOGY

This chapter discusses the methods used in carrying out the study. As a study that involves the generation of results from collected data and running a deep learning algorithm on the data, there were lots of trials and errors before getting the desired results. The data used were carefully selected and processed to create datasets that suit the AlexNet pre-trained model. The computational capacity of the machine used was considered in choosing the model, the amount of data and the training options for the network.

3.1 Datasets

The datasets for this study consist of chest X-ray images collected from kaggle COVID-19 radiography database (Chowdhury et al, 2020, Tawsifur et al, 2020) and chest CT scans from kaggle SARS-COV-2 CT scan dataset (Soares et al, 2020, Angelov and Soares, 2020). Out of the datasets, we constructed three sets of data that are compatible with the pre-trained CNN used in this study, and also which will help us in achieving our study objectives.

Dataset A

Dataset A is a CT dataset, designed for binary classification. It is made up of 1229 images, each for both COVID-19 and non-COVID-19, making a total number of the images in Dataset A to be 2458. The dataset was derived from kaggle SARS-COV-2 CT scan dataset with the link – https://www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset. (Soares et al, 2020, Angelov and Soares, 2020).

Dataset B

This dataset contains 1000 images of chest X-ray, 500 images each, for the class categories - COVID-19 and Normal. It was formed from the second update of kaggle COVID-19

radiography database with the link https://www.kaggle.com/tawsifurrahman/covid19-radiography-database (Chowdhury et al, 2020, Tawsifur et al, 2020).

Dataset C

This dataset contains 1000 images of chest X-ray, 500 images each, for the class categories - COVID-19 and Viral Pneumonia. It was also derived from the second update of kaggle COVID-19 radiography database with the link https://www.kaggle.com/tawsifurrahman/covid19-radiography-database (Chowdhury et al, 2020, Tawsifur et al, 2020).

Table 3.1: Datasets of CT and X-ray images

Dataset	**Image type**	**Class**				**Total**
		COVID	Non-COVID	Viral Pneumonia	Normal	
Dataset A	CT	1229	1229	-	-	2458
Dataset B	X-ray	500	-	-	500	1000
Dataset C	X-ray	500	-	500	-	1000

3.2 Image Processing of the Datasets

Image processing is an important step toward obtaining relevant information and correct classification by removing noisy or distorted pixels from an image. (Alam, N. A. et al, 2021). In running the AlexNet model on each of the datasets, we encountered errors in the terms of the correct input image, both from the pixel size and the channel. The collected datasets came in different pixels, with some having one channel and others three channels but AlexNet architecture input data are 227×227 pixels with 3 channels ($227 \times 227 \times 3$). To achieve this required image input size, we converted the images to 227×227 pixels and from grayscale to RGB using FastStone Photo Resizer.

3.3 Implementation

To implement the classification, we used MATLAB R2020a on a personal computer with a 64-bit window, 4 GB Random Access Memory (RAM), and an Intel®CoreTMi3-1005G1 CPU @ 1.20GHz, as well as AlexNet transfer learning as the pre-trained CNN model. The sequence of implementing the classification is as follows in subheading 3.3.

3.3. 1 Loading and Splitting the Image Data

Loading the Images for the Classification

We loaded the images for the classification from the dataset folder using imageDataStore syntax

```
(imds = imageDatastore(location))
```

For the imageDataStore to read and understand the folder names as category labels, we stored image categories in their sub-folders.

Splitting the image data into training and validation

Using the syntax;

```
splitEachLabel
```

We divided the image data into training and validation sets of data, where 70% of the images were used for training and 30% used for validation.

3.3.2 Loading the Pretrained Network

We loaded the pre-trained AlexNet using the function;

```
net = alexnet;
```

To display network architecture and detailed information about the layers, we used the code;

```
net.Layers
```

3.3.3 Modifying the Three Final Layers

We extracted all layers, except the last three, from the pre-trained network using the function from matlab;

```
layersTransfer = net.Layers(1:end-3);
```

With the matlab function;

```
numClasses = numel(categories(imdsTrain.Labels))
```

The model reads and understands the number of class categories in the folder containing the images for the classification. This eliminates the error of output size of last layer not matching with number of classes, making it possible for the model to be used to perform classifications with the various number of classes.

We transferred the layers for the classification task using the matlab code (MathWork, 2020) ;

```
layers = [
      layersTransfer;
      fullyConnectedLayer(numClasses,'WeightLearnRateFactor',20,'BiasLearnR
      ateFactor',20)
      softmaxLayer
      classificationLayer];(
```

3.3.4 Training the Modified Network

With the trainingOption syntax

```
(options = trainingOptions(solverName))
```

We set up the training options for the network using stochastic gradient descent with momentum (sgdm), and with the trainNetwork syntax

```
(net = trainNetwork(imds,layers,options))
```

We then train the modified network which is made up of transferred and new layers

3.3.5 Classifying the Validation Images

Classify the Validation Images

Using the classify syntax

```
([YPred,scores] = classify(net,imds))
```

We classify the validation images using the fine-tuned network

Display Predicted Images

To visualize the validation images with predicted labels, we plotted a nine randomly selected images using the codes;

```
   idx = randperm(numel(imdsValidation.Files),9);
   figure
for i = 1:9
    subplot(3,3,i)
    I = readimage(imdsValidation,idx(i));
    imshow(I)
    label = YPred(idx(i));
    title(string(label));
end
```

3.3.6 Plotting the Confusion Matrix and Generating the Performance Metrics

Plotting Confusion Matrix

Using the plotconfusion syntax (MathWork, 2020);

```
(plotconfusion(targets,outputs))
```

We plotted a confusion matrix for the true labels targets and predicted labels outputs

Measure Accuracy and Other Performance Metrics

We measured the classification accuracy and other performance metrics using the codes;

```
YValidation = imdsValidation.Labels;
YData = imdsValidation.Labels;
accuracy = mean(YPred == YValidation);
YPred;
accuracy = mean(YPred == YData);
YData;

y = grp2idx(YData);
test = grp2idx(YPred);
classperf(y,test)
```

CHAPTER 4

RESULT AND DISCUSSION

4.1 Results

The methodology we used in chapter 3 above generated the results which we arranged in this chapter in figures and table.

4.1.1 Training Progress

We created the training process as shown in Figures 4.1, 4.2 and 4.3. The training progress helped us to monitor and learn how the training was progressing. During the trial versions, we used the training progress to determine whether or not the network accuracy was improving as the training progressed from one epoch to the next. We also used the training progress to observe the network's training rate as the training progressed. These information from the training progress aided us in deciding whether to continue or discontinue the training.

As can be seen in the training cycles of the three figures, we used mini-batch size and number epoch to determine iterations. With arithmetic operations, the values at the training cycle are calculated with these equations;

$$\text{Iterations per Epoch} = \frac{\text{Number of Training Samples}}{\text{Mini Batch Size}} \tag{4.1}$$

$$\text{Maximum Iterations} = \text{Epoch} \times \text{Iterations per Epoch} \tag{4.2}$$

From the code for training the network, we set mini-batch size to be 32 and epoch to be 10 for both datasets.

For Dataset A

Total number of images in Dataset A is 2458

Number of training sample is 1740 (70% of the dataset images was used for training)

$$\text{Iterations per Epoch} = \frac{1720}{32} = 53.75 = 53$$

$$\text{Maximum Iterations} = 10 \times 53 = 530$$

For dataset B and dataset C

Since datasets B and C have the same number of images and also with same mini-batch size and epoch, they will also have the same iterations per epoch and maximum iterations.

Total number of images in each dataset is 1000.

Number of training sample is 700 (70% of the dataset images were used for training).

$$\text{Iterations per Epoch} = \frac{700}{32} = 21.875 = 21$$

$$\text{Maximum Iterations} = 10 \times 21 = 210$$

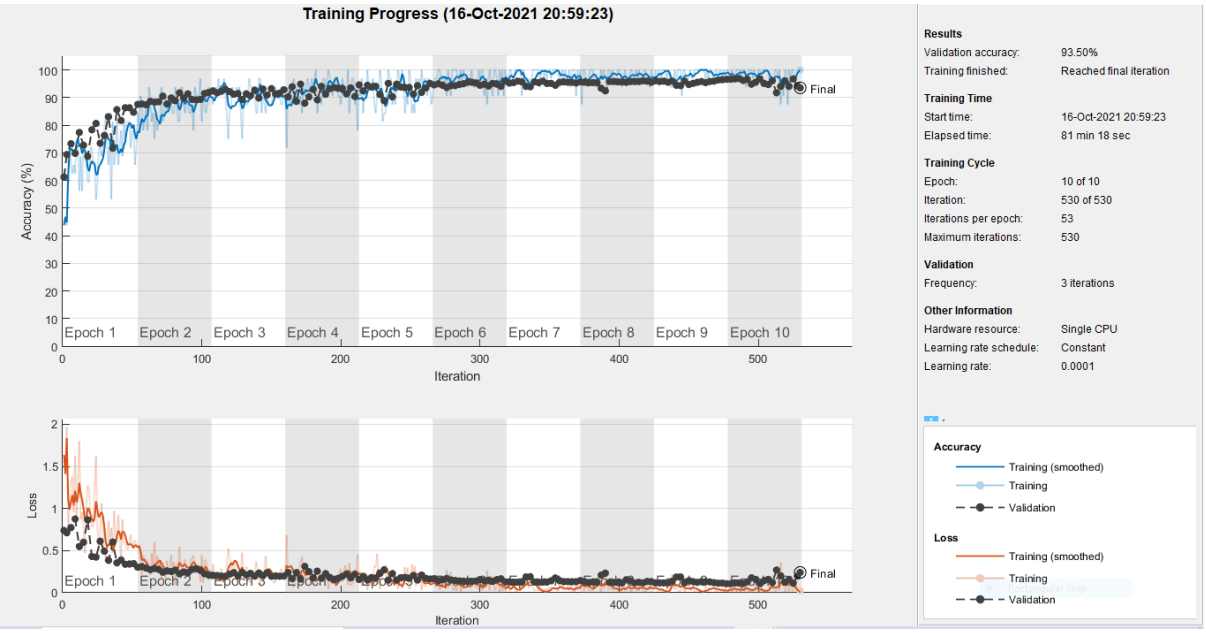

Figure 4.1: Training progress for dataset A

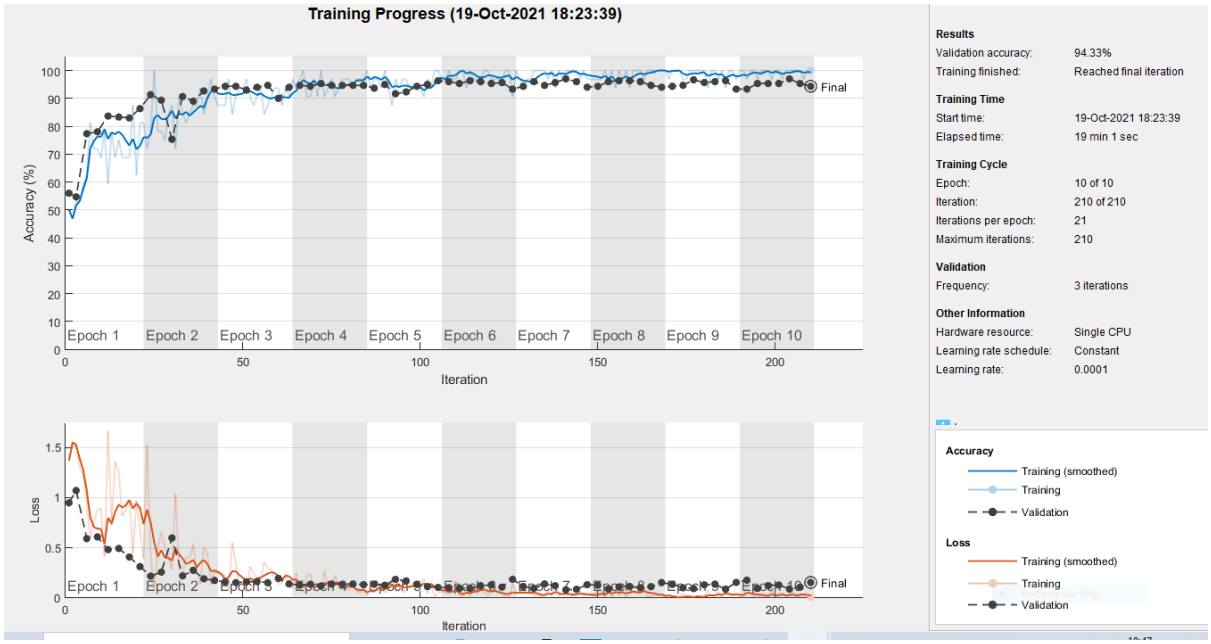

Figure 4.2: Training progress for dataset B

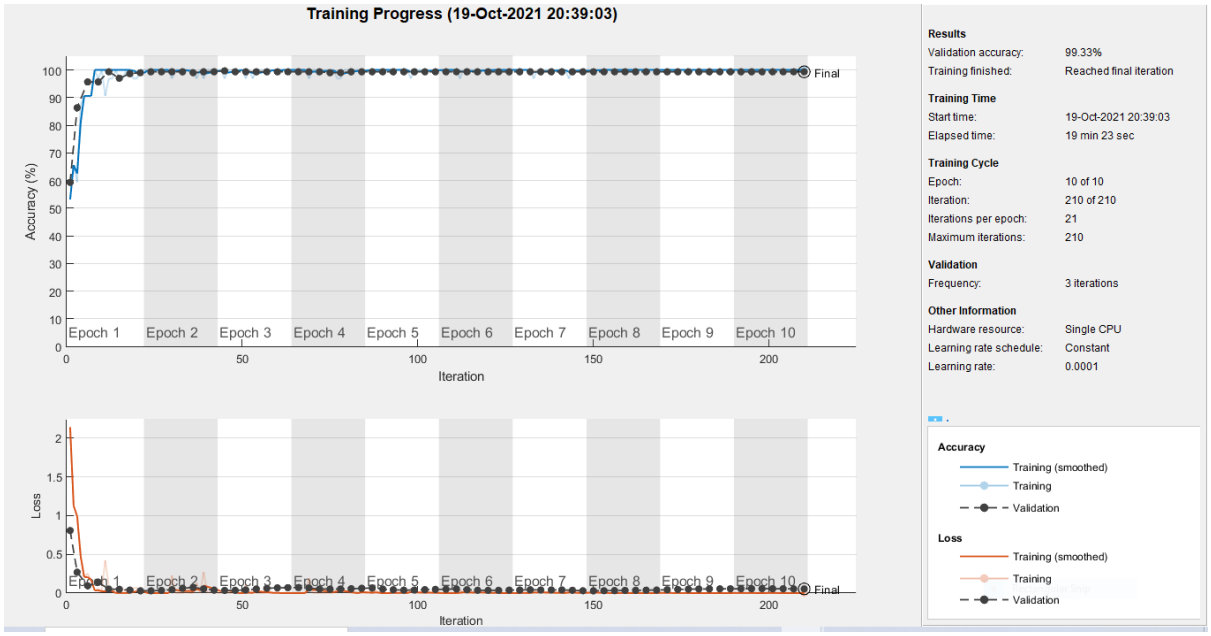

Figure 4.3: Training progress for dataset C

4.1.2 The Classified Images

This study aims at distinguishing radiographic images of COVID-19 from that of non-COVID-19. We created the code that will enable the algorithm to display 3by3 classified images with the names of the labels on them. Figure 4.4 depicts the classified CT images with their labels from dataset A, four images classified as COVID-19 and four images classified as non-COVID-19. Figure 4.5 shows the predicted X-ray images with their labels from dataset B. The dataset contains COVID-19 and Normal images, hence the images appeared with their respective classified labels. Figure 4.6 is the classified chest X-ray images from dataset C with COVID-19 and Viral Pneumonia labels. The displayed images were randomly selected by the model from the total validation data for each of the datasets.

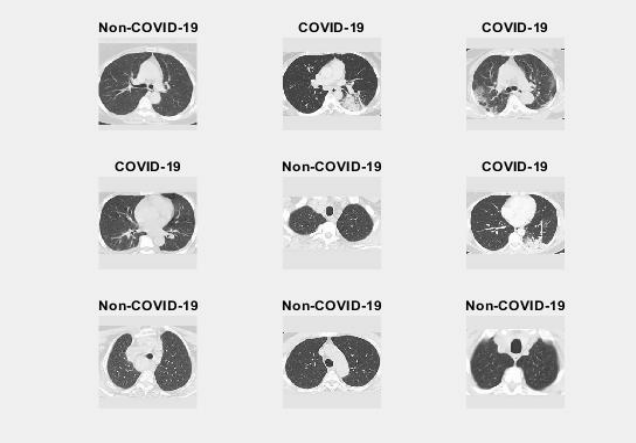

Figure 4.4: Classified CT images with their labels from dataset A

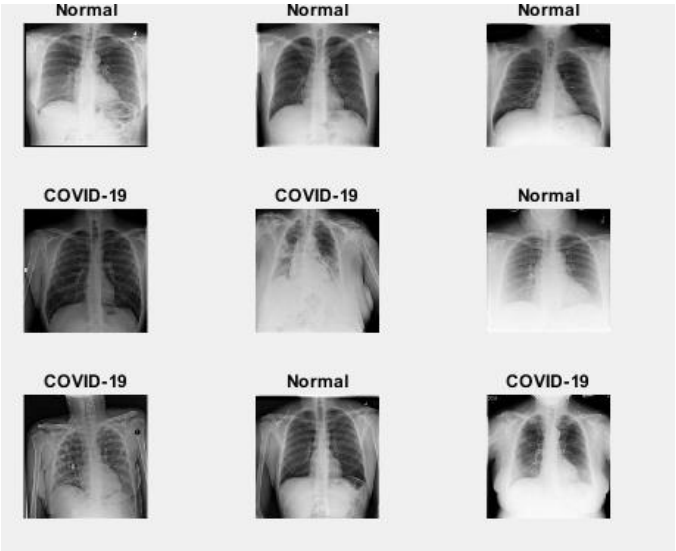

Figure 4.5: Classified X-ray images with their labels from dataset B

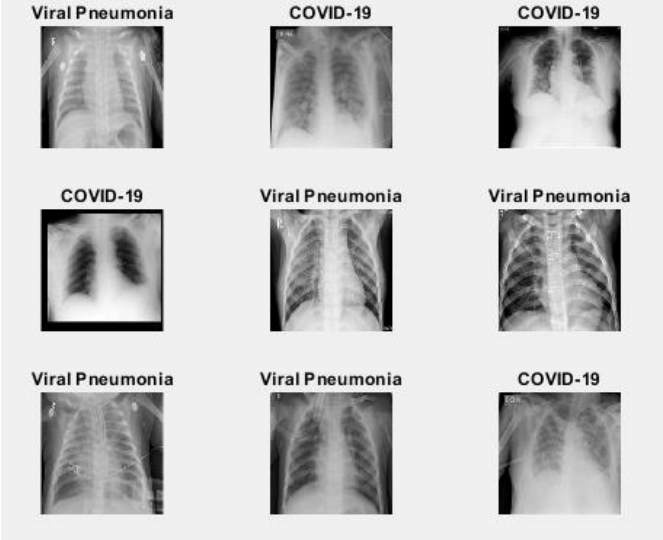

Figure 4.5: Classified X-ray images with their labels from dataset C

4.1.3 Confusion Matrix

A confusion matrix is a classification tool used to assess a model. It is a square matrix table that helps us understand how a classification model performs on a set of test data. As shown in Figures 4.7, 4.8 and 4.9, a confusion matrix tells us what our model did correctly and what it did incorrectly. The numbers along the diagonal (the green boxes) are the samples that the model classified correctly while the numbers along the off-diagonal (the pink boxes) are the

samples the model classified wrongly. The green and pink values in the white boxes indicate the percentage of correctly and wrongly predicted samples respectively. The green percentage value in the only grey box, at the bottom end of the diagonal, is the classification accuracy while the red percentage value is the misclassification rate.

4.3.1.1 Confusion Matrix of Dataset A

Confusion matrix of Dataset A is generated from the binary classification of chest CT images of COVID-19 and non-COVID-19. From the confusion matrix, 738 samples were used for the classification, 369 each for COVID-19 and non-COVID-19. The samples of these two classes are equal because we intentionally created a dataset with an equal number of images for each of the classes right from the design of the classification dataset. The 738 samples are from 30% of 2458 of the total sample mapped out for validation as written in the code. To analyze the confusion matrix, we looked at it these two ways;

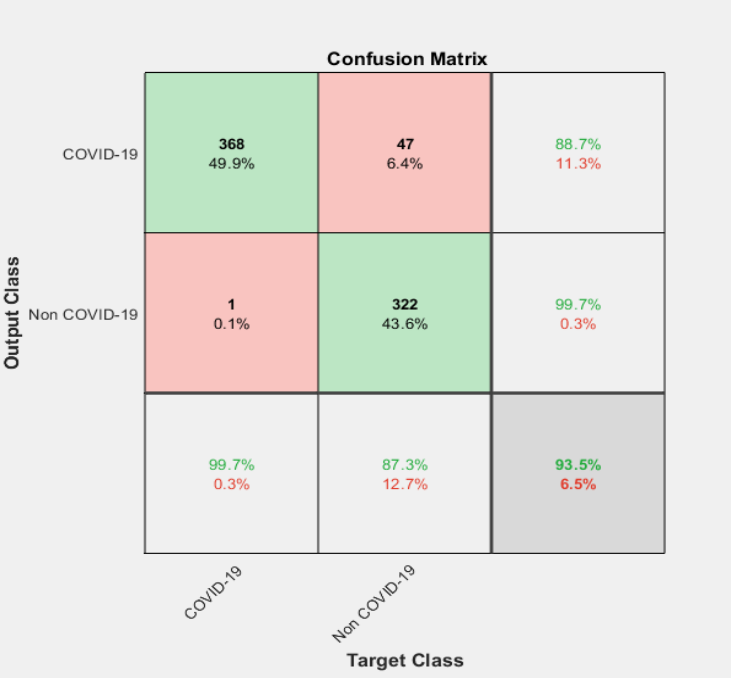

Figure 4.7: Confusion matrix of dataset A

From the Target Class (the column)

Out of the 369 (368 + 1) samples of COVD-19, 368 samples were correctly identified by the model as COVID-19 and it is our True Positive (TP). 1 out of the 369 samples of COVID-19 was incorrectly identified by the model as non-COVID-19 and it is our False Negative (FN). Out of the 369 (47 + 322) samples of non-COVID-19, the model correctly classified 322 samples as non-COVID-19 and it is our True Negative (TN). 47 out of the 369 samples of non-COVID-19 were wrongly identified by the model as COVID-19 and it is our False Positive (FP).

From the Output Class (the row)

Out of the 738 samples, the model classified 415 (368 + 47) as COVID-19 and 323 (322 + 1) as non COVID-19. Out of the 415 samples classified as COVID-19, 368 actually had COVID-19 while 47 were incorrect. Out of the 323 samples classified as non-COVID-19, 322 actual were non-COVID-19 while 1 was incorrect.

4.3.1.2 Confusion Matrix of Dataset B

Dataset B generated the confusion matrix shown in Figure 4.6. The confusion matrix is made up of 300 samples from two class labels – COVID-19 and Normal. From the x-ray dataset, each of the two-class labels has 500 images. In the code for the classification, 30% of the 1000 images were allotted for validation. 30% of 500 images for each of the classes gave 150 samples and 150 samples of two classes gave 300 samples, which was the total samples for the model to predict. From the confusion matrix, we were able to determine the model classification on the 300 samples.

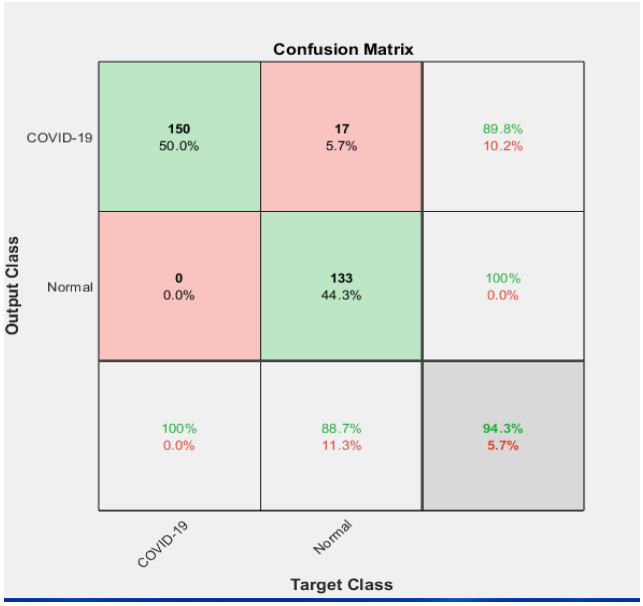

Figure 4.8: Confusion matrix of dataset B

From the Target Class (the column)

Out of the 150 (150 + 0) actual COVID-19 samples, 150 were correctly identified as COVID-19 by the classifier and this is the true positives (TP). The non-COVID-19 received zero classification and this is the false negatives (FN). All the samples were correctly identified as COVID-19. Out of the 150 (133 + 17) samples of non-COVID-19, 133 samples were correctly identified as non-COVID-19 by the classifier and this is true negatives (TN). 17 were wrongly identified as COVID-19 and it is the false positives (FP).

From the Output Class (the row)

Out of the 300 total samples for the classification, the model classified 167 (150 + 17) as COVID-19 and 133 (133 + 0) as non COVID-19. Out of the 167 samples classified as COVID-19, 150 actually had COVID-19 while 17 were incorrect. Out of the 133 samples classified as non-COVID-19, 133 actual were non-COVID-19 and non was incorrect classified.

4.3.1.3 Confusion Matrix of Dataset C

Figure 4.9 is a binary confusion matrix generated from dataset C. It is made up of 300 samples from two class labels – COVID-19 and Viral Pneumonia. From the X-ray dataset, the total number of images is 1000. With the 0.3 of 1000 allocation for validation, 300 samples were mapped for classification. From the confusion matrix, we deduced the model classification on the 300 samples as follows;

From the Target Class (the column)

Out of the 150 (150 + 0) samples of COVD-19, 150 samples were correctly identified by the model as COVID-19 and it is the true positives (TP). No sample was incorrectly identified by the model as non-COVID-19 and it is this false negatives (FN). Out of the 150 (148 + 2) samples of non-COVID-19, the model correctly identified 148 samples as non-COVID-19 and it is the true negatives (TN). 2 out of the 150 samples of non-COVID-19 were wrongly identified by the model as COVID-19 and it is the false positives (FP).

From the Output Class (the row)

Out of the whole 300 samples to be tested, the model classified 152 (150 + 2) as COVID-19 and 148 (148 + 0) as non-COVID-19. Out of the 152 samples classified as COVID-19, 150 actually had COVID-19 while 2 were incorrect. Out of the 148 samples classified as non-COVID-19, 148 actual were non-COVID-19 and non was incorrectly classified.

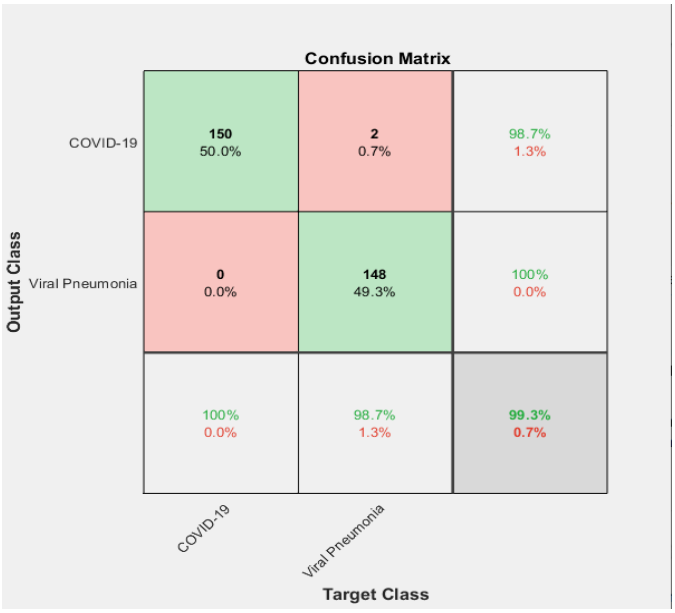

Figure 4.9: Confusion matrix of dataset C

4.1.4: Performance Evaluation

The performance of a ML model in any classification problem is assessed through the confusion matrix. We assessed the classification's performance using three main parameters: accuracy, sensitivity, and specificity. They were generated from the classification code and can also be determined manually using the elements of the confusion matrix.

Accuracy

Accuracy is defined as the proportion of correctly identified samples to total samples used for classification. It can be derived from the confusion matrix with this equation;

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4.3}$$

Sensitivity

It is the proportion of samples correctly classified as a disease with the total samples of the disease. Sensitivity is a measure of how often a model classifies the actual samples that are the disease. It can be calculated from the confusion matrix with this equation;

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (4.4)$$

Specificity

Specificity is the ratio of samples properly classified as not a disease with the total samples which are not the disease. It is a measure of how often a model classifies the actual samples that are not the disease. It can be determined from the confusion matrix with this equation;

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (4.5)$$

Table 4.1: Performance metric results

Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)
Dataset A	93.50	99.73	87.26
Dataset B	94.33	100	88.67
Dataset C	99.33	100	98.68

Table 4.1 shows the performance metric results of Dataset A, B and C obtained using the same batch size, epoch and learning rate as can be seen on their training progresses, that is, Figures 4.1, 4.2 and 4.3 respectively. Tables 4.2, 4.3 and 4.4 show the effects of varying batch size, epoch and learning rate on the model's performance.

Table 4.2: The effect of epoch on the model performance using Dataset A

Training	**Hyper-parameter**			**Performance Metric**		
	Batch Size	**Learning Rate**	**Epoch**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
2nd	32	0.0001	2	89.57	81.84	97.29
3rd	32	0.0001	3	92.55	94.85	90.24
4th	32	0.0001	4	89.57	80.76	98.37
5th	32	0.0001	5	91.87	99.49	84.28

Table 4.3: The effect of learning rate on the model performance using Dataset B

Training	**Hyper-parameter**			**Performance Metric**		
	Batch Size	**Learning Rate**	**Epoch**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
2nd	32	0.001	3	50.00	100	0.00
3rd	32	0.0001	3	89.67	82.00	97.33
4th	32	0.00001	3	88.33	86.00	90.67
5th	32	0.000001	3	63.33	50.67	76.00

Table 4.4: The effect of batch size on the model performance using Dataset C

Training	Hyper-parameter			Performance Metric		
	Batch Size	**Learning Rate**	**Epoch**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
2nd	8	0.0001	5	99.67	100	99.33
3rd	16	0.0001	5	99.67	99.33	100
4th	24	0.0001	5	98.67	98.67	98.67
5th	32	0.0001	5	99.33	98.67	100

4.2 Discussion

DL is a subfield of ML and an AI algorithm that needs a large amount of data to train its algorithm. A DL model is data dependant for better performance and gets improved as you feed it with more and more data. As a result of the huge amount of data that it needs, training a deep learning network could take several hours or days and needs a high-performance computing system. But with the transfer learning approach, we successfully apply DL on small data and produce high-performance results within 90 minutes using a low-performance computing system. This is proven from the results we generated.

4.2.1 Discussion of Results

Accuracy

Accuracy is used as a measure of classification performance on balanced data, but cannot be used as a classification performance metric on unbalanced data. This is because a machine learning algorithm could be biased on unbalanced data resulting in misleading performance results. What this implies is this; from Figure 4.8, that is, the confusion matrix of dataset B, the total number of validation samples for COVID-19 is 150 and that of non-COVID-19 is also

150 (balanced data). If our model had performed poorly, say generating the inverse of column 2, that is, TN becomes 17 and FP now becomes 133, our accuracy would have been;

$$\text{Accuracy} = \frac{150+17}{150+17+133+0} = 55.67\%$$

This is a poor performance. Accuracy of 55.67% is very low compared to the 94.30% our model generated. With balanced data, we can always determine whether a model performance is good or not from the accuracy. Since all our datasets are balanced, our classification accuracy is a valid metric to measure our model performance. Hence, using accuracy as one of the classification metrics is justified.

Sensitivity and Specificity

Sensitivity and specificity measure a model's ability to correctly classify samples as a disease or not a disease. They are critical indicators of test accuracy and make it possible for medical professionals to assess the suitability of a diagnostic tool (Shreffler and Huecker 2021). The sensitivity and specificity trade-off is that they are inversely related, meaning an increase in sensitivity will cause a decrease in specificity and an increase in specificity will cause a decrease in sensitivity. From equations (4.4) and (4.5) that define sensitivity and specificity respectively, adjusting the value of FN affects sensitivity while adjusting the value of FP affects specificity. Increasing FP or decreasing FN causes an increase in sensitivity and decrease in specificity while decreasing FP or increasing FN causes an increase in specificity and decrease in sensitivity.

Increasing FN means having more patients who have COVID-19 but have been classified as not having the infection. This is very dangerous in the medical field. It means declaring patients who have COVID-19 as not having COVID-19, which could lead to complications. This could also mean releasing the patients into a community, which could spike the spread of the virus. For a disease like COVID-19, the smaller the FN, the better the model. Increasing FP means having more patients who do not have COVID-19 but are classified as having the infection. This is not good also but it is better than having high FN. In a machine learning classification, the preference of sensitivity or specificity depends on the importance of the samples being

considered and the objective of the classification. For our case here, the importance is sensitivity.

In any ML classification, to get high sensitivity and specificity we must always keep the values of FN and FP as low as possible. From the confusion matrices, the model performs best with dataset C, followed by dataset B and then dataset A. From figure 4.9, we can see that the FN is zero and the FP is 2. Meaning that the classifier identified all the samples of patients with COVID-19 and only 2 which were Viral Pneumonia were misidentified as COVID-19. In Figure 4.8, no sample of patients with COVID-19 was misclassified but 17 samples of healthy patients were misclassified as having COVID-19. For Figure 4.7, a COVID-19 sample was misclassified as not having the infection and 47 samples of non-COVID-19 were classified as having COVID-19. Figure 4.7 has is a high number FP compared to Figure 4.8 and 4.9, though the total number of testing samples need to be considered. Testing samples in Figure 4.7 is two times that of Figures 4.8 and 4.9.

4.2.2 Discussion of Parameters

Using dataset C, we were able to determine the effects of varying the hyper parameters – batch size, learning rate and epoch.

Batch Size

Batch size is the number of training samples per iteration. It determines the rate of the neural network training progress and also a model's performance. From Table 4.4, we can see that keeping the learning rate and the epoch constant and varying the batch size, it affects the results generated by the model. With the size of our training dataset and the power of the computing device we used, the model performed better at batch sizes of 8 and 16. Increasing the batch size reduced the model performance.

Learning Rate

Learning rate is the value used to update the weights. It is a small positive value of the range 0.0 to 1.0. Keeping constant the batch size and epoch at 16 and 5 respectively, the model was

able to generate high performance results at the learning rates of 1e-4 and 1e-5, as shown in Table 4.3. Learning rates below and above these two values produced low performance metrics.

Epoch

Epoch is the number of times the learning algorithm runs through the entire training dataset. From Table 4.2, leaving the batch size and learning rate unchanged and varying the epoch from 2 to 8, there was no variation in the accuracy. The sensitivity and specificity variation were very little. In transfer learning, high epoch does not have much significance compared to training a model from scratch.

4.2.3 Discussion of CT and X-ray images

From the confusion matrices and Table 4.1, the X-ray images produced higher accuracy, sensitivity and specificity compare to the CT scan images. The model was able to correctly classify all the sample target disease in the X-ray datasets, making the FNs to be zero unlike the CT dataset. Also, the FP value of the CT dataset is very high compared to that of the two X-ray datasets.

Since the datasets are balanced classes for each of the binary classifications, the accuracy is a valid metric to measure the model performance. Batch size and learning rate are hyper parameters that can be varied to get desired results in pre-trained neural network. The model performed better on the X-rays images than on the CT scan images

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The use of transfer learning of AlexNet for binary classification of chest CT images of COVID-19 and non-COVID-19, and chest X-ray images of COVID-19, Viral Pneumonia and Normal conditions using the two datasets made available for public use has been presented and discussed. The high-performance metrics obtained from the datasets demonstrate the ability of the pre-trained networks to achieve good results with limited data, as opposed to training from scratch and using a large amount of data, which would necessitate a high-capacity device and time consumption. The results generated from this study have proven that we can differentiate radiographic images of COVID-19 from the radiographic images of non-COVID-19 using a deep learning model, which can be applied in healthcare for the COVID-19 screening method. As the world continues to seek solutions to the pandemic, this study will encourage researchers to investigate more on the applications of deep learning on radiographic images in diagnosing and treating COVID-19.

As a study based of the use of machine learning to classify medical images, accuracy together with sensitivity and specificity becomes a good performance metric provided the dataset of the class labels are equal. Since in this study we used equal datasets, the three performance metrics are valid parameters that can provide medical experts good results to draw their conclusions on the disease diagnosis. Since the model used transfer learning technique, varying the batch size and learning rate affected the model performance, the epoch has little effect on the performance. The model performed better on X-ray images than on CT images.

5.1 Recommendations

Seeing that COVID-19 is a pneumonia infection that affects human respiratory system when not properly attended to, it is crucial that we do not totally rely on laboratory testing methods

for COVID-19 only, but also on radiography which can detect both the infection and its impact on the respiratory system. More studies on the applications of deep learning on radiographic images of pneumonia infections need to be encouraged by making the medical images available for research work.

REFERENCES

Abbas, A., Abdelsamea, M.M., Gaber, M.M. (2021). Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. *Appl. Intell*. 2021, 51, 854–864.

Alafif, T., et al. (2021). Machine and deep learning towards COVID-19 diagnosis and treatment: survey, challenges, and future directions. *Int. J. Environ. Res. Public Health*, 18, 1117. https:// doi.org/10.3390/ijerph18031117

Alam, N. A., Ahsan, M., Based, A. M., Haider, J., Kowalski, M. (2021). COVID-19 detection from chest X-ray images using feature fusion and deep learning. *Sensors*. http://www.mpdi.com/journal/sensors

Al-Turjman et al. (2021). Artificial Intelligence and Machine Learning for COVID-19", *Springer Science and BusinessMedia LLC, 2021*. ISBN: 978-3-030-60188-1

Alzubaidi et al. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *J Big Data* (2021) 8:53 https://doi.org/10.1186/s40537-021-00444-8

Andrea Yoss (2020). Transfer Learning using Pre-Trained AlexNet Model and Fashion-MNIST. Retrieved on Sept. 16, 2021 from https://towardsdatascience.com/transfer-learning-using-pre-trained-alexnet-model-and-fashion-mnist-43898c2966fb

Angelov, P., & Soares, E. (2020). Towards explainable deep neural networks (xDNN). *Neural Networks*, 130, 185-194.

Balbi, M. et al. (2020). Chest X-ray for predicting mortality and the need for ventilator support in COVID-19 patients presenting to the emergency department. *Springer*. https://dio.org/10.1007/s00330-020-07270-1

Borkowski, A. A., et al. (2020). Using artificial intelligence for COVID-19 chest x-ray diagnosis. *Fed Pract.* 37(9):398-404. doi: 10.12788/fp.0045

Cascella, M., Rajnik, M., Aleem, A., Dulebohn, S. C., Di Napoli, R. (2020). Features, Evaluation, and Treatment of Coronavirus (COVID-19). *StatPearls Publishing*: 32150360.

Chaddad, A., Hassan, L., Desrosiers, C. (2021) Deep CNN models for predicting COVID-19 in CT and x-ray images, *J. Med. Imag.* 8(S1) 014502. https://doi.org/10.1117/1.JMI.8.S1.014502

Chowdhury et al. (2020). Can AI help in screening Viral and COVID-19 pneumonia? *IEEE Access*, Vol. 8, 2020, pp. 132665 - 132676.

Corman et al (2020). Detection of 2019 novel coronavirus (2019-nCoV) by real-time RT-PCR. *Euro Surveill;* 25(3): pii=2000045. https://doi.org/10.2807/1560- 7917.ES.2020.25.3.2000045

Dhillon, A., Verma, G.K. (2020). Convolutional neural network: a review of models, methodologies and applications to object detection. *Prog Artif Intell* 9, 85–112 (2020). https://doi.org/10.1007/s13748-019-00203-0

Dong, D.; Tang, Z.; Wang, S.; Hui, H.; Gong, L.; Lu, Y.; Xue, Z.; Liao, H.; Chen, F.; Yang, F.; et al (2020). The role of imaging in the detection and management of COVID-19: A review. *IEEE Rev Biomed Eng*. 14, 16–29.

Dos Santos, W. G. (2020). Natural history of COVID-19 and current knowledge on treatment therapeutic options. *Biomedicine & Pharmacotherapy*, 129, ISSN 0753-3322, https://doi.org/10.1016/j.biopha.2020.110493.

Fang, Z., Yi, F., Wu, K., Lai, K., Sun, X., Zhong, N., Liu, Z. (2020). Clinical characteristics of coronavirus disease 2019 (COVID-19): An updated systematic review. *medRxiv*. doi: https://doi.org/10.1101/2020.03.07.20032573

FDA (2021). Coronavirus testing basics. Retrieved April 20, 2021 from https://www.fda.gov/consumers/consumer-updates/coronavirus-disease-2019-testing-basics.

Halgurd, S. M., Ghafoor, K. Z., Sadiq, A. S., Curran, K., Rabie, K. (2020). A Novel AI-enabled framework to diagnose coronavirus COVID-19 using smartphone embedded sensors: design study. *arXiv reprint arXiv*: 2003.07434, 2020.

Hussain, E., et al. (2020). CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images. *Elsevier*. https://doi.org/10.1016/j.chaos.2020.110495 0960-0779

Ibrahim, A.U., Ozsoz, M., Serte, S. *et al.* (2021). Pneumonia classification using deep learning from chest X-ray images during COVID-19. *Cogn Comput*. https://doi.org/10.1007/s12559-020-09787-5

IDSA (2021). RT-PCR Testing. Retrieved June 24, 2021 from https://www.idsociety.org/covid-19-real-time-learning-network/diagnostics/RT-pcr-testing

Jiang, Z. Z., et al. (2020). The role of imaging techniques in management of COVID-19 in china: from diagnosis to monitoring and follow-up. *Med Sci Monit*, 26: e924582 DOI: 10.12659/MSM.924582, e-ISSN 1643-3750

Jiwon Jeong, (2019). The most intuitive and easiest guide for convolutional neural network. Retrieved on Nov. 24, 2021 from https://towardsdatascience.com/the-most-intuitive-and-easiest-guide-for-convolutional-neural-network-3607be47480

Kovács, K., Péter Palásti, P., Veréb, D., Bozsik, B., Palkó, A., Kincses, Z. T. (2020). The sensitivity and specificity of chest CT in the diagnosis of COVID-19. *Springer*. https://dio.org/10.1007/s00330-020-07347-x

Kugunavar, S. and Prabhakar, C. J. (2021). Convolutional neural networks for the diagnosis and prognosis of the coronavirus disease pandemic. *Vis Comput Ind Biomed Art*; 4(1):12. doi: 10.1186/s42492-021-00078-w. PMID: 33950399; PMCID: PMC8097673.

Krizhevsky A, Sutskever I, Hinton GE. (2017). Imagenet classification with deep convolutional neural networks. *Commun ACM*. 2017; 60(6):84–90.

Mishra, M., Choudhury, T., Sarkar, T. (2021). CNN based efficient image classification system for smartphone device. Electronic letters on computer vision and image analysis 0(0):1-7, 2021 DOI: https://doi.org/10.21203/rs.3.rs-428430/v1

Ren, L., et al (2020). Identification of a novel coronavirus causing severe pneumonia in human: a descriptive study, Chinese Medical Journal: Volume 133 - Issue 9 - p 1015-1024 doi: 10.1097/CM9.0000000000000722

Rokas Balsys. (May, 2019). Convolutional Neural Networks (CNN) explained. Retrieved on Nov. 24, 2021 from https://pylessons.com/CNN-tutorial-introduction

Shreffler, J. and Huecker. M. R. (2021). Diagnostic testing accuracy: Sensitivity, specificity, predictive values and likelihood ratios. *StatPearls Publishing*. https://www.ncbi.nlm.nih.gov/books/NBK557491/

Soares, E., Angelov, P., Biaso, S., Higa Froes, M., Kanda Abe, D (2020). SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification. *medRxiv*. doi: https://doi.org/10.1101/2020.04.24.20078584.

Song, Y., Jiang, J., Wang, X., Yang, D., Bai, C. (2020). Prospect and application of internet of things technology for prevention of SARIs, *Clinical eHealth*, vol. 3, p 1-4, https://doi.org/10.1016/j.ceh.2020.02.001.

Sumit Saha (2018). A Comprehensive Guide to Convolutional Neural Networks — the ELI5 way. Retrieved on Nov. 24, 2021 from https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Tang Y-W., Schmitz, J., Persing, D., Stratton C. (2020). Laboratory diagnosis of COVID-19: current issues and challenges. *J Clin Microbiol*. 58, e00512-20. https://doi.org/10.1128/JCM.00512-20.

Tawsifur, R., Amith, K., Yazan, Q., Anas, T., Serkan, K., Saad BinAbul, K., Mohammad, T., SomayaAl, M., Susu, Z., Muhammad, S., Muhammad, E. H. C. (2020). Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images. *Elsevier*. https://doi.org/10.1016/j.compbiomed.2021.104319

Towards data science (2018). Convolutional neural network. Retrieved October 20, 2021 from https://towardsdatascience.com/convolutional-neural-network

MathWorks (2020). Transfer learning using AlexNet from MATLAB R2020a

Vandenberg O., Martiny D., Rochas O., van Belkum A., Kozlakidis Z. (2021). Considerations for diagnostic COVID-19 tests. *Nature Reviews*. 19. https://doi.org/10.1038

Vinh, T. Q., Duy, L. H., and Nhan, N. T. (2020). Vietnamese handwritten character recognition using convolutional neural network. *IAES International Journal of Artificial Intelligence (IJ-AI)*. Vol. 9, No. 2, DOI: 10.11591/ijai.v9.i2.pp276-283

Waheed, A., Goyal, M., Gupta, D., Khanna, A., Al-Turjman, F., Pinheiro, P.R. (2020). CovidGAN: data augmentation using auxiliary classifier GAN for improved covid-19 detection, *IEEE Access*, 8, 91916-91923. https://dio.org/10.1109/ACCESS.2017

Weinstock, M. et al. (2020). Chest X-ray findings in 636 ambulatory patients with COVID-19 presenting to an urgent care centre: a normal chest X-ray is no guarantee. J. *of Urgent Care Med.* 14(7), 13-18.

WHO (Feb.2020). WHO Director-General's remarks at the media briefing on 2019-nCoV, February 11, 2020. Retrieved July 24, 2021 from https://www.who.int/director-general/speeches/detail/who-director-general-s-remarks-at-the-media-briefing-on-2019-ncov-on-11-february-2020.

WHO (March 11, 2020). WHO Director-General's opening remarks at the media briefing on COVID-19. Retrieved July 20, 2021 from https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020.

Wu, T. et al. (2021). ULNet for the detection of coronavirus (COVID-19) from chest X-ray images. *Computers in Biology and Medicine.* Vol. 137:104834-104834. DOI: 10.1016/j.compbiomed.2021.104834

Yamashita, R. et al (2018). Convolutional neural networks: An overview and application in radiology. *Insights into Imaging* (2018) 9:611–629 https://doi.org/10.1007/s13244-018-0639-9

APPENDICES

The matlab code for the classifications:

```
%LOADING THE INPUT DATA
%Loading the new input images
imds = imageDatastore('images', ...
    'IncludeSubfolders',true, ...
    'LabelSource','foldernames');

% Splitting the images datastore into two new datasores - 70%
for training and 30% for validation
[imdsTrain,imdsValidation]=
splitEachLabel(imds,0.7,'randomized');

% To visualize the loaded images
numTrainImages = numel(imdsTrain.Labels);
idx = randperm(numTrainImages,4);
figure
for i = 1:4
    subplot(2,2,i)
    I = readimage(imdsTrain,idx(i));
    imshow(I)
    title('training')
end

% LOAD THE PRETRAINED NEURAL NETWORK

% Load Alexnet
net = alexnet;

% Display the network architecture and information about the
network layers.
net.Layers


% REPLACE THE FINAL LAYERS
% Extract the layers from the pretrained network except the last
three.
layersTransfer = net.Layers(1:end-3);

% For the output size of the last layer to match the number of
classes
numClasses = numel(categories(imdsTrain.Labels))

% Transfer the layers for the classification task
```

```
layers = [
    layersTransfer;

fullyConnectedLayer(numClasses,'WeightLearnRateFactor',20,'Bia
sLearnRateFactor',20)
    softmaxLayer
    classificationLayer];

% TRAIN THE NETWORK

%Specify the training options
 options = trainingOptions('sgdm', ...
    'MiniBatchSize',32, ...
    'MaxEpochs',10, ...
    'InitialLearnRate',1e-4, ...
    'ValidationData',imdsValidation, ...
    'ValidationFrequency',3, ...
    'ValidationPatience',Inf, ...
    'Verbose',true, ...
    'Plots','training-progress');


%Train the network which is now made up of the new and the
tranferred
%layers
netTransfer = trainNetwork(imdsTrain,layers,options);


% CLASSSIFY THE VALIDATION IMAGES
% Classifying the validation images using the fine-tuned
network.
[YPred,scores] = classify(netTransfer,imdsValidation);

% Displaying some of the validation images with their predicted
labels.
idx = randperm(numel(imdsValidation.Files),9);
figure
for i = 1:9
    subplot(3,3,i)
    I = readimage(imdsValidation,idx(i));
    imshow(I)
    label = YPred(idx(i));
    title(string(label));
end

% To determine the classification accuracy on the validation set
and other performance metrics.
```

```
YValidation = imdsValidation.Labels;
YData = imdsValidation.Labels;
accuracy = mean(YPred == YValidation);
YPred;
accuracy = mean(YPred == YData);
YData;

y = grp2idx(YData);
test = grp2idx(YPred);
classperf(y,test)

% Display the confusion matix
figure,plotconfusion(imdsValidation.Labels,YPred)
```