Detection of Covid and Viral Pneumonia: A transfer learning model-based approach

BY

Md. Salman Sakib Rahman Jishan
ID: 191-15-2494

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Amatul Bushra
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised By

Md.Aktaruzzaman
Associate Professor
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled **"Detection of Covid and Viral Pneumonia: A transfer learning model-based approach"**, submitted by Md. Salman Sakib Rahman Jishan, to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 23-01-2023.

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Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

23-01-23

Dr. Dewan Md Farid — **External Examiner**
Professor
Department of Computer Science and Engineering
United International University

DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Amatul Bushra, Assistant Professor,** Department of CSE, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

21.01.23

Amatul Bushra
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised by:

Md.Aktaruzzaman
Associate Professor
Department of CSE
Daffodil International University

Submitted by:

28.01.23

Md. Salman Sakib Rahman Jishan
ID: -191-15-2494
Department of CSE
Daffodil International University

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ABSTRACT

A worldwide epidemic known by the name Covid-19 is said to have posed the greatest threat to public health in the last century and resulted in catastrophic health, social, and economic disasters. Fever and chills were this virus' early symptoms. Although the symptoms of viral pneumonia are extremely similar to the second phase of the virus-caused coughing and acute shortness of breath, the two illnesses require entirely distinct approaches to treatment. Sometimes, because of a lack of appropriate diagnostic tests, patients are unsure whether they have Covid-19 or pneumonia. As a result, a dangerous treatment like death is possible. In this study, MobileNetV2 and RestNet50, two well-known transfer learning approaches, were used and tested to see which model performed the best in properly classifying both of these illnesses from X-ray pictures. After examining the performance, MobileNetV2 had the best accuracy, which was around 95% as opposed to RestNet50's 80%.

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CHAPTER 1

Introduction

1.1 Introduction

Bangladesh is a natural and attractive middle-income country in South East Asia. Its economy is fast expanding. Over the previous decade, there has been tremendous progress in many aspects of life, including women's empowerment. However, Bangladesh's entire economy has been negatively impacted by the COVID-19 pandemic. Bangladesh has a population of over 160 million people who live in peace and harmony in an area of approximately 1,47,570 square kilometers. Naturally, compared to other wealthy nations worldwide, this nation has a relatively high population density. As a result, the COVID-19 epidemic has become the biggest danger to the people, the economy, and the development of this country. In humans and other mammals, coronaviruses are non-segmented positive sense RNA viruses that are common [3]. They belong to the Nidovirales order and the Coronaviridae family. It is now thought that the virus needs between two and ten days to incubate. The global pandemic's cause, COVID-19, was discovered in 2019. According to our knowledge, the first contamination occurred at a Wuhan market where wild animals and birds were sold. Consequently, China is the first affected nation and the source of bat and human COVID-19 contamination. Later, it spread to several other nations worldwide, varying degrees. The virus was once known as 2019-nCoV and is now known as "Wuhan coronavirus." Because COVID-19 has nothing to do with any location, animal, person, or group of people that can lead to stigma, the World Health Organization gave it that name. The virus, which is genetically identical to the SARS Coronavirus, is officially known as SARS CoV-2. The vast family of viruses known as coronaviruses usually causes upper respiratory tract infections including the common cold and respiratory distress. Notwithstanding, multiple times in the twenty-first 100 years, COVID pestilences have risen out of creature repositories, remembering the ongoing viral pandemic in Wuhan, China. Animals like pigs, camels, bats, and cats spread the majority of the virus. Only occasionally have animal coronaviruses been found to infect humans and spread. However, the most pressing issues of the present time are COVID-19 community transmission and death tolls. The researchers performed this study to give an outline of Bangladesh's COVID-19 status as of May 14, 2020, based on a survey of secondary literature. Experts have started utilizing cutting-edge deep-learning algorithms to pinpoint the automated location of the virus in patients because of the fast global spread of the coronavirus.

Throughout the process, researchers were compelled to create models utilizing pre-trained networks due to the challenging nature of gathering COVID-19 data in its early phases. Only a limited number of COVID-19 samples, however, were used in the bulk of these tests. The claimed findings of this research are difficult to generalize when these models are tested on bigger datasets, and there is assurance that the output that was reported will be kept. The transfer learning method for COVID-19 X-ray image identification has to be validated using a sizable dataset. The accuracy attained by merging healthy and pneumonia patients are not correct since the model would make an effort to disregard infraclass heterogeneity between these two groups. It has been demonstrated that deep learning may assist distinguish between viral and bacterial pneumonia and identify the most prevalent thoracic disorders. Additionally, developing an algorithm that can identify a COVID-19-positive patient presents a challenge. This task is difficult despite the possibility that COVID-19 and other pneumonia types have radiographic similarities. When the training dataset only included bacterial cases, MobileNetV2 struggled to discriminate COVID-19 patients from other pneumonia cases, according to the authors of the study. Rapidly identifying COVID-19 clusters brought on by a new virus will allow us to distinguish COVID-19 from viral pneumonia (not bacterial pneumonia). The COVID-19 classification is additionally hampered by a major imbalance in the number of COVID-19 samples compared to non-COVID-19 samples since it is challenging to collect an acceptable number of positive COVID-19 samples. The following is a summary of the contributions made by this work:

- A system based on a pertained deep learning model is suggested for diagnosing COVID-19 and viral pneumonia. This essay is divided into the following sections.
- We compare well-known pre-trained CNN models with different frameworks using many trials on a large dataset of X-rays from COVID-19 patients.

- Selecting the model that performs the best and reassessing it on the test set to make sure it is more generalizable.

The methods used in this study are described in part 2. In part 3, the quantitative results and discussion are presented, and in part 4, the method used for comparison with previous studies is shown. In part 5, the study's conclusion is finally presented.

1.2 Motivation

Coronavirus is an intensely settled illness; however, it can likewise be lethal, with a 2% case casualty rate. Due to significant alveolar injury and gradual respiratory failure, serious sickness may cause mortality. Nations might profit from the brief reference to isolation, quick intubation of serious cases in particular medical clinics, and checking of the illness' spread with an early and programmed determination of Coronavirus. Despite the fact that diagnosis has become relatively speedy, the financial problems caused by the expense of diagnostic tests harm both states and patients, especially in countries with privatized health systems or with limited access to health systems due to exorbitant charges. In March 2020, more X-rays from healthy cases and Covid-19 patients will be available to the public. Along these lines, we can inspect the clinical pictures and search for designs that could prompt a programmed conclusion about the infection. The development of deep learning applications over the past five years seems to have come at the right time. Object recognition and medical image classification are two common applications of transfer learning, a combination of machine learning techniques primarily used for automatic image feature extraction and classification. In the field of artificial intelligence applications for data mining, analysis, and pattern recognition, the fields of deep learning and machine learning are well established. With the emergence of new data, it is becoming increasingly difficult to reclaim the advancements made in those fields for the benefit of computer-aided systems and clinical decision-making. The term "deep learning" frequently refers to a method in which automatic mass feature extraction is accomplished with deep convolutional neural networks, also known as "convolution." Nonlinear data is processed by the layers [3]. At each layer, the data is transformed into a higher, more abstract level. The further we go into the association; the more difficult the data to learn. Parts of the information that are important for segregation are enhanced by higher levels of portrayal, while unimportant characteristics are obscured. Typically, the term "deep learning" refers to a greater number of large-scale, deep networks than the traditional machine learning ones. Therefore, a broad range of research in the basic sciences, policy, public health sciences, clinical sciences, system studies, and implementation science is needed to fill these gaps in order to manage and control the COVID-19 epidemic effectively as well as to prevent and respond to future epidemics.

1.3 Rationale of the Study

It is the third COVID to have crossed causes and species of serious disease in humans. The COVID sickness 2019 (Coronavirus) is the result of contamination by the clever and intense respiratory ailment COVID 2. Physical interventions like wearing masks, physically distancing oneself from infectious people, and isolating them from others are the only ways to prevent transmission in the absence of specific antiviral agents or effective vaccine distribution. Even though respiratory droplets or aerosols and direct contact are both common ways for COVID-19 to spread, many high-income countries with robust health infrastructures have been unable to manage the disease. The virus that is causing the problem can be found in the blood using a blood culture test; similarly, a virus test is performed with a swab of the nose or throat. Rapid antigen tests (ELISA tests) are very effective for accurately diagnosing viral pneumonia. Pneumonia is frequently diagnosed with an X-ray. A CBC is a blood test that checks to determine whether your body is fighting an infection. The amount of oxygen in your blood is measured using pulse oximetry. Pneumonia can prevent your lungs and blood from receiving sufficient oxygen. Many researchers already research about Covid-19. Some of them work with machine learning algorithms and some of them work with different types of algorithms of deep learning. Global public health continues to be a concern due to the ongoing coronavirus disease (COVID-19) epidemic. One of the first lines of defense against this pandemic is early infection identification, which aims to stop the spread of illnesses. That is the reason, we are intrigued to figure out these problems.

1.4 Research Question

- What is the purpose of this study?
- How many models are used here?
- Is it feasible to apply machine learning and deep learning models simultaneously??
- What are the difficulties that COVID-19 and viral pneumonia in Identification?
- Which model gets the highest accuracy in this research?
- What is the future scope of the research?

1.5 Expected output

We are trying to detect COVID-19 and viral pneumonia. Through our project, we can find out whether we are infected and if it is infected, we can also take out the percentage of it that is infected. Thinking about the future, we have worked on such a program so that in the future we can detect COVID-19 and viral pneumonia very early and get good quality treatment for it.

1.6 Project Management and Finance

To enhance patient experience and satisfaction, reduce costs, and improve patient care, today's healthcare leaders are constantly improving and developing their processes. Over the course of the past ten years, the application of project management (PM) principles in the healthcare industry have significantly increased. These principles have become increasingly significant to facilities because they aid in cost control, risk mitigation, and overall project outcomes. There are countless electronic framework executions (for example EHRs, CACs, CDI Programming, and so on.) within health care. Project management has therefore emerged as one of the most sought-after business skills. The management of a project's financial aspects, such as its cost, revenue, and profit, is referred to as project financial management, or project accounting. In order to accomplish this, it integrates billing, estimation, budgeting, funding, and project expense management. Of this large number of parts of the monetary task, the executive's, viable undertaking planning is by a long shot the most significant. From there, managing that budget over the course of a project is the challenge, with the goal to ensure is finished within the allotted budget. To better understand emerging patterns of roles and responsibilities, data from the survey of project management roles and responsibilities was acquired. Project management includes scheduling and planning meetings, facilitating the entire study, and entering data into databases. Study progress was recorded via the timely release of meeting agendas and minutes outlining progress and action items. These resources accumulated throughout time to create an archive that is centrally accessible via the Madcaps communication platform. To produce high-quality data that can influence disease prevention and control as well as policy requirements, taking competent project management is essential for executing health-related research that involves taking into account the local and nationwide political and social situations. This is owing to the fact that efficient project management enables the administration and adherence to the appropriate tools, methodologies, tactics, and predictable approaches. By incorporating project management abilities into efforts to establish health systems in low- and middle-income nations, the population's health may be boosted.

Finance: bill-paying and account balance, grant administration, and budget creation.

1.7 Report Layout

- Background study
- Research Methodology
- Experimental Result and Discussion
- Summary, Conclusion and Future Analysis
- Reference

CHAPTER 2

Background study

2.1 Preliminaries

The COVID-19 respiratory disease is caused by a novel coronavirus. Fever, cough, sore throat, and difficulty breathing are the most common signs of infection. Some patients may also experience a loss of taste, tiredness, aches, and a blocked nose. It is possible that 14 days pass between contamination and the onset of symptoms. This virus is spread by patients coughing and sneezing, which release droplets into the air. A person becomes infected if they come into direct or indirect contact with an infected individual. The aggressiveness of the viral pathogens toward the structures of the lungs is what causes viral pneumonia. Viral pneumonia was included in the broad category of typical pneumonia due to its clinical and radiologic features. It is necessary to distinguish between viral pneumonia and the other types of atypical bacterial pneumonia in this category. Clinical, radiologic, and microbiologic criteria should be used to make this distinction, which can be challenging at times. Deep learning, machine learning, and hybrid modeling techniques were employed during the COVID-19 pandemic to more accurately anticipate the transmission of the SARS-CoV-2 virus over a wider time range and simulate its complicated, non-linear spread.

2.2 Related Works

Ibrahim, A. et al. [1] worked to identify with the use of deep learning, COVID-19. The AlexNet model's algorithm can be used for diagnosis. The AlexNet model's input dimensions are 227*227*3, its filter dimensions are 3*3, and its window dimensions are 2*2. COVID-19 and healthy CXR scans are classified using the AlexNet model together with bacterial and healthy CXR scans, viral pneumonia and healthy CXR scans, COVID-19 and healthy CXR scans, COVID-19 and healthy CXR scans, and COVID-19 and healthy CXR scans. There are 371 datasets for pneumonia caused by COVID-19, 4237 datasets for viral pneumonia, and 2882 datasets for healthy or (normal) individuals. There are two different dataset kinds; 70% of the time is used for training and 30% for testing. The model allowed COVXNet to achieve 97.4% accuracy. For Covid-19, an accuracy of 87 percent was attained using the ResNetv2 algorithm. For COVID-19 pneumonia, bacterial pneumonia, and healthy pneumonia, the accuracy is 98.92%. Kumar, R. et al. [2] the ResNet152 model can accurately predict pneumonia and COVID-19. There are 5840 x-ray pictures total for covid-19 with pneumonia. 5216 of the 5840 images are used for training, while 624 are used for testing. They have also included the smote algorithm for balancing after using the Smote algorithm for all image processing. The model is obtaining a 97.3% accuracy on Random Forest. Additionally, the model is attaining an accuracy of 97.7% while using XGBoost. An 86% accuracy rate for COVID-19 pneumonia and bacterial pneumonia was reported by DRE-Net, a modified version of the pre-trained ResNet-50 network. XGBoost was the classifier that produced the best results.

Karar, M.E. et al. 3] used the CNN Model Algorithm to find diseases like viral pneumonia and Covid-19. This paper makes use of three different kinds of algorithmic models. VGG16, ResNet5V2, and DenseNet169 are examples. For COVID 19 and viral pneumonia, the VGG16 model has an accuracy of 54.17% and 99.00%, respectively. The ResNet50 V2 model's classification accuracy for COVID 19 and viral pneumonia is 95.83 percent. Covid-19 and viral pneumonia had final DenseNet169 model classifications of 99.90% and 99.90%, respectively. Infections with COVID-19 in chest X-ray images are the study's principal finding.

Basu, S. et al. [4] discovered New strain COVID-19, also known as SARS-CoV2 that had never been seen in humans before. From four open-source databases, 305 COVID-19 X-ray images were collected. There are three well-known CNN models, ranging in layer count from AlexNet (8 layers), ResNet (50 layers), and VGGNet (16 layers), were utilized. We used kernels of size 3 * 3 in VGGNet, ResNet and AlexNet (11 * 11). AlexNet, ResNet and VGGNet had 5-fold cross-validation accuracy of 82.98%, 85:98%, 90:13%, respectively. VGGNet and ResNet had the highest validation accuracy on Data-A and Data-B, respectively, but VGGNet did not have the best results for COVID cases or normal cases in most of the validation folds of Data- B.

Zhang, J. et al. [5] gathered additional pneumonia images as non-COVID-19 cases from the public ChestX-ray14 dataset. To address the disparity in data between COVID-19 patients and non-COVID-19 cases. During the training phase, they optimize using the conventional stochastic gradient descent (SGD) technique with a batch size of 128. The maximum number of epochs was set at 500, and the learning rate was set at 10*4. Large convolutions with 7*7 kernels and a stride of 2 are used in the initial stage, which is followed by a 3*3 max-pooling layer. In this investigation, our model has a specificity of 70.6 percent and a sensitivity of 90 percent when T=0:25 is taken into account..

A.I. Khan and others [6] CoroNet is a model for a Deep Convolutional Neural Network that automatically detects COVID-19 infection using chest X-ray pictures. At the time this study was written, the database had about 290 COVID-19 chest radiography pictures. The dataset contains 1203 instances of typical pneumonia, 660 cases of bacterial pneumonia, and 931 cases of viral pneumonia. We obtained 1300 photos in total from these two sources. They then reduced the size of each photograph to 224 × 224 pixels. The first model is the main multi-class model, four-class CoroNet, and it has been trained to categorize chest X-ray pictures into four categories: normal, bacterial, and COVID-19-caused viral pneumonia. The binary two-class CoroNet model and the three-class CoroNet model (COVID-19, Normal, and Pneumonia).

Ozturk, T. et al. [7] taught the DeepCovidNet deep learning model to categorize X-ray images into three groups: Pneumonia, No Findings, and COVID-19 Second, the DarkCovidNet model is taught to distinguish between two categories: Categories for COVID-19 and No Findings. We made advantage of a COVID-19 X-ray image database that Cohen JP built from pictures from several free resources.. Additionally, the researchers experimented with various models and methodologies in combination. Sethy and Behera classified image features using the SVM classifier after extracting them from CNN models. ResNet50 and SVM were used with 50 images in this study to achieve an accuracy of 95.38 percent.

Hemdan, E.E.D. et al. [8] utilized a brand-new framework for deep learning; specifically, COVIDX-Net, which enables radiologists to make an automatic COVID-19 diagnosis from X-ray images. For automatically determining the status of COVID-19 in 2D conventional

X-ray images, they proposed a new deep learning framework. The overall workflow of our proposed COVIDX-Net uses seven distinct DCNN architectures; VGG19, InceptionV3, DenseNet201, InceptionResNetV2, ResNetV2, MobileNetV2, and Xception, are just a few examples. All By-ray pictures have been compiled into a single dataset and loaded for scaling at a fixed size of 224 x 224 pixels in order to make them acceptable for additional processing inside the deep learning pipeline. The model training and testing phases of the COVIDX-Net have been successfully completed using data from 80 to 20 percent of X-ray pictures, respectively.

Wang, S. et al. [9] 1065 CT scans of COVID-19 patients with confirmed pathogens and those who had previously been diagnosed with normal viral pneumonia were collected. Inward approval accomplished an all-out precision of 89.5% with explicitness of 0.88 and responsiveness of 0.87. The external testing dataset had a specificity of 0.83 and sensitivity of 0.67, with a total accuracy rate of 79.3%. 85.2% of the time, the system correctly recognized a COVID-19 positive. They were able to achieve an accuracy of over 89.5% by utilizing feature extraction from CT images. Biology and medicine problems with a lot of data have been solved using deep learning techniques. They will focus more on deep learning in the future.

Toaçar,M. et al. [10] involved two models of calculations for this situation. a. MobileNetV2, b. SqueezeNet. The SqueezeNet model had the option to accomplish 95.85% precision. The SqueezeNet model's matrices; i) the original dataset; ii) the dataset that was reorganized using the fuzzy method; and iii) the dataset that was combined using the stacking method. The accuracy of SqueezeNet and Original Data is 84.56%, the accuracy of SqueezeNet and Structured dataset (Fuzzy Technique) is 95.58%, and the accuracy of SqueezeNet and Stacked dataset (Stacked Technique) is 97.06%. With the model, MobileNetV2 was able to achieve an accuracy of 96.28 percent. The MobileNetV2 model's matrices; i) the original dataset; ii) the dataset that was reorganized using the fuzzy method; and iii) the dataset that was combined using the stacking method. The accuracy of MobileNetV2 and Original Data is 96.32%. The accuracy of the MobileNetV2 and Stacked dataset (Stacked Technique) is 97.06 percent, while that of the structured dataset (Fuzzy Technique) is 97.05 percent. Using the SVM method, the overall classification accuracy rate was 98.25 percent. For Covid-19 data, accuracy is 100%, and for normal and viral pneumonia classification, it is 99.27%. Using deep learning, they will discuss various organ diseases in the future.

Hammoudi, K. et al. 11] utilized in ResNetV2 in order to find COVID-19 and pneumonia. The Resnetv2 model has found the fewest false negatives to the blind test set. Which is 0.7% for pneumonia and COVID-19. It could be possible to successfully use the knowledge gained from pediatric chest X-ray training to adult infection trials. Here, the dataset is divided into two sections: both the training data set and the test data set. The pneumonia dataset had an average success rate of 84%. The data set makes use of a wide variety of different model algorithms. ResNet50, VGG-19, DenseNet, ResNet34, Inception, RNN, ResNet50 are some tailored CNN-based architectures for classification. Using a variety of architecture types in conjunction with chest X-ray images, classification accuracy was achieved for each class. DenseNet was 99.3 percent, VGG19 was 92.56 percent, and inception ResNetV2 was 99.3 percent. There is a desire to further develop deep learning in the future.

S.R. Nayak et al. 12] utilized eight CNN models with prior training, namely AlexNet, VGG-16, GoogleNet, MobileNet-V2, Squeezenet, ResNet-34, ResNet-50, and Inception-V3, for a thorough study of COVID-19 image prediction experiments. We compared eight CNN models and examined the effects of a number of hyperparameters associated with these models. The CNN models were assessed utilizing chest X-beam tests gathered from the Coronavirus chest x-ray-dataset and ChestX-ray8 dataset. Using Inception-V3, GoogleNet, AlexNet, SqueezeNet, VGG16, MobileNetV2, ResNet50, ResNet34, and 299 X 299 we used the PyTorch toolbox to put our algorithms into action. In these instances, performance is still lacking and comparatively lower. For instance, the accuracy levels achieved in and are respectively 92.60% and 87.02%.

2.3 Comparative Analysis and Summary

A timely reminder of the nature and consequences of international public health catastrophes is provided by the (COVID-19) coronavirus pandemic. Since the pandemic started, there have been more than 314 million cases and more than 5.5 million fatalities as of January 12, 2022. In terms of cases and fatalities, the COVID-19 pandemic manifests itself in different ways in various countries and areas of the world. More than 314 million illnesses and 5.5 million fatalities related to the pandemic were documented globally as of January 12, 2022. The number of cases per million people declined from 7410 in Africa to 131,730 in Europe, but the number of fatalities per million people climbed from 110 in Oceania to 2740 in South America. South America had a CFR of 2.9%, whereas Oceania's was 0.3%. COVID-19 is more likely to influence nations and areas with high HDIs, which are composite indices of measures of education, life expectancy, and per capita income. Together, Europe and North America are responsible for 51% and 55%, respectively, of cases and fatalities. Despite having high global health security and universal health coverage indices, regions with high HDI are nonetheless impacted by COVID-19. Table 1 displays a comparison of the results with earlier research.

Table 2.3. Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Ibrahim, A. et al. [1]	COVXNet, ResNetv2	ResNetV2=98.92%
2.	Kumar, R. et al. [2]	ResNet152, DRE-Net	ResNet152=97.7%,
3.	Karar, M.E. et al. [3]	VGG16, ResNet50 V2, DenseNet169	VGG16=99.00%,
4.	Karar, M.E. et al. [3]	AlexNet, VGGNet16, ResNet50	Vgg16=90.13%
5.	Zhang, J. et al. [5]	SGD	SGD=90.00%
6.	Khan, A.I. et al. [6]	CoroNet	CoroNet=98.08%
7.	Ozturk, T. et al. [7]	ResNet50, DRE-Net, CNN,	ResNet50=95.38%,

		DarkCovidNet	
8.	Hemdan, E.E.D. et al. [8]	DCNN,VGG19, DenseNet201,InceptionV3, ResNetV2,Inception, Xception,MobileNetV2	—
9.	Wang, S. et al. [9]	CNN	89.5%
10.	Toğaçar, M. et al. [10]	MobileNetV2, SqueezeNet	96.28%
11.	Hammoudi, K. et al. [11]	ResNetV2, ResNet-34, ReNet-50, DenseNet,VGG-16	99.6%
12.	Nayak, S.R. et al. [12]	AlexNet, ResNet-34, GoogleNet, MobileNetV2, VGG-16, SqueezeNet, ResNet-50	92.60%

2.4 Scope of the Problem

We have read many researchers' papers on this research. They used various kinds of machine learning and deep learning algorithms to tackle viral pneumonia and COVID-19. Data collection is a major problem in developing transfer learning projects. In this paper, we had some trouble collecting data but we couldn't collect much data.

2.5 Challenges

- **Data collection**
- **Model selection**
- **Model train**

Chapter 3

Research Methodology

3.1 Research Subject and Instrumentation

To diagnose the covid-19 illness, my method largely employs deep learning to evaluate x-ray records. The algorithm we employ can determine from a picture of the x-ray report if a patient has covid19 infection. We need to utilize a Python notebook to put this into practice. It is currently a fairly well-known fact. Because it is always and easily available over the internet. As a result, the machine owned by Google Collaborator doesn't need a dedicated GPU or TPU hardware. Google provides GPU support to users via its own servers. Only computers with browsers and Google accounts may access it. Using the notebook, the user may do the assignment rather easily. Anyone can sign in with Google to view their Python script on other computers if they'd like to.so, For Python programming, we utilized Google's Collab Notebook Tools. We applied the Resnet50 and MobileNetV2 deep learning models in Collab. The condition may be precisely diagnosed using the MobileNetV2 model. We get maximum accuracy with the MobileNetV2 algorithm since it employs three classes. When training data, there are several procedures to take into account. TensorFlow training, preprocessing, and noise reduction are mostly required for picture data. The data is then forwarded for testing after this phase. The Python library picks out photos at random and verifies them. As a framework, we employed the high-level computational model Keras API. When using Keras, a low level of backend operations is necessary. Tensorflow has been set up for this. And created numerous graphs and visualizations using the matplotlib package.

3.2 Data Collection Procedure/Dataset Utilized

Our study's primary goal is to detect CODIV patients using machine learning techniques with the use of x-ray report pictures.

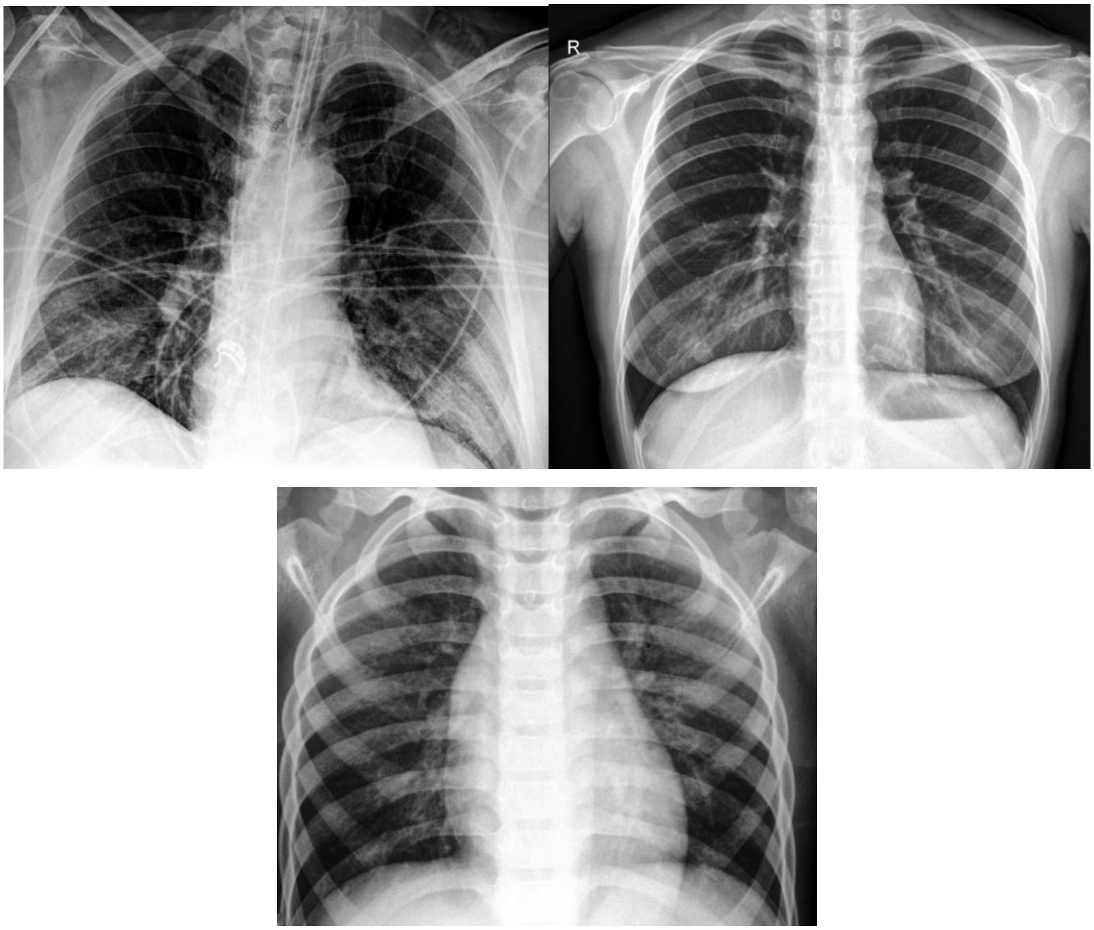


Figure 3.2.1 dataset sample

Scientists representing Qatar University, Qatar, Qatar, and Dhaka University in Bangladesh, together they have displayed a database of chest X-ray images for COVID-19-positive patients as well as natural and viral pneumonitis images with their colleagues from Pakistan and Malaysia. They cooperate with medical experts. This dataset on benign and several lung infections, along with COVID-19, is made accessible in stages. They submitted the dataset to Kaggle, where we then downloaded it [13]. The information combines numerical references with X-ray picture examples. To assess whether a patient has COVID or pneumonia in this study, machine learning is applied. For diagnosing illnesses, our module has a 96% accuracy rate.

Table 3.2.1: Detailed image gathering data

Classes	No of images	Image format	Image size
Pneumonia	90	.png	224*224
Covid	137	.png	224*224
Normal	90	.png	224*224

For the project, we used roughly 317 photos at 224*224 pixels. Our dataset consists of three classes. They are Pneumonia, Covid, and Normal.

Table 3.2.2:training and testing data count for each categorization

Classes	Train set images	Test set images
Pneumonia	70	20
Covid	111	26
Normal	70	20

In this instance, 20% of the data is used for testing while 80% is used for the train.

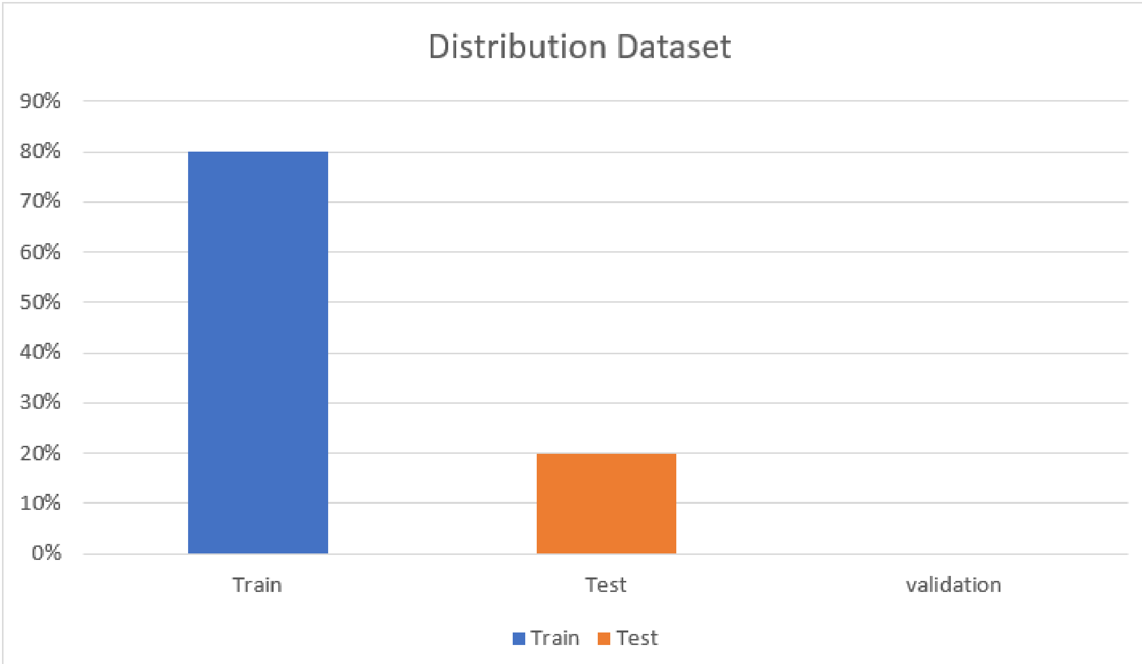


Figure 3.2.2 Distribution dataset

3.3 Statistical Analysis

To train the model in this case, we utilized batch size 32. 20 and 25 epochs were employed. In addition, 80% of the data is collected for turning and 20% for testing. 224*224*3 pixels of the picture are utilized here.

Table 3.3.1 Training parameter

Batch size	32
Epoch	15/15
Training	80%
Testing	20%
Total classes	3
Input shape	224*224*3
Train samples	251
Test samples	66

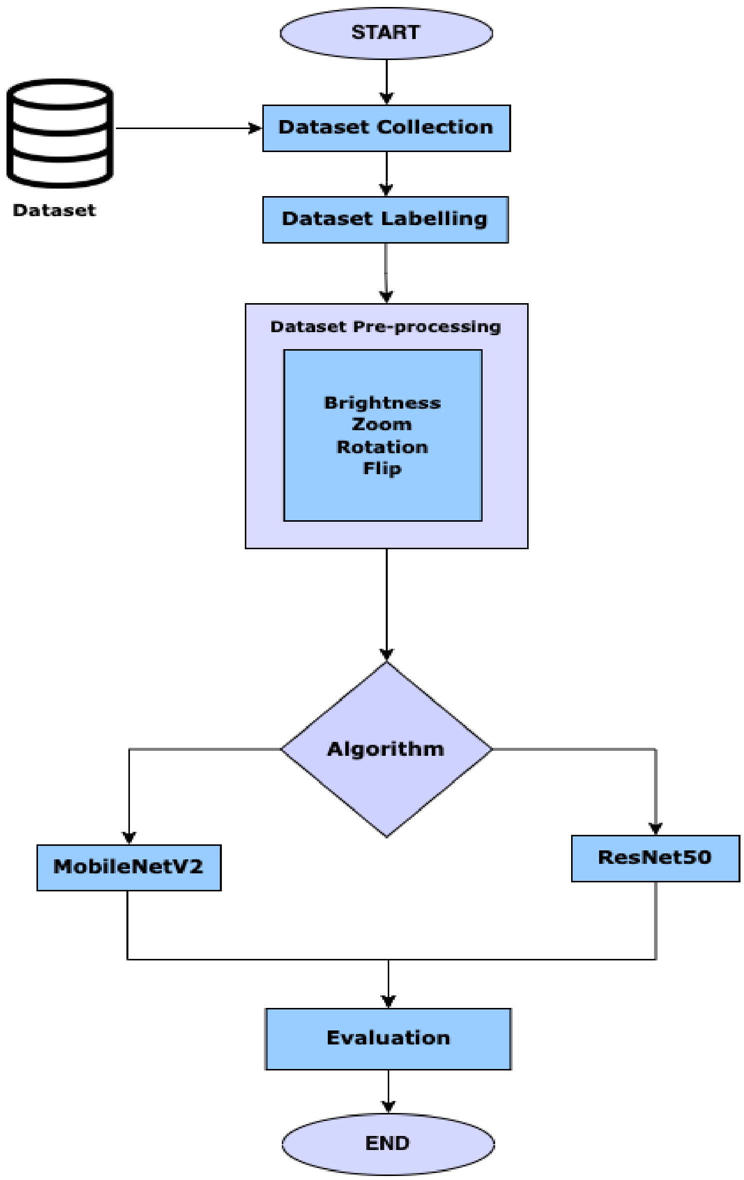


Figure 3.3.1 execution process for the study

Our study's major goal is to use x-rays of human lungs to detect covid-19 patients. In order to do this, we gathered data and used an algorithm to train the model. We used data input from the dataset, data gathering, and data labeling as a starting point for this. after preprocessing the data. The model was then developed once the algorithm was used.

Below is a detailed discussion of the procedures:

3.3.1 Dataset Collection:

A set of data used to train the model is known as a machine learning dataset. To educate the deep learning method on how to generate predictions, a dataset is used as an illustration. Text data is one of the common sorts of data, image data.

3.3.2 Dataset labeling

The datasets labeling method employs artificial intelligence to categorize the original data and then also permits the labeling of useful and relevant data to give the data perspective. Deep learning may then utilize that information to extract information from the specific data. Data labeling is a crucial step since it can provide background for information before it is used in a learning algorithm, which enables us to choose the best strategy for increasing both adaptability and reliability. For instance, if there is an image, labeling can tell us whether it contains a mammal or a vehicle and that term may appear in the voice tape. A similar thing can occur if we possess an x-ray document that includes information about the patient. It has ways like the internal approach, outsourcing strategy, community approach, and computer strategy. The data labeling may be performed using a variety of techniques or a combination of methods [14].

3.3.3 Data pre-processing

In the real world, data is usually unfinished: it needs data points, certain relevant qualities are absent, or it is only an aggregation of information. The information is chaotic because of errors or anomalies. Shaky: characterized by differences in names or codes. We help you convert raw disc information to a tf. File using the Keras datasets pre-processing tools. An assortment of information that can be utilized to train a program is referred to as data. Causes of the data's pre-processing are:

- Boost the database's reliability. Any data that really are incorrect or absent because of human oversight or issues are removed.
- There should be more uniformity. If there are redundancies or inaccuracies in the data, the findings are less accurate.

- Create a database that is as comprehensive as you can. We can add the missing attributes if needed.
- The data need to be uniform. We simplify its application and interpretation in this way.

3.3.4 Performance Measures

The overall precision, recall, and F1-score, which are indicators of the architecture's effectiveness and accuracy, have been established using our datasets. TP stands for True Positive and FP for False Positive in this study. Once more, FN stands for false negative, while TN stands for genuine negative. Our datasets show that the best accuracy is about 95.45%.

By dividing the entire number of successful outcomes by the quantity of successful precise positive accuracy results, precision is obtained. The recall is calculated by dividing the total number of genuine positive results by the anticipated positive class results. A balance between them is provided by the harmonic mean of recall and accuracy, often known as the F1 score.

Precision, recall, and F1 score serve as performance indicators for classification tasks.

Precision: How many of the elements that were expected to be positive really are positive is a measure of precision. In other words, it is the ratio of the number of actual positives to the total number of positive predictions.

Recall: It measures the percentage of events that were really expected to be favorable and turned out to be such. To put it another way, it is the proportion of overall positives to true positives.

F1 score: The F1 score is a statistic that combines recall and accuracy. It is accurate and evokes harmonic mean. When two quantities must be balanced that are in disagreement with one another, the harmonics mean is the sort of average that is employed.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

TP = True positive

TN = True negative

FP = False positive

FN = False negative

3.4 Implementation Requirements

ResNet50 and MobileNetV2 deep learning models are used in the implementation of this project. We find the best accuracy in MobileNetV2

3.4.1 ResNet50

Deep networks, like the well-known ResNet-50 model, are neural networks (CNNs) with more than 50 layers. A Deep Residual Net (ResNet) is a form of Artificial Neural Network (ANN) that creates a network by layering residual connections. [15]

```
conv_base = ResNet50(
    include_top=False,
    weights='imagenet')

for layer in conv_base.layers:
    layer.trainable = False
```

```
[ ] x = conv_base.output
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dense(128, activation='relu')(x)
    predictions = layers.Dense(3, activation='softmax')(x)
    model = Model(conv_base.input, predictions)
```

```
[ ] model.compile(
        optimizer='adam',
        loss=tf.keras.losses.CategoricalCrossentropy(from_logits=False),
        metrics=['accuracy']
    )
```

Figure 3.4.1.1 ResNet50 model

ResNet stands for residual network. The original presentation of this innovative neural network was made by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 paper, which examined a computer vision article titled "Advanced Residual Training for Machine Vision." Other ResNet variants with different numbers of layers but the same fundamental concept exist. Resnet50 is the name of a form that can function with 50 layers of neural networks. [15]

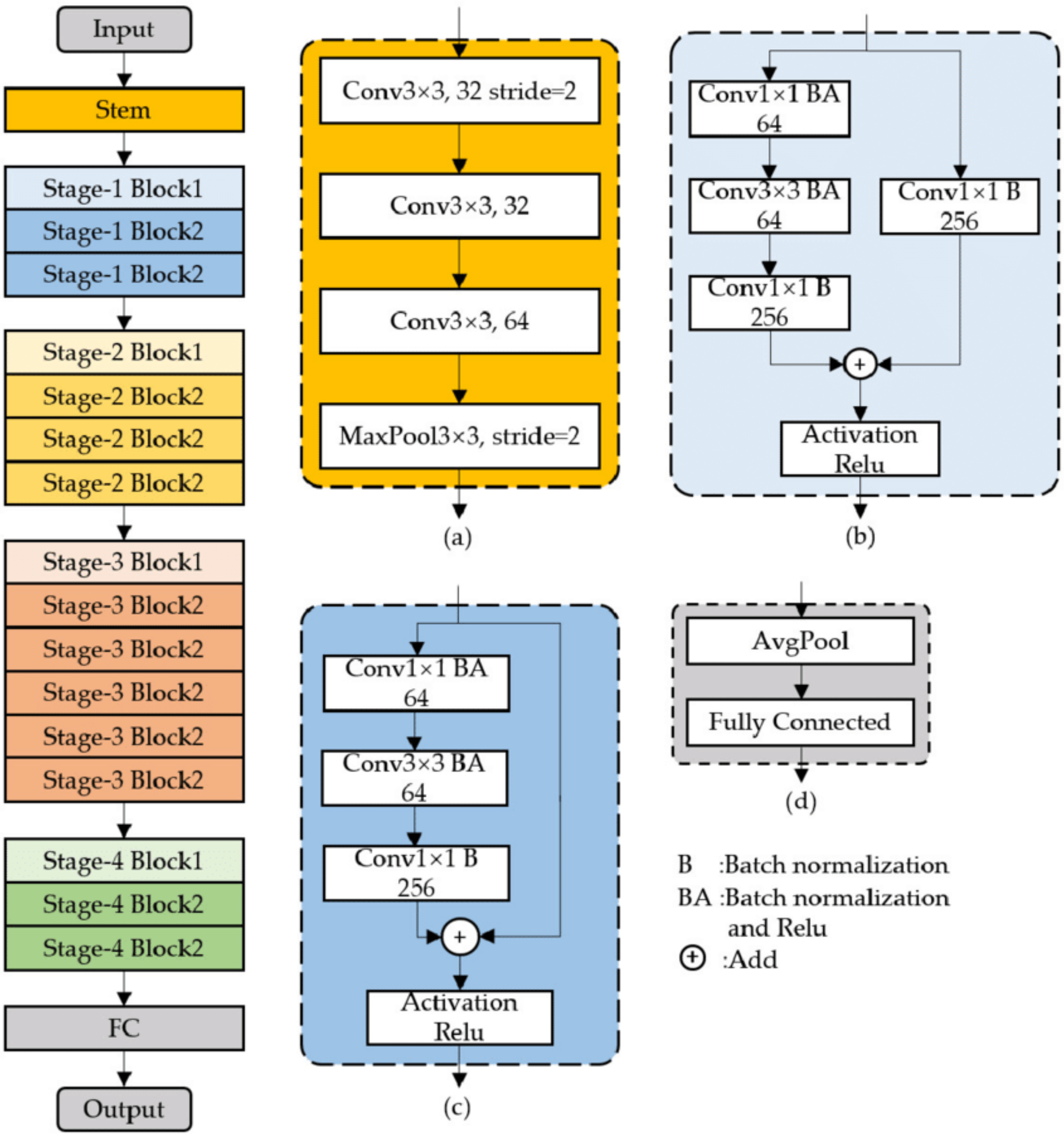


Figure 3.4.1.2: renet50 model architecture

This approach was quite successful, as seen by the fact that ensembles won the ILSVRC 2015 classification competition with just a 3.57% loss. Furthermore, it triumphed in the 2015 ILSVRC & COCO competitions for ImageNet localization, COCO sensing, and COCO delineation. [15]

To handle a vision-based difficulty, supervised learning professionals build extra layers while employing deep neural networks. Because the various layers may be trained to do a range of tasks in order to create extremely exact outcomes, these extra layers help in the more effective resolution of complex challenges. Although the number of layers may improve the model's properties, a deep system may disclose a disadvantage. In other words, as the neural network's layer count grows, accuracy levels may get overburdened and gradually deteriorate. As a result, the model's performance is negatively impacted by both the learning process and the test dataset. Overfitting did not contribute to this degeneration. Instead, it might be a consequence of optimization, a network setup issue, or, more critically, a gradient vanishing or inflation issue. [15]

The Resnet50 design is derived from the idea mentioned above, however, there is one noteworthy difference. Due to worries about the length of time required to train the levels, the foundational element in this instance was changed into a choke design. Rather than the preceding 2 layers, this utilized a stack of 3. Each of the two hidden layers blocks in ResNet34 was converted into a 3-layer bottleneck block to form the ResNet50 architecture. It has much higher accuracy compared to the 34-layer ResNet model. The efficiency of the 50-layer ResNet is 3.8 billion FLOPS [15]. In conclusion, residual network, often known as ResNet, was a significant advancement that altered the learning of machine learning algorithms for object detection algorithms. Authentic ResNets all had 34 layers and 2-layer bottleneck blocks, while more advanced models, such the Resnet50, used 3-layer bottleneck frames to guarantee greater accuracy and faster training.

3.4.2 MobileNetV2

Google created the categorization model known as MobileNetV2. In devices such as smartphones, it offers real-time categorization skills within processing restrictions. This application makes use of ImageNet's learning algorithms for your datasets. MobileNet-v2 is a 53-layer deep convolutional layer. A pre-trained model variant of the network that has been constructed on much more than a million images may be found in the ImageNet database. A variety of animals, a keyboard, a mouse, and a pencil are among the 1000 different item categories that the pre-trained models' network can classify photographs into. A trained model for picture categorization is called MobilenetV2. Deep learning methods that have been trained to use a large picture dataset are called pre-trained models. The developers can save time by using pre-trained algorithms rather than having to create or train a neural network from scratch.

```
dense = tf.keras.applications.mobilenet_v2.MobileNetV2(input_shape=(224,224,3),
                                                       weights='imagenet',
                                                       include_top=False)
for layer in dense.layers:
    layer.trainable = False

x = Flatten()(dense.output)
prediction = Dense(3, activation='softmax')(x) #customize the model with our dataset
model = Model(inputs=dense.input, outputs=prediction)

model.compile( #compiling our customize model
  loss='categorical_crossentropy',
  optimizer='adam',
  metrics=['accuracy']
)

callbacks = [tf.keras.callbacks.TensorBoard(log_dir='log/{}'.format(dt.datetime.now().strftime("%Y-%m-%d-%H-%M-%S")))]
```

Figure 3.4.2.1: MobileNetV2 model

An excellent feature map for object recognition and categorization is MobileNetV2. For instance, the latest design is approximately 35% quicker for detection when used with the recently released SSDLite and has the same precision as MobileNetV1.

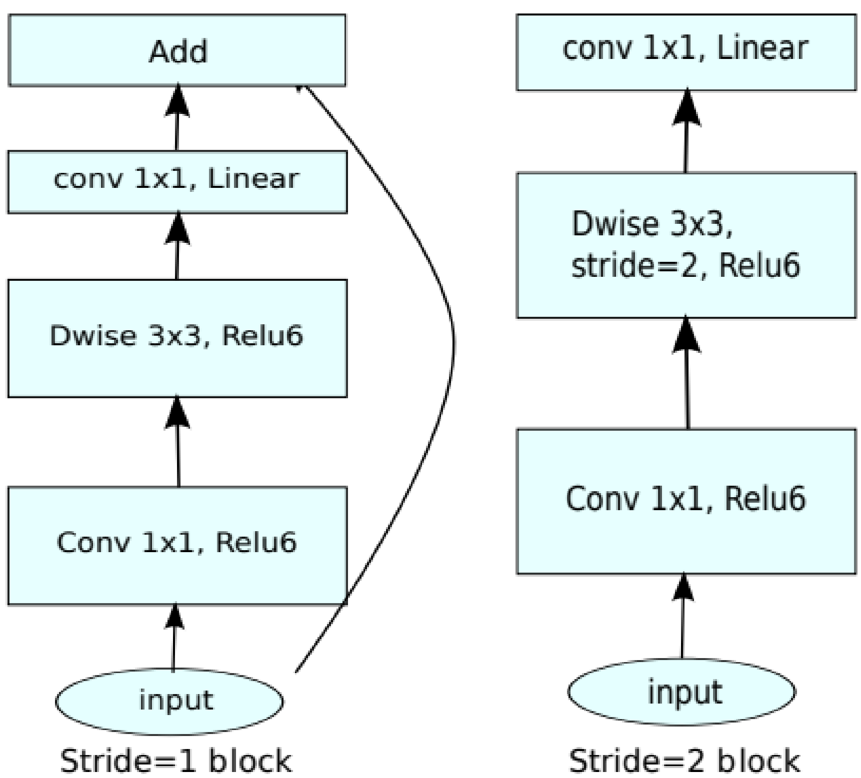


Figure 3.4.2.2: MobileNetV2 model architecture

Applications for embedded and mobile vision use convolutional neural networks, such as MobileNet. They are constructed with depth-wise separable convolution layers, which are lightweight convolutional neural networks with low latency for embedded and portable systems. A network architecture called MobileNet uses depth-wise separable compression as its fundamental building block. MobileNet handles any size of data bigger than 32×32, with higher picture sizes delivering superior performance. Its feature extraction conversion comprises two layers: strived to combine and point convolution.

Chapter 4

Experimental Results and Discussion

4.1 Experimental Setup

This book uses actual data to investigate the effects of the last stage of the procedure. We were capable to reach a very precise efficiency with our calculations. We have 317 X-RAY photos from three courses here. After that, we created a new notebook in Google Collab. Collabs allow anybody to create and run random Python scripts over the internet, making it suitable for computer science, data processing, and education. Google Collab must be built using Google Drive. Anyone, at any time, can access the notebook using only a browser.

4.2 Experimental Results & Analysis

Every model has been examined here. Prior to that, we needed to create the model and choose the greatest accuracy models. Furthermore, we normalized the data to achieve exact and consistent accuracy. We utilize ResNet50 and mobilenetV2 for maximum accuracy. However, we determined that the accuracy of the mobilenetV2 is 95.45%, which is our highest performance. And this model is a loss for 26.04% of the overall. The efficiency of each model is displayed in Table 4.2.1.

Table 4.2.1 test Result

Model name	Accuracy score	Loss function
ResNet50	86.36%	0.6784
MobileNetV2	96.96%	0.2414

The MobileNetV2 models have the maximum accuracy, as seen in the table below. It had a 95.45% accuracy and a loss function of 0.012. However, with an error function of 0.6420 and an efficiency of 80.30%, resnet50 has the lowest error. The model's accuracy, recall, and f1 score are analyzed to gauge overall performance. Table 4.2.2 displays the efficiency findings for the model.

Table 4.2.2 the model's performance results

Catagories	Classes	Model	
		ResNet50	MobileNetV2
Covid	Precision	0.89	1
	Recall	0.96	1
	F1 score	0.93	1
Normal	Precision	0.92	0.95
	Recall	0.55	0.90
	F1 score	0.69	0.92
Pneumonia	Precision	0.65	0.90
	Recall	0.85	0.95
	F1 score	0.74	0.93

Precision: Precision is distinct from accuracy. That is, it is conceivable to be exact but just not precise, and it is also conceivable to be accurate but not precise. The finest statistical inferences are both exact and accurate.

Recall: The recall is determined as the proportion of Positive samples that were actually accurately identified as Positive to all Positive samples. The recall of the model gauges how well it can identify positive samples. More positive samples were discovered as recall increased.

F1-score: The geometric mean of accuracy and recall is used to get the F1 score. It is used to rate execution statistically. In other terms, an F1-score (from 0 to 9, with 0 being the lowest and 9 being the greatest) is a mean of a person's execution based on two variables accuracy and recall.

	precision	recall	f1-score	support
0	0.89	0.96	0.93	26
1	0.92	0.55	0.69	20
2	0.65	0.85	0.74	20
accuracy			0.80	66
macro avg	0.82	0.79	0.78	66
weighted avg	0.83	0.80	0.80	66

Figure 4.2.1: Report on Classification for ResNet50

	precision	recall	f1-score	support
0	1.00	1.00	1.00	26
1	0.95	0.90	0.92	20
2	0.90	0.95	0.93	20
accuracy			0.95	66
macro avg	0.95	0.95	0.95	66
weighted avg	0.96	0.95	0.95	66

Figure 4.2.2: Report on Classification for MobileNetV2

The accuracy of a test relates to how near it is to the real or acceptable value. Precision refers to how closely two results of the exact same thing are. Accuracy each epoch's accuracy is specified. In this circumstance, doubling the number of epochs improves accuracy. The precision of each era is depicted in the Figure below.

```
Epoch 1/20
8/8 [==============================] - 79s 8s/step - loss: 1.2185 - accuracy: 0.3785 - val_loss: 1.0383 - val_accuracy: 0.6061
Epoch 2/20
8/8 [==============================] - 15s 2s/step - loss: 1.0743 - accuracy: 0.3865 - val_loss: 1.0195 - val_accuracy: 0.5758
Epoch 3/20
8/8 [==============================] - 14s 2s/step - loss: 1.0354 - accuracy: 0.5179 - val_loss: 0.9273 - val_accuracy: 0.5303
Epoch 4/20
8/8 [==============================] - 14s 2s/step - loss: 0.9841 - accuracy: 0.5219 - val_loss: 0.9003 - val_accuracy: 0.6667
Epoch 5/20
8/8 [==============================] - 14s 2s/step - loss: 0.9496 - accuracy: 0.5657 - val_loss: 0.8544 - val_accuracy: 0.5606
Epoch 6/20
8/8 [==============================] - 14s 2s/step - loss: 1.0037 - accuracy: 0.5219 - val_loss: 0.8380 - val_accuracy: 0.6818
Epoch 7/20
8/8 [==============================] - 14s 2s/step - loss: 0.9291 - accuracy: 0.5737 - val_loss: 0.7904 - val_accuracy: 0.7121
Epoch 8/20
8/8 [==============================] - 14s 2s/step - loss: 0.9185 - accuracy: 0.6295 - val_loss: 0.7684 - val_accuracy: 0.6667
Epoch 9/20
8/8 [==============================] - 14s 2s/step - loss: 0.8729 - accuracy: 0.6016 - val_loss: 0.7313 - val_accuracy: 0.8333
Epoch 10/20
8/8 [==============================] - 14s 2s/step - loss: 0.8678 - accuracy: 0.6135 - val_loss: 0.7607 - val_accuracy: 0.6515
Epoch 11/20
8/8 [==============================] - 14s 2s/step - loss: 0.9201 - accuracy: 0.5657 - val_loss: 0.7757 - val_accuracy: 0.6364
Epoch 12/20
8/8 [==============================] - 14s 2s/step - loss: 0.9634 - accuracy: 0.5299 - val_loss: 0.7689 - val_accuracy: 0.6515
Epoch 13/20
8/8 [==============================] - 14s 2s/step - loss: 0.8689 - accuracy: 0.6056 - val_loss: 0.6835 - val_accuracy: 0.8030
Epoch 14/20
8/8 [==============================] - 14s 2s/step - loss: 0.8975 - accuracy: 0.6335 - val_loss: 0.7653 - val_accuracy: 0.6515
Epoch 15/20
8/8 [==============================] - 14s 2s/step - loss: 0.8420 - accuracy: 0.5777 - val_loss: 0.6706 - val_accuracy: 0.7424
Epoch 16/20
8/8 [==============================] - 15s 2s/step - loss: 0.8919 - accuracy: 0.5737 - val_loss: 0.7087 - val_accuracy: 0.6515
Epoch 17/20
8/8 [==============================] - 14s 2s/step - loss: 0.8775 - accuracy: 0.6016 - val_loss: 0.6959 - val_accuracy: 0.7121
Epoch 18/20
8/8 [==============================] - 14s 2s/step - loss: 0.8888 - accuracy: 0.6096 - val_loss: 0.7532 - val_accuracy: 0.6212
Epoch 19/20
8/8 [==============================] - 14s 2s/step - loss: 0.9334 - accuracy: 0.5498 - val_loss: 0.6514 - val_accuracy: 0.8030
Epoch 20/20
8/8 [==============================] - 14s 2s/step - loss: 0.8626 - accuracy: 0.6215 - val_loss: 0.6420 - val_accuracy: 0.8030
```

Figure 4.2.3: Accuracy of ResNet50

Here we use 20 epochs to train our dataset and after training, we get 80.30% accuracy and 0.6420 are the loss function in resnet50

```
Epoch 1/25
8/8 [==============================] - 14s 2s/step - loss: 0.0219 - accuracy: 0.9920 - val_loss: 0.6860 - val_accuracy: 0.9091
Epoch 2/25
8/8 [==============================] - 14s 2s/step - loss: 0.0868 - accuracy: 0.9880 - val_loss: 0.2778 - val_accuracy: 0.9394
Epoch 3/25
8/8 [==============================] - 14s 2s/step - loss: 0.0017 - accuracy: 1.0000 - val_loss: 0.3888 - val_accuracy: 0.9545
Epoch 4/25
8/8 [==============================] - 14s 2s/step - loss: 0.0862 - accuracy: 0.9880 - val_loss: 0.2601 - val_accuracy: 0.9545
Epoch 5/25
8/8 [==============================] - 13s 2s/step - loss: 0.0123 - accuracy: 0.9960 - val_loss: 0.5417 - val_accuracy: 0.9394
Epoch 6/25
8/8 [==============================] - 13s 2s/step - loss: 0.1472 - accuracy: 0.9801 - val_loss: 1.0106 - val_accuracy: 0.8939
Epoch 7/25
8/8 [==============================] - 14s 2s/step - loss: 0.1425 - accuracy: 0.9920 - val_loss: 0.4981 - val_accuracy: 0.9545
Epoch 8/25
8/8 [==============================] - 14s 2s/step - loss: 0.1238 - accuracy: 0.9841 - val_loss: 0.3655 - val_accuracy: 0.9545
Epoch 9/25
8/8 [==============================] - 14s 2s/step - loss: 0.0443 - accuracy: 0.9960 - val_loss: 0.7505 - val_accuracy: 0.9242
Epoch 10/25
8/8 [==============================] - 13s 2s/step - loss: 0.0077 - accuracy: 0.9960 - val_loss: 0.8949 - val_accuracy: 0.9091
Epoch 11/25
8/8 [==============================] - 14s 2s/step - loss: 0.0509 - accuracy: 0.9960 - val_loss: 0.9628 - val_accuracy: 0.9091
Epoch 12/25
8/8 [==============================] - 13s 2s/step - loss: 3.0935e-04 - accuracy: 1.0000 - val_loss: 0.4512 - val_accuracy: 0.9394
Epoch 13/25
8/8 [==============================] - 13s 2s/step - loss: 0.0100 - accuracy: 0.9920 - val_loss: 0.4438 - val_accuracy: 0.9242
Epoch 14/25
8/8 [==============================] - 14s 2s/step - loss: 0.0012 - accuracy: 1.0000 - val_loss: 0.8264 - val_accuracy: 0.9242
Epoch 15/25
8/8 [==============================] - 14s 2s/step - loss: 0.0614 - accuracy: 0.9920 - val_loss: 0.2296 - val_accuracy: 0.9394
Epoch 16/25
8/8 [==============================] - 13s 2s/step - loss: 0.0100 - accuracy: 0.9960 - val_loss: 0.4687 - val_accuracy: 0.9394
Epoch 17/25
8/8 [==============================] - 13s 2s/step - loss: 0.0171 - accuracy: 0.9960 - val_loss: 0.3945 - val_accuracy: 0.9394
Epoch 18/25
8/8 [==============================] - 13s 2s/step - loss: 0.0172 - accuracy: 0.9960 - val_loss: 0.8164 - val_accuracy: 0.8939
Epoch 19/25
8/8 [==============================] - 13s 2s/step - loss: 0.0031 - accuracy: 1.0000 - val_loss: 0.8215 - val_accuracy: 0.8939
Epoch 20/25
8/8 [==============================] - 13s 2s/step - loss: 0.0176 - accuracy: 0.9920 - val_loss: 0.3024 - val_accuracy: 0.9394
Epoch 21/25
8/8 [==============================] - 13s 2s/step - loss: 1.1361e-05 - accuracy: 1.0000 - val_loss: 0.4874 - val_accuracy: 0.9545
Epoch 22/25
8/8 [==============================] - 13s 2s/step - loss: 0.0775 - accuracy: 0.9920 - val_loss: 0.2782 - val_accuracy: 0.9545
Epoch 23/25
8/8 [==============================] - 13s 2s/step - loss: 0.0310 - accuracy: 0.9920 - val_loss: 0.3272 - val_accuracy: 0.9697
Epoch 24/25
8/8 [==============================] - 13s 2s/step - loss: 8.5095e-05 - accuracy: 1.0000 - val_loss: 0.4791 - val_accuracy: 0.9394
Epoch 25/25
8/8 [==============================] - 14s 2s/step - loss: 0.0077 - accuracy: 0.9960 - val_loss: 0.2604 - val_accuracy: 0.9545
```

Figure 4.2.4: Accuracy of MobileNetV2

In this case, we utilize 25 epochs to train our dataset, and after training, we acquire 95.45% accuracy with a loss function of 0.2604 in MovibeNetV2.

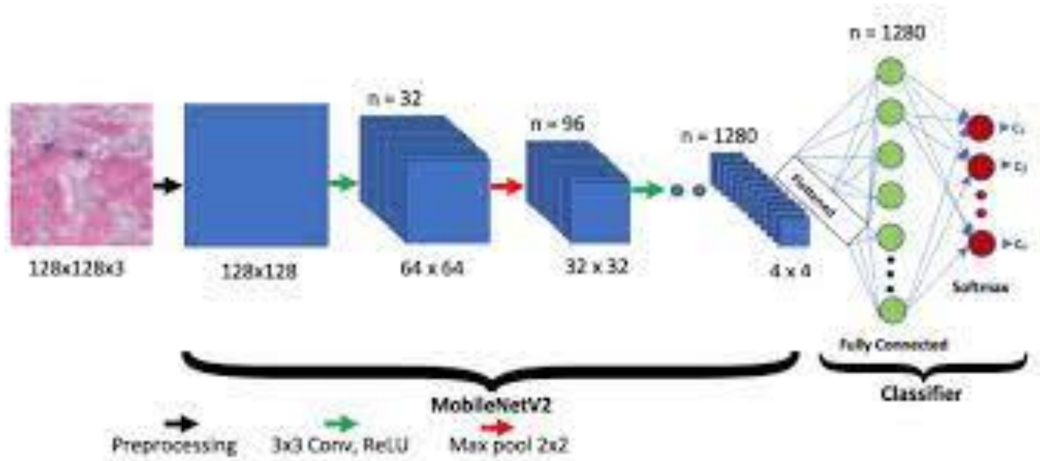


Figure 4.2.5: Structure of MobileNetV2

A convolutional neural network architecture called MobileNetV2 was created specifically for mobile devices. It is based on a leftover architecture that has been inverted and yet has links between bottleneck layers. The intermediate expansion layer uses light depth-wise convolutions to filter features as a source of non-linearity. The first full convolution, with 32 filters, is included in the MobileNetV2 architecture, along with 19 more bottleneck layers.

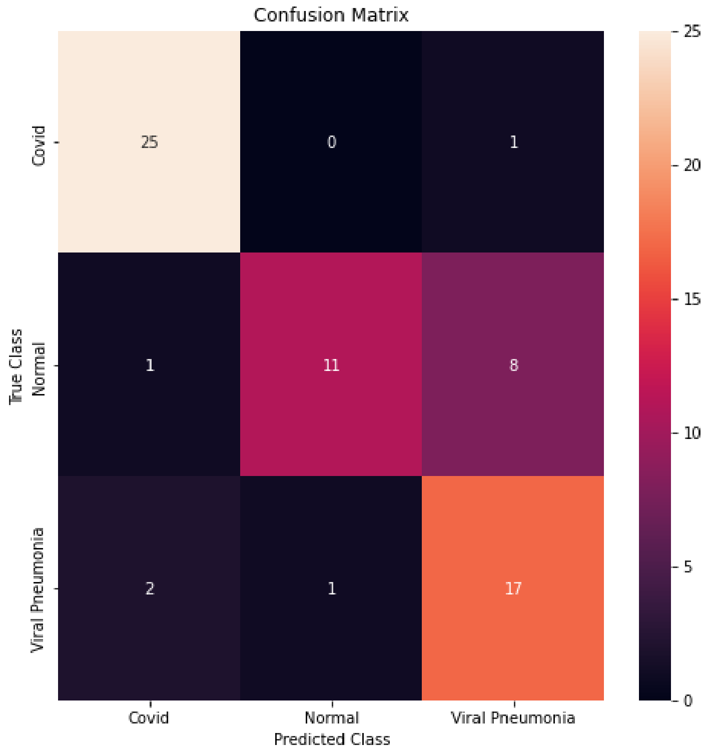
4.3 Discussion

We interrupt the dataset into two distinct parts: training and testing. For training, we used 80% of the data and for testing, we used 20% of the data, and our accuracy rate was 96%. We work with 32 batches and 25 epochs. We also test this class to see if its predictions itself or not. If it’s forecasted, the outcome will be true; else, it will be false.

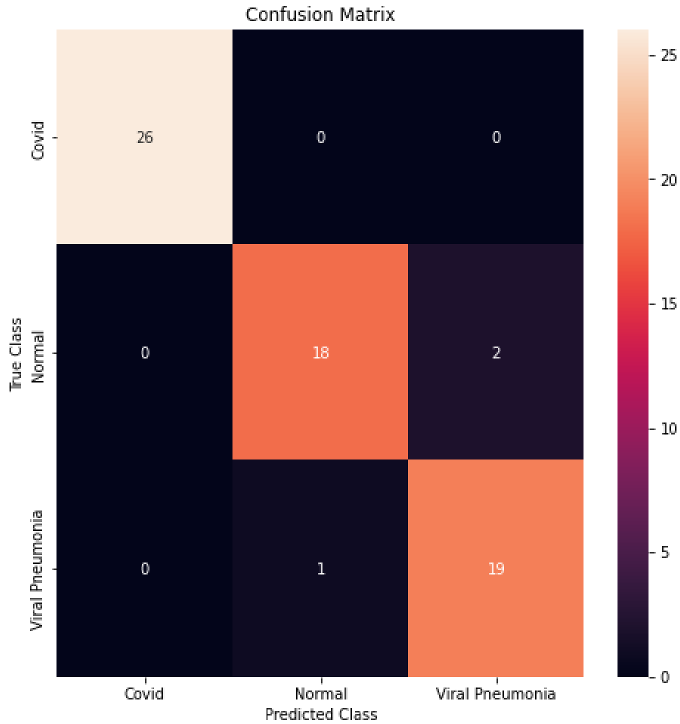
A method for gauging the success of machine learning categorization is the confusion matrix. It is a type of table that enables you to observe how a classification model is applied to a set of test data in order to ascertain the real values. Although the notion confusion matrix is evident, the language used to describe it may be unclear.

A confusion matrix is a matrix used to assess the success of a classification approach. A confusion matrix represents and emphasizes the performance of a classification algorithm. [16]

Figure 4.3.1 illustrates the overall confusion matrix.



ResNet50



MobileNetV2

Figure 4.3.1: Confusion Matrix

Chapter 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

Today's coronavirus, also known as Covid-19, causes a terrible illness. For a few months, it put an end to human existence on Earth. 6.7 million Individuals have passed away and 663.4 million people have been infected so far. In most cases, the virus that inflicts serious lung illness on people weakens other organs gradually over time. The following are signs of COVID disease: The major symptoms are fever, coughing, and breathing difficulties in addition to respiratory symptoms. Since it often affects the lungs, the symptoms begin with a dry cough and fever before breathing difficulties develop. The social system is currently experiencing an unheard-of catastrophe because of the Covid-19 epidemic. Adherence to social seclusion (such as lockdowns and home quarantines) is being used as the primary method of containing the disease. As a result, billions of people throughout the world are being compelled to remain at home.

With the use of x-ray imaging, corvids can be located thanks to our research. Therefore, during the corvid lockdown time, only one test can identify COVID. People will gain social benefits as a consequence. Since there are no difficulties involved and the findings come in a timely manner—in contrast to lab tests, which often take two to three days to produce a report—our technique allows us to obtain the results quickly and at a lower cost.

5.2 Impact on the Environment

The Covid-19 pandemic's effects are becoming worse. This worldwide epidemic affects human life and other industries, in addition to wreaking havoc on health and the economy (such as the environment and climate). The continued exploitation and commercialization of wild resources (plants and animals) pose a serious danger to the survival of many species. Through viruses, this destructive activity has greatly endangered human civilization. Our organization's shortcomings in managing medical waste are clear. Medical center garbage is disposed of in accordance with the 2008 Bangladesh Medical Waste Management and Processing Rules. However, this nation has no laws governing the handling or processing of medical waste. Rules 8 mandates the establishment of dumping zones in seven departments for the management and processing of medical waste; however, only Dhaka has such a zone, which is woefully insufficient given the increasing number of hospitals.

Using our project has prevented any medical waste from being produced. Only a lung X-ray image is required to detect the ailment, which poses no risk to the environment or pollutants. Therefore, it may be concluded that our job is excellent for the environment.

5.3Ethical Aspects

From the laboratory to clinical trials, and then onward to information translation into medical care, cancer researcher investigates years, if not generations. The statistical chance of a fresh theory of preventing disease, diagnosis, and treatment being effective is typically quite low. But a wide range of research initiatives has led to the corpus of information that is currently in existence. The ethical guidelines for scientific research urge clinical scientists to notify people in the study of any potential drawbacks and lack of efficacy of the proposed change under consideration. However, neither patient's nor the specialist's role is easy. Moreover, the likelihood of using medicine to treat disease is far higher than it is for treating other diseases. On only one side, this helps the underprivileged population, who might not be able to pay for the treatment, but it raises significant ethical concerns whenever the clinical study is completed and the potential customer fails to obtain the same medication. Additional ethical concerns in a study on the chronically sick include the technique of informed consent and who can agree on behalf of a hospice patient, who is typically unable to consent due to a lack of understanding. Furthermore, a terminally sick patient or family member may feel driven to approach the investigator, which may result in accidental or unwillingly coerced permission. Palliative care treatment standards are so much more probably to be poor compared to other fields due to insufficient financing. Because treating such difficulties clinically may be difficult, this may pose moral considerations for work on improving.

5.4 Sustainability Plan

Durability or the continuation of a program and its essential ideals after funding and out aid have stopped, is an important goal for population health. Given the significant resources committed to the development and evaluation of prevention and treatment, it is critical to focus on how successfully proof efforts translated and sustain their effects in at-risk populations across time. Workplace preventative strategies can address the increased prevalence of covid-19 illness by focusing on prevention and early detection. People are advised by health specialists to avoid crowded areas.

Avoiding public transportation or exercising extreme care is critical. Coronavirus can be found on the handles or seats of buses, trains, or any other mode of transportation. As a result, doctors recommend wearing a mask while going by any mode of transportation and properly washing hands after exiting. Even sharing the same workplace workstation and computer increases the danger of viral infection. According to experts, the coronavirus spreads by sneezing and coughing. The coronavirus can remain active for hours or even days everywhere. Before you sit at your workplace desk, clean the computer, keyboard, and mouse. Handshakes and conversations can potentially transfer the coronavirus. The coronavirus can be passed on to others if you hug and shake hands with someone who has it. That is why specialists advise against shaking hands or hugging. According to experts, keeping yourself clean is the key to everything.

CHAPTER 6

Summary, conclusion, recommendation, and implication for future research

6.1 Summary of the Study

The motivation behind this study was to foster a profound learning model to foresee the improvement of pneumonia in patients with COVID (Coronavirus). The model was created using a series of chest radiographs from patients in the Covid-19 cohort. The model was trained using a transfer learning technique, and it had a 95% prediction accuracy rate. This study demonstrates the use of deep learning to detect pneumonia in Covid-19 patients early. This research paper's findings suggest that pneumonia and the Coronavirus can be accurately predicted using deep transfer learning. This is a useful instrument that can be used to assist medical professionals in diagnosing and treating patients who suffer from these conditions. This research could take many different paths in the future. Expanding the research into other respiratory diseases like tuberculosis is one option. Recurrent neural networks, for example, are a type of deep learning architecture that could be used to improve prediction accuracy.

6.2 Conclusions

This study aimed to compare how well two transfer learning models, MobileNetV2 and ResNet50, predicted whether coronavirus disease (COVID-19) patients would develop pneumonia. After being tested on a different set of X-ray images, the dataset of COVID-19 patients' X-ray pictures served as the training set for the two models. MobileNetV2 outperformed ResNet50 in terms of accuracy, specificity and sensitivity, as demonstrated by the outcomes. A patient's corona or pneumonia status was predicted using the mobilenetv2 and ResNet50 models. The ResNet50 model was not as accurate as the mobilenetv2 model. The ResNet50 model was 80.30 percent accurate, while the mobilenetv2 model was 95.45 percent accurate. We can use the mobilenetv2 and ResNet50 models to predict whether a person has pneumonia or corona after training them. We can use the mobilenetv2 model to make predictions with more assurance because it is more accurate than the ResNet50 model.

6.3 Implication for Further Study

I will work with more data sets and use more algorithms to determine the accuracy and try to work on our exhibition. In addition, in the future, we will develop an android app where anyone can check their diseases very easily.

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