# Diagnosis of Covid-19 Pneumonia using Deep Learning and Transfer learning Techniques

MSc Research Project
Data Analytics

Paritosh Diwakar Mohite
Student ID: x19199554

School of Computing
National College of Ireland

Supervisor: Prof. Hicham Rifai

**National College of Ireland**
**Project Submission Sheet**
**School of Computing**

| | |
|---|---|
| **Student Name:** | Paritosh Diwakar Mohite |
| **Student ID:** | x19199554 |
| **Programme:** | Data Analytics |
| **Year:** | 2021 |
| **Module:** | MSc Research Project |
| **Supervisor:** | Prof. Hicham Rifai |
| **Submission Due Date:** | 16/08/2021 |
| **Project Title:** | Diagnosis of Covid-19 Pneumonia using Deep Learning and Transfer learning Techniques |
| **Word Count:** | 5006 |
| **Page Count:** | 23 |

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

**ALL** internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

| | |
|---|---|
| **Signature:** | |
| **Date:** | 22nd September 2021 |

**PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST:**

| | |
|---|---|
| Attach a completed copy of this sheet to each project (including multiple copies). | ☐ |
| **Attach a Moodle submission receipt of the online project submission**, to each project (including multiple copies). | ☐ |
| **You must ensure that you retain a HARD COPY of the project**, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer. | ☐ |

Assignments that are submitted to the Programme Coordinator office must be placed into the assignment box located outside the office.

| **Office Use Only** | |
|---|---|
| Signature: | |
| Date: | |
| Penalty Applied (if applicable): | |

# Diagnosis of Covid-19 Pneumonia using Deep Learning and Transfer learning Techniques

Paritosh Diwakar Mohite
x19199554

**Abstract**

Coronavirus-2019 (Covid-19) is a deadly virus that has flu symptoms. It originated in a small town called Wuhan (China) and it soon rapidly spread across the world, starting an era of a pandemic. In many countries lockdown was imposed due to this pandemic. This illness causes pneumonia in many situations. As radiography images can be used to monitor pulmonary infections. Therefore, this study helps to detect and analyze chest X-rays by using deep learning models and transfer learning models with the intention that it can provide strong tools to medical doctors and workers to deal with this deadly virus. Specialized deep learning models have been introduced to detect pneumonia, it is assumed that detection of pneumonia will increase the chances of a patient having Covid-19 infection. Furthermore, health tools are suggested for predicting whether a patient is diagnosed with Covid-19, normal and viral pneumonia. From the results of experiment, the CNN model gave an accuracy of 71% and VGG-19 model with 91%, InceptionV3 with 83% and Xception model with 89% of accuracy. By comparing the models CNN model outperforms over other three models. To conclude, these findings suggest that implemented model's capacity to assess the seriousness of COVID-19 lung infections might be utilized for health as well as medication performance assessment, particularly throughout the critical care unit.

**Keywords: Deep Learning, Transfer Learning, COVID-19, Chest X-ray, Convolution Neutral Network, Pneumonia, Image processing, InceptionV3, VGG-16, Xception**

# 1 Introduction

A new form of the disease is due to the emergence of the new coronavirus that occurred between late 2019 and early 2020. It was identified as Coronavirus 2019 by the World Health Organization (WHO) on 12 February 2020 (COVID-19) **Liu et al. (2020)**, which brought a substantial amount of attention to worldwide community issues **Maghdid et al. (2021)**. COVID-19 is very contagious and may spread by droplets and touch. Throughout 204 million individuals around the world were infected as of 11 Aug 2021. Clinically speaking, the virus exhibits clinical symptoms of respiratory illnesses, including cough, fever, and lung inflammation. Although the death rate in COVID-19 is relatively low, it is amazing and even asymptomatic virus carriers are susceptible to spread, compared to prior severe respiratory syndrome (SARS) and Middle East respiratory disease (MERS) **Wang et al. (2020)**. The disease might lead to fatal cardiopulmonary effects,

especially for older people with comorbidity, in susceptible persons **Mei et al. (2020)**. Therefore the disease can assist patients to accept treatment early so that the person afflicted can be properly managed for isolation sooner and avoid the disease from spreading rapidly **Zu et al. (2020)**.
A novel three-step deep network technique is utilized in this study for the diagnosis of instances of pneumonia produced by Covid-19.

1. In the early phase of model building, a clinical data set is loaded and balanced to avoid biases in a specific category and different pre-processing techniques such as and data augmentation normalization is used to avoid over-fitting.

2. In second stage, deep learning model called convolution neural network and transfer learning model such as VGG-16, InceptionV3 and Xception is used to analyze and evaluate two clinical cases named Covid-19 and Viral pneumonia from normal cases.

3. lastly, the models are analyzed and compared based on the performance metrics, and best model is decided which outperformed to evaluate to research question.

This three-stage technique gives the patient a quick and reliable initial chest x-ray test to diagnose clinical conditions.

## 1.1 Background and Motivation

As a new outbreak of respiratory illnesses, the new COVID-19 strain spreads from Asia to the world by the end of 2019. COVID-19 has been proclaimed officially by the World Health Organization (WHO) as an unprecedented health epidemic and a pandemic outbreak following rapid worldwide COVID-19 spread and major clinical events. **Aslan et al. (2021)**. For clinical treatment planning, patient monitoring, and treatment result, the early identification of COVID-19 illness is of key significance **Irmak (2020)**. For the current testing technology called reverse-transcription polymerase chain reactions (RT-PCR) of Covid-19 disease swabs are taken from the nose and throat **Ozturk et al. (2020)**, this testing process seems to have the disadvantage that is this test takes a longer time to get the results around 48 hours and also vulnerable to sampling error. This technique, therefore, has limitations, such as a shortage of kits, extended detection times, and delayed findings. The diagnostic abilities of physicians can be increased and the time taken with computer-aided automated detection and diagnostic systems for accurate diagnosis can be reduced. A tendency for study has been developed to use clinical characteristics extracted from chest CT or chest XR images with automatic detection objectives to identify rapid, accurate, and precise techniques which may complete the diagnosis and assessment of the disease. Although many diverse methods of imaging exist, X-ray images by doctors are commonly used for Covid 19 and pneumonia diagnosis, with the obvious truth that the X-ray photographic system is a crucial part of worldwide health care. X-ray images can be used in absence of screening workbenches and kits for detection of Covid-19. There may be situations in which the patient's radiograph image and their scans show that COVID-19 might perhaps be suggestive. The major issue is that it takes a lot of time to examine and the presence of medical specialists is necessary for this field to look at and extract every X-ray image medical practitioners will require computer assistance. In that case, Deep learning techniques can contribute to diagnosing medical images. Therefore this work deals with a two-stage approach which is a novel design to detect Covid-19 induced pneumonia cases.

In the past 2 years, many studies in the field of medicine are conducted on the subject Covid-19 and different precautionary measures are available in this field to avoid them. The state of art methods is implemented in which CT scan or X-ray images are used by considering deep learning techniques. In previous years, different questions appeared whether to use machine learning or deep learning approach based on different features of the research. Although deep learning approaches are considered to be best compared to machine learning due to their advantages i.e unstructured data can be used, less requirement of feature engineering, high quality of results. Therefore the previous research is considered as state of art in which the paper**Apostolopoulos and Mpesiana (2020)** VGG-19 model is used to classify Covid-19 with an accuracy of 97.8%. In a paper **Ozturk et al. (2020)**) two evaluations using the DarkCovidNet model, one evaluation for binary classification with covid 19 and no finding with an accuracy of 98.08% and other with multi-class category Covid-19, pneumonia and no findings which have an accuracy of 87.02%. The most up-to-date research, however, does not aim at distinguishing Covid-19 induced pneumonia cases from other healthy cases. This is required to avoid the misdiagnosis of COVID-19 as a typical viral pneumonia infection, as there is a different line of therapy in the infection with COVID-19. The goal of this research is structured into two stage:

1. Implement deep learning and transfer learning model to diagnose Covid-19 induced pneumonia cases and diagnose cases at an early stage.

2. Implementing this solution will help the radiologist and medical expert to diagnose Covid-19, Viral pneumonia and Normal cases in the beginning before the infection spread for long time in human body.

The current research is structured as follow: In section **2** several research work on deep learning and transfer learning for Covid19 induced pneumonia is examined. In section **3** proposed methodology is discussed for this research. In section **4** work flow of current project is discussed. In section **5** different deep learning and transfer learning models are evaluated. In section **6** each model is evaluated and result of all models are compared. In section **7** the research is concluded and future work is discussed.

## 1.2 Research Question

"To what extend, the severity of COVID-19 induced pneumonia cases are diagnosed from healthy cases using Deep learning and Transfer learning technique..?"

## 1.3 Research Objective

In accordance to the research question there are 7 research objectives those are explained bellow:

| Research Objectives | Description | Evaluation Metrics |
|---|---|---|
| First Objective | critical review of this research identify any gap in previous research that has been implemented | - |
| Second Objective | Pre-processing technique to visualize the data and balance the imbalanced dataset and perform data augmentation | - |
| Third Objective | CNN model implementation and evaluation | Accuracy, precision recall loss function |
| Fourth Objective | VGG-16 model implementation and evaluation | Accuracy, precision recall loss function |
| Fifth Objective | InceptionV3 model implementation and evaluation | Accuracy, precision recall loss function |
| Sixth Objective | Xception model implementation and evaluation | Accuracy, precision recall loss function |
| Seventh Objective | Comparison of all model | Accuracy |

**Table 1- Research Objective of this research**

# 2 Related Work

This section contains a brief summary of the articles analyzed on the issues of Covid-19 and Pneumonia using Deep Learning techniques. The research article are categorized by proposed technique, clinical data set that are done by the past researchers. The proposed deep learning techniques are mainly classified into two techniques called CNN and transfer learning for diagnosing Covid-19 and pneumonia diseases, and also categorized based on clinical data that is used in this study and data pre processing technique called data augmentation method as these research articles are explained bellow.

## 2.1 Survey and comments

In this Research (***Preventing the spread of the coronavirus*; 2020**) the author has proposed an idea how prevention measures can be taken such as reducing travel, avoiding crowds, increasing social distance, and thorough and frequent hand washing can slow the occurrence of new cases of COVID-19 and reduce the likelihood of the health-care system being overburdened. In this article **Shi et al. (2021)**, Coronavirus is inspected for its capacity to give a perfect, exact, profoundly productive imaging arrangement. In COVID-19, the entire AI-improved imaging measure was extensively considered, including brilliant stages for imaging, clinical diagnostics, and advancement science. Two imaging strategies, X-beam and CT, are utilized to survey the viability of AI-empowered clinical imaging for COVID 19. It was additionally featured in this investigation that photos just give halfway data on COVID-19 patients. Imaging information with both clinical manifestations and lab discoveries should subsequently be incorporated to up-

grade COVID-19 screening, ID, and finding. At long last, the authors speculate that AI will show its regular tendency to consolidate information from a few sources to make exact and proficient treatments just as examinations.
In this work, a thorough survey is completed. **Hryniewska et al. (2020)** of different aspects of the proposed models. This examination uncovered a few mistakes all through different information gathering stages, model structure, and investigations, just as regular blunders emerging from an intensive handle of radiography. What's more, while assessing the model, this examination gives the points of view from both deep learning engineers and radiologists. To foster precise models for recognizing Covid-19, a last agenda with less conditions is prescribed as an end to this work. In this paper **Mohammadi et al. (2020)** The objective is to offer an outline of the current circumstance, difficulties, and possibilities for creating models for extensive COVID-19 disease testing and observing. Specifically, the investigation opens with a survey of late improvements in clinical conclusion and treatment of COVID-19 hyper signs. Besides, this investigation presents assets and hindrances for future examination in the fight against Covid-19 or related pandemics.

## 2.2 Clinical Data

In this research the data set is taken from publicly available repository called kaggle. In this reposiotry there are two main source from the data is gatthered first is Italian Society of Medical and InterventionalRadiology (SIRM) **Rahman et al. (2021)** and second is Radiological Society of North America (RSNA) **Chowdhury et al. (2020)**. The first source consist of Covid-19 images and the second source consist of Healthy images as well as pneumonia image. The final repository of Kaggle which is created by using the following research total 15,377 images are present in which 10346 images are of normal case, 3686 are covid 19 images and 1345 are viral pneumonia images. The physicians from different countries Qatar, Doha, Dhaka university and Bangladesh gathered images of chest x-ray of image covid-19, normal and viral pneumonia.

## 2.3 Data Augmentation technique for pre-processing

This paper **Nayak et al. (2021)** has used data augmentation technique along with pre-trained models called lexNet, VGG-16, GoogleNet, MobileNet-V2, SqueezeNet, ResNet-34, ResNet-50 and Inception-V3. X-ray images are used in this research as a input data set. After implementing the data augmentation technique the ResNet-34 gave a good accuracy of 94% after implementing data augmentation images as input to model. This study uses binary classification and in future work use of multi-class classification is suggested. With the guide of pre-prepared CNN models, deep learning is used to mechanize the screening of Covid-19 utilizing X-beam photos of the chest. These models were inspected utilizing different boundary ages, learning rate group size, and different elements, and the best performing model was picked for Covid-19 determination. In spite of the fact that chest x-beam pictures are utilized, the information is lopsided, along these lines this work utilizes an information expansion way to deal with address the issue. Taking everything into account, the proposed model is easy to apply, and with the arrangement of the information unevenness issue, the model is exact in recognizing Covid-19, which will help radiologists in tolerant screening. **Rahman et al. (2021)** Utilizing chest x-ray pictures, the examination gives a speedy and solid methodology for diagnosing Covid-19 ailment. While in this investigation, the accentuation is on picture expansion and lung division approaches for pre-preparing. Typical, non-Covid-19, and Covid-19 x-beam pictures are used with the openly open informational index. Five picture improving procedures, just as a few profound learning models, were used to analyze Covid-19 in this examination. Since the informational index for Covid-19 is so minimal in contrast with different pictures, it produces information irregularity. To address this, an information expansion approach is utilized, in which Covid-19 photos are enhanced twice to adjust the information. Picture turn information expansion is utilized in this examination. Taking everything into account, the model prepared successfully when information expansion was executed, and the model's precision was additionally improved.

### 2.4 Deep Learning technique for Covid-19 and Pneumonia detection

In this study **Liu et al. (2020)**,The CT outputs of COVID-19 people were considered utilizing a mix of profound learning objective discovery and picture characterization methods in this paper. A novel Coronavirus identification approach that depends on time-spatial sequencing convolution is delivered through get-together just as assessing the qualities of injuries in different occasions. A repetitive neural organization structure and a 2D convolutional layer structure are utilized in the procedure.The location procedure introduced in this investigation might deliver more exact extensive identification results when contrasted with Faster RCNN, YOLO3, and SSD calculation models.In paper **Wang et al. (2020)** the researcher has explained how covid-19 got evolved in this world what were the previous symptoms.

In this study **Maghdid et al. (2021)**, the objective is to build a complicated image dataset of CT-scan images and X-rays from various data sources so that it can provide efficient methodology to detect Covid-19 with the help of deep learning models and transfer-learning model using AlexNet. A simple yet effective Convolutional Neural Network was built and pre-trained AlexNet. After critically evaluating, CNN model provides accurate result of 98% and through AlexNet, the accuracy is 94.1%. The study **Irmak (2020)** provides a strong and powerful Convolutional Neural Network to detect whether a person is Covid-19 infected or not. The proposed model have achieved accuracy of 99.20%. Evaluated outcome shows the efficiency of the model on publicly available dataset. Various evaluation metrics such as Accuracy, Specificity, Senstivity and Precision are used. In paper **Mei et al. (2020)** is used to diagnose covid-19 infected individuals, the study uses artificial intelligence techniques on CT-scan images with clinical symptoms. The study did RT-PCR on 905 individuals out of that more than 45% tested positive. When coordinated to a senior thoracic radiologist, the AI framework got a region under the bend of 0.92 and had comparative affectability in a test set of more than 270 patients. The AI approach also enhanced the identification of COVID-19 positive patients with normal CT scans who've been positive by RT–PCR, accurately identifying 17 of 25 (68%) patients, although radiologists categorized every one of these patients as COVID-19 negative.

Paper **Zu et al. (2020)** depicts Albeit switch record polymerase chain response stays the best quality level, certain chest CT attributes and a background marked by Wuhan openness or close contact with a patient with Covid disease 2019 (COVID-19) are unequivocally characteristic of COVID-19 pneumonia. Multifocal reciprocal ground-glass opacities with sketchy solidifications, critical incidentally subpleural dispersion, and back part or lower projection inclination are generally normal CT discoveries of COVID-19 pneumonia. Meager cut chest CT can support the early location, direction of clinical dy-

namic, and observing of infection advancement, making it a significant apparatus in the avoidance and the board of COVID-19. Whereas the paper **Ozturk et al. (2020)** depicts an original model for computerized COVID-19 recognizable proof using crude chest X-beam pictures is given in this examination. The recommended approach is intended to give dependable diagnostics for parallel and multi-class arrangement (COVID versus No-Findings) (COVID versus No-Findings versus Pneumonia). For parallel classes, the model had a grouping precision of 98.08 percent, and for multi-class occasions, it had an exactness of 87.02 percent. In our exploration, the DarkNet model was used as a classifier for the YOLO (you just look once) continuous item distinguishing proof framework. The study utilized 17 convolutional layers and applied different channels to every one. In paper **Reshi et al. (2021)** CNN model is used to evaluate the problem associated with this research and in pre-processing data augmentation is used before model building. The CNN model gave an accuracy of 99% with only 100 x ray images. The author has suggested in future to go with large number of images so that this situation of overfitting can be avoided. Paper **Musleh and Maghari (2020)** is based on Stanford research, where a chexnet model is used to detect covid 19 and pneumonia. This model similar to chexnet model, 550 chest xray images are used. The accuracy obtained from this model is 89%.
In research **Sahinbas and Catak (2021)** an alternative solution is implemented to detect covid-19, x-ray as an input images is used in this study. In total 100 images are used, The model used in this paper are VGG16, VGG19 and Resnet from those model VGG16 moedel gave an accuracy of 80% for this small amount of dataset. Similarly, in paper In research **Taresh et al. (2021)** a pre-trained cnn model is used with x ray images as an input, 1200 xray images covid-19, 1345 xray of viral pneumonia, and 1341 xray images of healthy case. The model used in this case is VGG16 which gave an accuracy of 97.8%. In **Guefrechi et al. (2021)** paper solution has been implemented to combat with new covid 19 disease , feature extraction is perfomed. Three powerful models are used VGG16, ResNet and InceptionV3. Fine tuning is performed to get better accuracy. The mentioned model InceptionV3 model outperformed with an accuracy of 98.30%. Similarly, the paper **Dutta et al. (2021)** diagnose the lung disease using CT scan images CNN model is used as base model for transfer learning model called InceptionV3 as this model will train on previous model which CNN. After playing with the epoch value the pre-trained model gave an accuracy of 84% after trying different value the proposed gave a good accuracy with no over fit problem. Paper **Özlem POLAT (2021)** detect covid-19 using chest ct scan images, and proposed a model called xception and CNN, feature extraction is performed by xception modeel and the performance metric considered in this study are precision, recall, f1 score and accuracy. The model gave a best accuracy of 98%.

# 3 Methodology

In this research, CRISP-DM methodology is used, where CRISP-DM is Cross Industry Standard Process for Data Mining. The CRISP-DM is six steps structured method that describes Data Science Life Cycle. CRISP-DM is the widely used framework. In this research, CRISP-DM helps to propose a systematic data mining project.

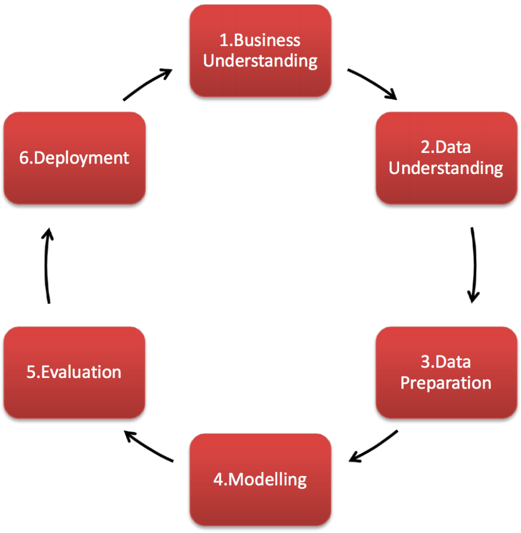



**Figure 1: CRISP-DM Methodology**

## 3.1 Business Understanding

Business understanding is the first and most critical step in the CRISP-DM solution. To sum up, Covid-19 is a deadly disease that was first started in Wuhan which is a small town in China. As it rapidly spread across the world, the lockdown was imposed in many countries. As a consequence, in many countries such as the USA, Italy, and India, their GDP was declined and the economic crisis increased. Many people have lost their job because of the pandemic. Majorly death rate of most countries was also at its peak. Many researchers have been working to put an end to this pandemic. And as a solution, this study implements a deep learning model with the use of transfer learning to provide a better solution to the health care workers, to detect the novel coronavirus-2019 as early as possible. So that many lives can be saved and the growth of countries can also be improved.

## 3.2 Data Understanding

The Dataset used in this research is taken from a publicly available repository called Kaggle. This repository has two main sources from which images are gathered, first source is the Italian Society of Medical and Interventional Radiology (SIRM) from which Covid-19 images are collected Rahman et al. (2021) and the second source is the Radiological Society of North America (RSNA) from which Viral Pneumonia and Normal case images are gathered Chowdhury et al. (2020). There were no human participants or sensitive details in the data collection which may violate any legal or ethical regulations. This data set consists of overall 15,377 images, where 3686 images are of Covid-19 cases, 10346 images are of Normal cases and 1345 images are of Viral Pneumonia. Figure 2 shows example Chest x-ray images in which first images of Positive Covid-19, second is healthy cases images i.e Negative Covid-19 and last is Viral pneumonia x-ray image.

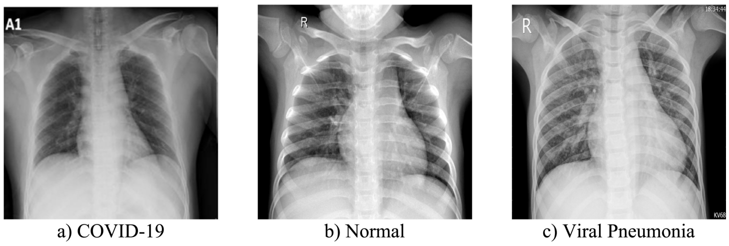



Figure 2: Example of Covid-19 and Pneumonia detection data set

## 3.3 Data Preparation

The first step before proceeding with the X-ray image to the model, pre-processing of the image is required. In pre-processing the first step is to perform data normalization, the importance of using data normalization is each input parameter i.e pixels of an image have equal data distribution. Normalizing an image will help the model to train faster. The second step into pre-processing is Image Augmentation, in this step image size is increased without taking other new images in training a model. This will help a model to train on a large data set which helps the model to get well trained on training data set which will further increase the model performance. In conclusion to this, the detailed discussion of Normalization and Image augmentation is explained.
Considering the number of images present in the data set which has total 15,377 in which normal case has 10,346 images, Covid-19 cases has 3686 and Viral pneumonia has 1345 images. So as the main concern is prediction Covid-19 and Viral pneumonia cases from normal case so as the normal cases has more images than the other cases it will create biases on one case i.e normal case. So in order to avoid the imbalanced data before implementing the model the data needs to be balanced. So after performing the balancing of data the Covid-19 image are 3686, Normal images is 4686 and the viral pneumonia images are 1345. Those images are further used to build a model.

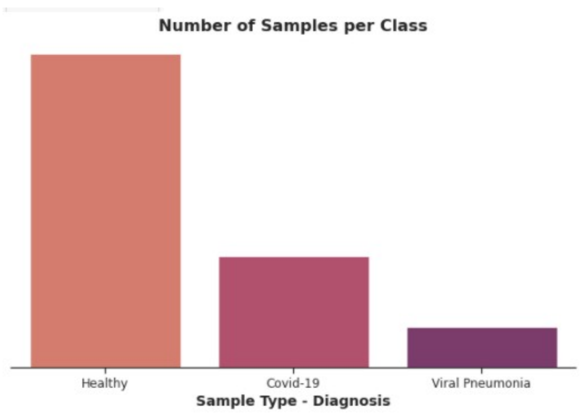



Figure 3: Exploratory Data Analysis for number of images per class

### 3.3.1 Normalization

Data normalization is a crucial step that is usually applied in CNN systems in order to preserve numerical stability. Implementing this step model will be trained at a faster rate and will help to achieve better performance. In data normalization, each pixel value is standardized between o and 1. In this research, training, testing, and validation data is rescaled by 1./255 **Nayak et al. (2021)**. Basically images are of two types grey-scale and black-white images. The Black-white images are complete black i.e '0' and complete white i.e '1'. The values are in between '0' and '1'. The grey-scale images has shades of gray. These values are also in same range of '0' and '1'. Whereas, '0' is dark black, '0.1' is slightly dark and '1' is white color. Every AI algorithm input pixel of image data set is standardized which will help to increase training model accuracy. The distributions of pixel are subtracted and separated by standard deviation and those scaled standard deviation values are used to produce results.

### 3.3.2 Data Augmentation

In order to achieve better performance of the model, the model needs to be trained well. This can be possible by providing more images to model. Image augmentation is a process in which images are increased without adding any new images to the model. The image augmentation is always performed on the training data set not on the testing data set. In some cases, images are very few to train the model in that case image augmentation will play a vital role. **Nayak et al. (2021)**. In Image augmentation image is transformed by defining various parameters such as rotation, scaling, shifting, zooming **Rahman et al. (2021)**. In this research, the parameter used is rotation, shifting, zoom, and filling. The figure **??** shows the detailed implementation steps which are referred in this research. This approach can achieve accurate classification, but it also takes longer training time, and utilizes more memory.

# 4 Project Design Specification

The given design architecture 4 is adopted to complete the proposed project. It involves various layers such as Data Layer, Business Layer, and Client layer.
1st Layer (Data Layer): In the data layer, various steps such as data gathering, image pre-processing, and EDA are performed in this stage. Data set of chest X-ray images are extracted from the Radiological Society of North America (RSNA) and the Italian Society of Medical and Interventional Radiology (SIRM). The image data set includes 3686 samples of Covid infected patients, 10346 Normal patients, and 1345 viral pneumonia infected patients. As data was getting biased on the Normal category, to overcome this problem, a data balancing technique was implemented. In the next step, data normalization is performed. As the image data set is small and to avoid an over-fitting problem, a data augmentation technique was adopted.
2nd Layer (Business Layer): In the second layer that is the business layer, deep learning models such as CNN and Transfer Learning Models such as InceptionV3, VGG-16 and Xception have been built on python language. And also various critically evaluated results are covered in this section.
3rd Layer (Output Layer): After evaluating results, outcomes will be analyzed by doctors or radiologist experts so that they can provide effective treatment to the patients. Various graphs are plotted to understand whether a patient is infected by Covid or pneumonia. The architecture underlies the implementation and the associated requirements are identified and presented in this section.

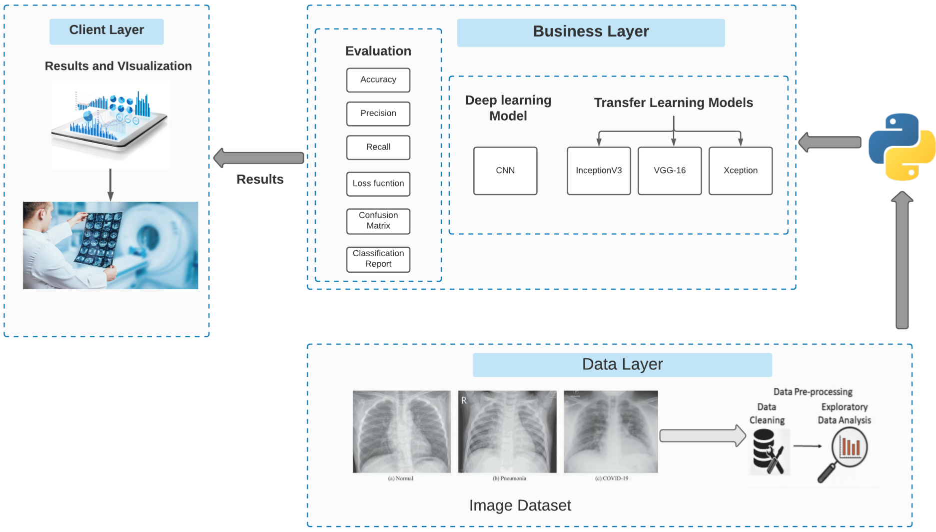



Figure 4: Process Design Architecture

# 5 Project Implementation

In this section implementation of Convolution neural network (CNN), VGG-16, InceptionV3, and Xception model are discussed to detect Covid-19 Pneumonia. Those models consist of model weights, fully connected layer, convolution layer, dense layer, different types of the optimizer, and network layer which helps to perform feature extraction. For this study, multi-class classification is considered and the mentioned algorithm used in this research is well suited for a multi-class category. The models are splitted by 80% of training and 20% of test data.

## 5.1 Implementation of Convolution Neural Network (CNN)

In this section, first the implementation of CNN model is discussed. Convolution Neural Network is a deep learning technique which consist a image as an input, model weights and bias are assigned which is equally important to differentiate one image from other. For CNN model pre-processing is not much required with respect to other deep learning models. While CNN model requires a higher learning rate, when model is trained, in return to get better performance. The CNN model consist of three layer which are convolution layer, pooling layer and fully connected layer. Those layer are connected and CNN architecture is build. Other than this CNN architecture has two important parameters called activation function and dropout layer. Looking into Figure **5** shows the first two layer are used for feature extraction in which it separates and identifies the feature of an input image. The output of feature extraction is applied to classification which is fully connected layer. Where the fully connected layer uses the output of previous layers and predict the class of an image. The Figure **6** shows the CNN model implemented in this research. The model is trained using 13 2D convolution layers, this layer is used to extract the features from the input image **Musleh and Maghari (2020)**. The pooling layer used in this case are 5, this layer reduces the computational cost by decreasing size of the feature map. The pooling layer are of different types such as Max, sum and average in this case Max pooling is used. This layer acts as connecting bridge for convolution layer

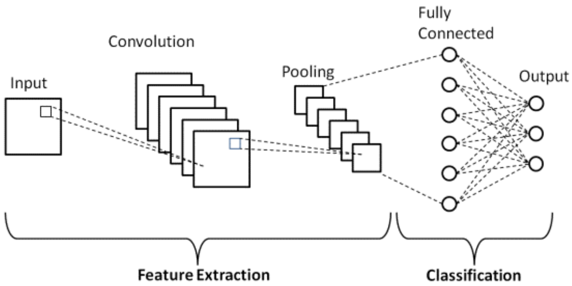



Figure 5: Convolution Neural Network Architecture

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_42 (Conv2D)           (None, 224, 224, 64)      1792
_________________________________________________________________
conv2d_43 (Conv2D)           (None, 224, 224, 64)      36928
_________________________________________________________________
max_pooling2d_17 (MaxPooling (None, 112, 112, 64)      0
_________________________________________________________________
conv2d_44 (Conv2D)           (None, 112, 112, 128)     73856
_________________________________________________________________
conv2d_45 (Conv2D)           (None, 112, 112, 128)     147584
_________________________________________________________________
max_pooling2d_18 (MaxPooling (None, 56, 56, 128)       0
_________________________________________________________________
conv2d_46 (Conv2D)           (None, 56, 56, 256)       295168
_________________________________________________________________
conv2d_47 (Conv2D)           (None, 56, 56, 256)       590080
_________________________________________________________________
conv2d_48 (Conv2D)           (None, 56, 56, 256)       590080
_________________________________________________________________
max_pooling2d_19 (MaxPooling (None, 28, 28, 256)       0
_________________________________________________________________
conv2d_49 (Conv2D)           (None, 28, 28, 512)       1180160
_________________________________________________________________
conv2d_50 (Conv2D)           (None, 28, 28, 512)       2359808
_________________________________________________________________
conv2d_51 (Conv2D)           (None, 28, 28, 512)       2359808
_________________________________________________________________
max_pooling2d_20 (MaxPooling (None, 14, 14, 512)       0
_________________________________________________________________
conv2d_52 (Conv2D)           (None, 14, 14, 512)       2359808
_________________________________________________________________
conv2d_53 (Conv2D)           (None, 14, 14, 512)       2359808
_________________________________________________________________
conv2d_54 (Conv2D)           (None, 14, 14, 512)       2359808
_________________________________________________________________
max_pooling2d_21 (MaxPooling (None, 7, 7, 512)         0
_________________________________________________________________
flatten_4 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_12 (Dense)             (None, 4096)              102764544
_________________________________________________________________
dense_13 (Dense)             (None, 4096)              16781312
_________________________________________________________________
dense_14 (Dense)             (None, 3)                 12291
=================================================================
Total params: 134,272,835
Trainable params: 134,272,835
Non-trainable params: 0
_________________________________________________________________
```

Figure 6: Model Summary of Implemented Convolution Neural Network Architecture

and fully connected layer. The next layer is fully connected layer, this layer is present before output layer Reshi et al. (2021). It consist of neuron, weights and biases, which are used to connect the neurons with two different layers. Before proceeding the output of previous layer, input image is flattened. The classification of class takes place in this layer. All the layers are trained by 512 layer and for activation all the CNN layer ReLu function is used and to activate output layer Softmax activation function is used, Usually, it is used in case of multi-class classification. The flatten, pooling and convolution layer are used to establish connection between Convolution layer and output layer which is dense layer. The dropout layer is used to avoid over-fitting. The use of activation function is to decide which information should go forward and which not at the end of network layer.

## 5.2 Implementation of VGG-16 model

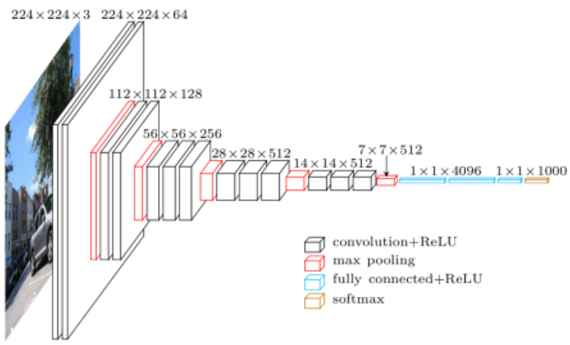
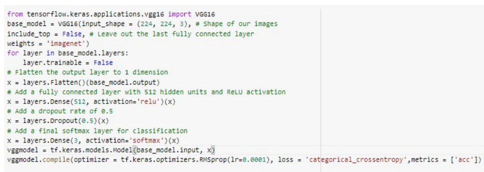



Figure 7: VGG-16 architecture



```
from tensorflow.keras.applications.vgg16 import VGG16
base_model = VGG16(input_shape = (224, 224, 3), # Shape of our images
include_top = False, # Leave out the last fully connected layer
weights = 'imagenet')
for layer in base_model.layers:
    layer.trainable = False
# Flatten the output layer to 1 dimension
x = layers.Flatten()(base_model.output)
# Add a fully connected layer with 512 hidden units and ReLU activation
x = layers.Dense(512, activation='relu')(x)
# Add a dropout rate of 0.5
x = layers.Dropout(0.5)(x)
# Add a final softmax layer for classification
x = layers.Dense(3, activation='softmax')(x)
vggmodel = tf.keras.models.Model(base_model.input, x)
vggmodel.compile(optimizer = tf.keras.optimizers.RMSprop(lr=0.0001), loss = 'categorical_crossentropy',metrics = ['acc'])
```

Figure 8: Implemented VGG-16 Architecture

The VGG stands for Visual Geometry Group. It consist of 16 weights layer, 13 convolution layer, 3 fully connected layer and 1 output layer. In VGG-16 first step is to download the weights of Imagenet, looking into figure 8 variable called VGG16 is given with an input image size of (224,224,3). The VGG-16 model is not trained again, because as the same suggest pre-trained model the model is trained on several images and used to classify several classes So the we will set layer of VGG-16 model to 'FALSE'. So till now all the layer are stopped and removed the output layer which is a classification layer, a new classification layer will be added at the end of the model to train the data set images. For that we will flatten the layer and add a 512 fully connected layer with activation function 'ReLu'. In order to avoid overlapping a dropout layer is added with rate of 0.5 Taresh et al. (2021). The output dense layer is added for classification with an activation function called 'Softmax'. Sahinbas and Catak (2021).

## 5.3 Implementation of InceptionV3 model

A modified pre-trained Inception-v3 Transfer Learning modell was built for the classification model. The model Inception-v3 might contribute to the convolution layer that can minimize the number of parameters without changing the precision. Again the max pooling and convolutionary layer were used to increase the effectiveness of reducing features. The model has the benefit of extracting output from any specific node. It was named as a mixed stratum and has a total of 11 mixed layer. It consist of 48 convolution layer, this

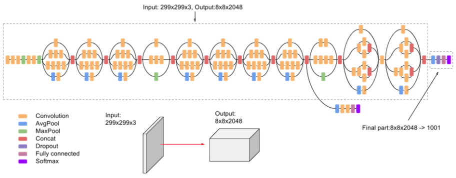
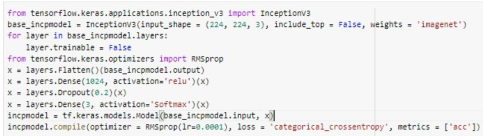



Figure 9: InceptionV3 architecture



```python
from tensorflow.keras.applications.inception_v3 import InceptionV3
base_incpmodel = InceptionV3(input_shape = (224, 224, 3), include_top = False, weights = 'imagenet')
for layer in base_incpmodel.layers:
    layer.trainable = False
from tensorflow.keras.optimizers import RMSprop
x = layers.Flatten()(base_incpmodel.output)
x = layers.Dense(1024, activation='relu')(x)
x = layers.Dropout(0.2)(x)
x = layers.Dense(3, activation='Softmax')(x)
incpmodel = tf.keras.models.Model(base_incpmodel.input, x)
incpmodel.compile(optimizer = RMSprop(lr=0.0001), loss = 'categorical_crossentropy', metrics = ['acc'])
```

Figure 10: Implemented InceptionV3 Architecture

pre-trained model can classify upto 1000 category Guefrechi et al. (2021). In VGG-16 first step is to download the weights of Imagenet, looking into figure 10, variable called InceptionV3 is given with an input image size of (224,224,3). The InceptionV3 model is not trained again, because as the same suggest pre-trained model the model is trained on several images and used to classify several classes. So the we will set layer of InceptionV3 model to 'FALSE'. So till now all the layer are stopped and removed the output layer which is a classification layer, a new classification layer will be added at the end of the model to train the data set images. For that we will flatten the layer and add a 1024 fully connected layer with activation function 'ReLu'. In order to avoid overlapping a dropout layer is added with rate of 0.2. The output dense layer is added for classification with an activation function called 'Softmax' Dutta et al. (2021).

## 5.4 Implementation of Xception model

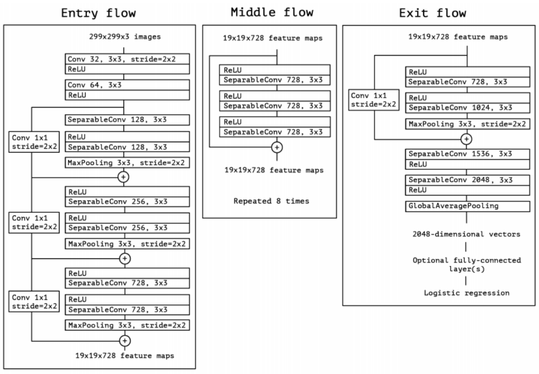



Figure 11: Xception architecture

```python
from tensorflow.keras.layers import Input, Lambda, Dense, Flatten, AveragePooling2D, Dropout
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.applications import Xception
xception = Xception(weights="imagenet", include_top=False,
    input_tensor=Input(shape=(224, 224, 3)))

outputs = xception.output
outputs = Flatten(name="flatten")(outputs)
outputs = Dropout(0.5)(outputs)
outputs = Dense(3, activation="softmax")(outputs)

xcep_model = Model(inputs=xception.input, outputs=outputs)

for layer in xception.layers:
    layer.trainable = False

xcep_model.compile(
        loss='categorical_crossentropy',
        optimizer='adam',
        metrics=['accuracy']
```

Figure 12: Implemented Xception Architecture

The Xception model consist of three flow entry, middle and exit flow. This consist of 36 convolution layer. Xception model starts from first flow i.e entry flow which has 4 modules in total and 2 each convolution layer. All the flow has 3x3 size filter, In put entry flow the input is of 299,299, size with it converts to 19,19,728 size by performing feature map on all outputs. The middle flow has three different convolution module layer. The output of middle flow is given to the input of exit flow. IN exit flow two module are present First with 728 and 1024 filters and second with 1536 and 2084 filters. the output of exit flow is fed to fully connected layers Özlem POLAT (2021). In Figure 12 variable called Xception is given with an input image size of (224,224,3). The Xception model is not trained again, because as the same suggest pre-trained model the model is trained on several images and used to classify several classes. So the we will set layer of

Xception model to 'FALSE'. The model is build on its input, the variable 'x' consist of outputs of the Xception model which further given to droupout layer. In order to avoid overlapping a dropout layer is added with rate of 0.5. The output dense layer is added for classification with an activation function called 'Softmax'.
The Model Summary Implemented architecture of InceptionV3 and Xception is similar to VGG-16 the only difference is in InceptionV3 1024 hidden unit along with fully connected layers are added and in VGG-16 512 hidden unit along with fully connected layers are added. Considering Xception model has dropout value 0.5 similar to VGG-16.

# 6 Evaluation and Results

In this section, a comprehensive evaluation of deep learning and transfer learning model are carried out. The metric considered to evaluate the model are Confusion matrix, Classification report, loss function, Precision, recall, accuracy and F1-score. After successful evaluation of the models will an optimal solution which model outperformed to detect Covid-19 pneumonia.

## 6.1 Hyperparameter tuning

The hyperparameter in each model, firstly activation function at the input stage activation function called 'relu' used it is used to avoid any problem of vanishing gradient. 'softmax' activation function is used at the output layer in all the model. The dropout is used to avoid the issue related to over-fitting, the dropout value must be in the range of 0.2 to 0.8. The dropout value considered for VGG-16, InceptionV3 and Xception is 0.5, 0.2, and 0.5 respectively. Another hyperparameter considered is the optimizer, which is used to change weights and learning rate to reduce the losses. The optimizer used in the case of the CNN model and Xception is Adam and for VGG-16, InceptionV3 is RMSprop are used. The loss function is another hyperparameter tuning function which is prediction error. The categorical crossentropy loss function is used as it is multi-class research. Another hyperparameter is early stopping criteria, which is used to monitor the accuracy and validation loss or validation accuracy of the model, using this hyperparameter we can monitor at which particular the epoch early stopping rate has occurred. So that next time we can decide the exact value epoch to be run.

## 6.2 Evaluation of CNN model

Considering the figure **14** the CNN model gave an accuracy of 71%. After tuning the hyperparameter the Adam is used an optimizer, categorical cross-entropy as loss function, the epoch value considered after tuning is 20, the batch size is 32. The precision value is total number of predicted values are correctly classification so in this case for label Covid, Normal and Viral pneumonia correctly classified percentage is 75%, 74% and 60% respectively. The recall which is actual correct classification in this case actual value classified are 61%, 72% and 96% for covid, normal and viral pneumonia resp. The F1 score is nothing but the average of Recall and precision. Looking into the Figure **13** confusion matrix for Covid case, 282 value are correctly diagnosed covid images but 147 images are misclassified as normal images, but the images belongs to covid class and 32 images are misclassified as viral pneumonia but belongs to covid class. Considering the Normal label, 419 images are correctly diagnosed normal images, but 93 images are misclassified

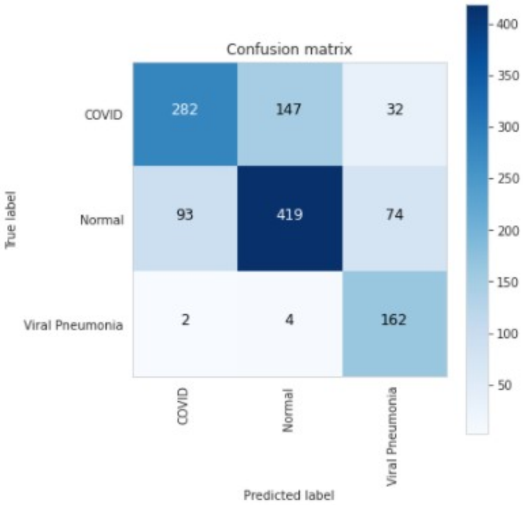
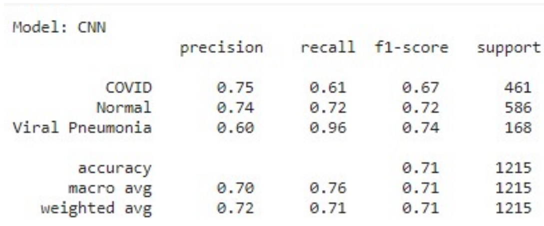



Figure 13: Confusion matrix of CNN model



Model: CNN

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| COVID | 0.75 | 0.61 | 0.67 | 461 |
| Normal | 0.74 | 0.72 | 0.72 | 586 |
| Viral Pneumonia | 0.60 | 0.96 | 0.74 | 168 |
| accuracy | | | 0.71 | 1215 |
| macro avg | 0.70 | 0.76 | 0.71 | 1215 |
| weighted avg | 0.72 | 0.71 | 0.71 | 1215 |

Figure 14: Classification report of CNN

as Covid but the images belongs to normal class and 74 images are misclassified as viral pneumonia but belongs to normal class. Lastly, for Viral Pneumonia, 162 images are correctly diagnosed Viral pneumonia images, but only 2 images are misclassified as normal but the images belongs to Viral Pneumonia class and 4 images are misclassified as covid but belongs to viral pneumonia class. Basically confusion matrix is table of actual vs predicted values. Now the Looking into the figure **15** and **16** which are accuracy and


Figure 15: Accuracy vs Epoch plot of CNN model

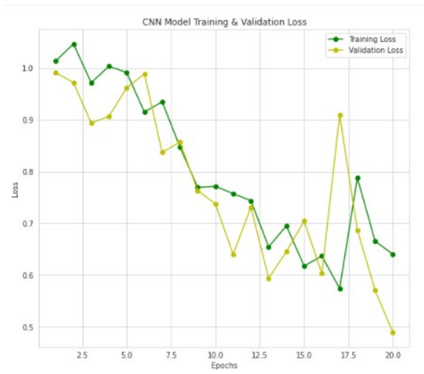



Figure 16: Loss vs Epoch plot of CNN model

loss graph, where the number of epochs considered is 20 after tuning the CNN model the graph how the accuracy of training and validation increases or decreases with respect to epochs. Looking into accuracy graph the training accuracy gradually increases upto 70%. Whereas, the accuracy of has certian spikes of increase and decrease with gradual increase in accuracy wrt to epoch value, the validation accuracy goes upto 80%. Looking the loss vs epoch graph the training loss and accuracy loss gradually decreased wrt the epochs.

## 6.3 Evaluation of VGG-16 model

The figure 18 the overall accuracy of VGG-16 model is 91%. After tuning the hyperparameter the RMSprop is used an optimizer, categorical cross-entropy as loss function,and learning rate is 0.0001 is used while compiling the model. Different values of epoch were tried and the final epoch value which gave better accuracy was epoch=20, the batch size considered for this model is 32. The precision value is total number of predicted values are correctly classification so in this case for label Covid, Normal and Viral pneumonia correctly classified percentage is 87%, 93% and 97% respectively. The recall which is actual correct classification in this case actual value classified are 93%, 90% and 89% for covid, normal and viral pneumonia resp. The F1 score is nothing but the average of Recall and precision. Looking into the Figure 17 confusion matrix for Covid case, total images for testing are 1215, so from the total images 431 images are correctly classified as Covid, 526 images are correctly classified as Normal and 149 images are correctly classified as Viral Pneumonia images. The misclassified images in case of Covid are 29 images misclassified as Normal and only 1 images misclassified as Viral pneumonia. In case of Normal, 57 images misclassified as Covid and only 3 images misclassified as Viral pneumonia. Lastly, for Viral pneumonia cases, 7 images misclassified as Covid and 12 images misclassified as Normal. Now the Looking into the figure 19 and 20 which are accuracy

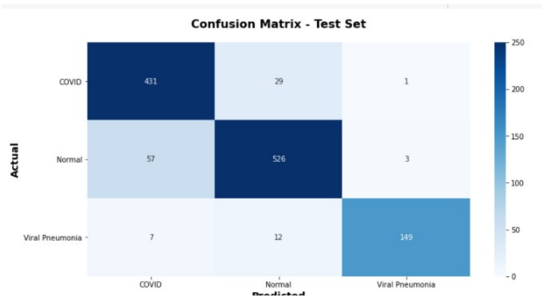



Figure 17: Confusion matrix of VGG-16 model

Model: VGG16

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| COVID | 0.87 | 0.93 | 0.90 | 461 |
| Normal | 0.93 | 0.90 | 0.91 | 586 |
| Viral Pneumonia | 0.97 | 0.89 | 0.93 | 168 |
| accuracy | | | 0.91 | 1215 |
| macro avg | 0.92 | 0.91 | 0.91 | 1215 |
| weighted avg | 0.91 | 0.91 | 0.91 | 1215 |

Figure 18: Classification report of VGG-16

and loss graphs, looking in the accuracy graph the accuracy started increase from 1st epoch to the end which is 20th epoch with respect to validation accrаucy of the model there are some minor fluctuations in the accuracy but at 1st epoch the value accuracy is above 70% while going toward the last epoch we can see fluctuations those can be signs of unrepresentative data set i.e less data is trained while training the model. Same with the loss graph the loss of training and validation are decreasing simultaneously. As the training loss decreases the validation loss also decreases wrt to epochs, this can be the sign of good model, as the model gave an accuracy of 91%.

## 6.4 Evaluation of InceptionV3 model

The figure 22 the overall accuracy of VGG-16 model is 91%. The RMSprop optimizer is used because it gives a better learning rate, as the output is multi-class classification categorical cross-entropy is used as loss function. After hyperparameter tuning epoch value considered for this model is same as previosu which is epoch=20 along the batch size of 32. The overall accuracy of this model is 83%, the precision value i.e predicted value of true positive for covid, normal and viral pneumonia is 96%, 75% and 97% resp.

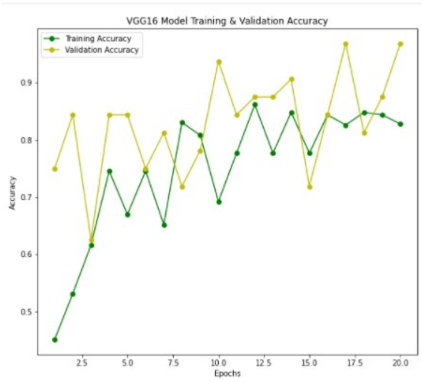



Figure 19: Accuracy vs Epoch plot of VGG-16 model

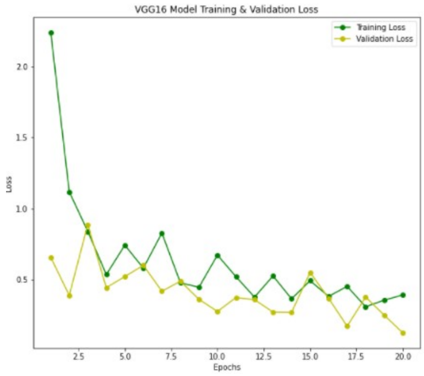



Figure 20: Loss vs Epoch plot of VGG-16

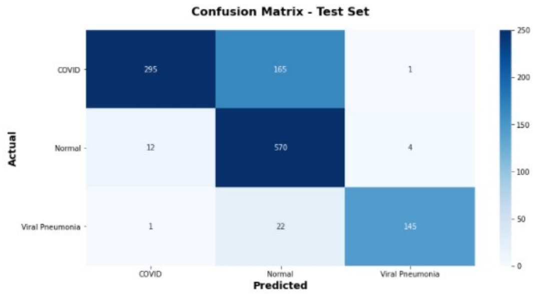
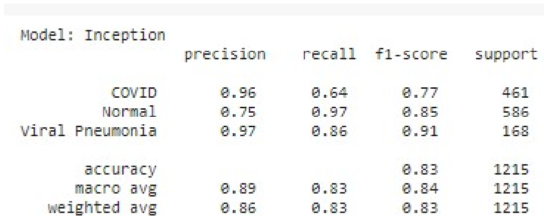



Figure 21: Confusion matrix of InceptionV3 model



Model: Inception

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| COVID | 0.96 | 0.64 | 0.77 | 461 |
| Normal | 0.75 | 0.97 | 0.85 | 586 |
| Viral Pneumonia | 0.97 | 0.86 | 0.91 | 168 |
| accuracy | | | 0.83 | 1215 |
| macro avg | 0.89 | 0.83 | 0.84 | 1215 |
| weighted avg | 0.86 | 0.83 | 0.83 | 1215 |

Figure 22: classification report of InceptionV3 model

whereas the recall, i.e actual values of true positive for covid, normal and viral pneumonia is 64%, 97% and 86% resp. The confusion matrix 21 explains from the overall testing images i.e 1215, the correct classified images wrt to the cases are Covid with 295 images, normal with 570 images and viral pneumonia with 145 images. Whereas, the misclassified images Covid cases are 165 misclassified images as normal and 1 images misclassified as viral pneumonia. For Normal cases, 12 images as Covid and only 4 images as viral pneumonia. Lastly, for viral pneumonia case, 22 images are misclassified as normal and only 1 images misclassified as covid.

## 6.5 Evaluation of Xception model

The figure 26 The hyperparamter used in this model are optimizer as adam, loss function as categorical cross-entropy, epoch value 20 and batch size of 32 by using tuning this parameter model gave an accuracy of 89%. the precision value i.e predicted value of true positive for covid, normal and viral pneumonia is 87%, 90% and 94% resp. whereas the recall, i.e actual values of true positive for covid, normal and viral pneumonia is 89%, 88% and 94% resp. The confusion matrix 25 of this model explain 412 images are correctly classified as Covid case, 517 as normal case and 158 as Viral pneumonia cases. Rest of all values are misclassified i.e 45 images misclassified as Normal and 4 images misclassfied as Viral pneumonia but they belong to Covid class. Secondly, 63 images misclassified as Covid and 6 images misclassfied as Viral pneumonia but they belong to


Figure 23: Accuracy vs Epoch plot of InceptionV3 model

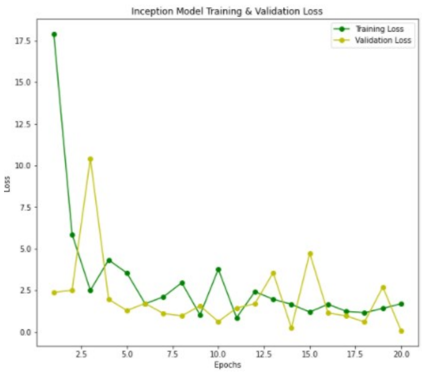



Figure 24: Loss vs Epoch plot of InceptionV3 model

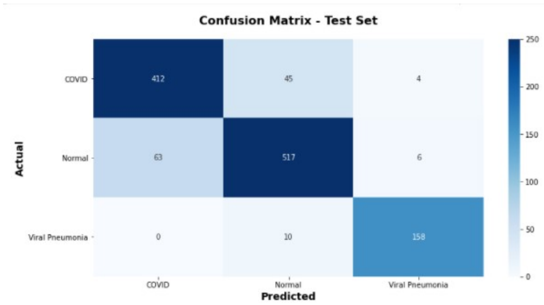



Figure 25: Confusion matrix of Xception model

Model: Xception

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| COVID | 0.87 | 0.89 | 0.88 | 461 |
| Normal | 0.90 | 0.88 | 0.89 | 586 |
| Viral Pneumonia | 0.94 | 0.94 | 0.94 | 168 |
| accuracy | | | 0.89 | 1215 |
| macro avg | 0.90 | 0.91 | 0.90 | 1215 |
| weighted avg | 0.90 | 0.89 | 0.89 | 1215 |

Figure 26: classification report of Xception model

Normal class. Lastly, 10 images misclassified as Normal and 0 images misclassfied as Covid but they belong to Viral Pneumonia class. In Figure 27 the accuracy of training

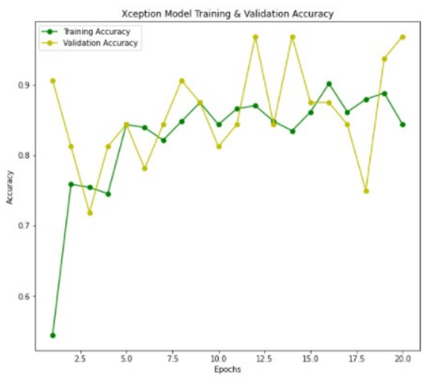



Figure 27: Accuracy vs Epoch plot of Xception model

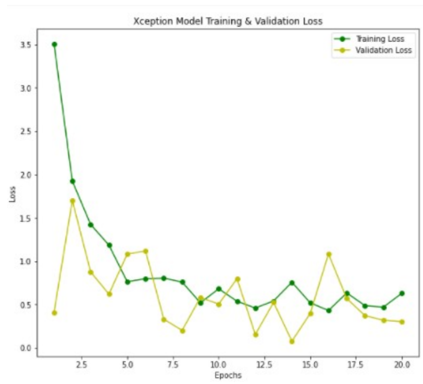



Figure 28: Loss vs Epoch plot of Xception model

is gradually increasing along with the validation accuracy wrt to epochs. Similarly, the Loss of training is gradually Decreasing along with the validation Loss wrt to epochs.

## 6.6 Discussion

In details discussion of performance metrics, the performance of the models can be evaluated and can be compared with other models to find out which is the best suitable performance of the model for Covid-19 and pneumonia detection. In this section, results of each models are critically analyzed and compared to find out which model is well suited for Covid-19 induced pneumonia cases from healthy cases. Model used in this study are CNN, VGG-16, InceptionV3 and Xception which gave an accuracy of 71%, 91%, 83%, and 89% respectively. While comparing the models with correctly classified the classes i.e covid, normal and viral pneumonia. The VGG-16 model has more number of correctly diagnosed cases. As well in terms of accuracy VGG-16 gave good accuracy of 91% the models also doesn't seems to be overfit. In order to avoid overfit the model was well balanced as the original data set was imbalanced i.e biased on one category. To evaluate the overfit criteria the accuracy and loss graph were used considering the accuracy graph for VGG-16 model, there are some fluctuations those can be signs of unrepresentative data this can be avoid by adding more data to the training model. In conclusion to this discussion from all the models VGG-16 model outperformed in comparision to accuracy, correctly predicted images and loss as well.

# 7 Conclusion and Future Work

In conclusion to this research, detection of Covid-19 pneumonia at early stage was the main motive of this project. In order to accomplish this research research question, different objective and three stage novel approach were addressed. Considering the first novel approach which is balancing the imbalanced data before model building, considering the section **3.3** the solution for this first approach is resolved. The second approach which is implementing a deep learning and transfer learning model for early diagnose of Covid-19 induced pneumonia from healthy case, so for that section **5** is used to analyze and evaluate each model. Lastly, the third approach is to evaluate and compare all the implemented models by using performance metrics which is discussed in section **6**. So by after careful consideration of all the metric from all the models VGG-16 proved to be best model to correctly diagnose the cases (Covid-19, normal and viral pneumonia). The VGG-16 model gave an accuracy of 91%, by implementing this solution the radiologist and medical expert will able to diagnose Covid-19, Viral pneumonia and Normal cases in the beginning before the infection spread for long time in human body. However, in future studies more data set will be required to work on training a model and to enhance the accuracy. Hyperparameter tuning can also be modified to evaluate a better model. Considering the different deep.

# Acknowledgement

Prof. Hicham Rifai helped and guided throughout implementation of the research project. Prof. Hicham Rifai played an important role and inspired me to complete my research. I would also want to thank my mother and father for their financial support and moral support throughout my masters.

# References

Apostolopoulos, I. D. and Mpesiana, T. A. (2020). Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks, *Physical and Engineering Sciences in Medicine* **43**(2): 635–640.

Aslan, M. F., Unlersen, M. F., Sabanci, K. and Durdu, A. (2021). Cnn-based transfer learning–bilstm network: A novel approach for covid-19 infection detection, *Applied Soft Computing* **98**: 106912.
**URL:** *https://www.sciencedirect.com/science/article/pii/S1568494620308504*

Chowdhury, M. E. H., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M. A., Mahbub, Z. B., Islam, K. R., Khan, M. S., Iqbal, A., Emadi, N. A., Reaz, M. B. I. and Islam, M. T. (2020). Can ai help in screening viral and covid-19 pneumonia?, *IEEE Access* **8**: 132665–132676.

Dutta, P., Roy, T. and Anjum, N. (2021). Covid-19 detection using transfer learning with convolutional neural network, *2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, pp. 429–432.

Guefrechi, S., Jabra, M. B., Ammar, A., Koubaa, A. and Hamam, H. (2021). Deep learning based detection of COVID-19 from chest x-ray images, *Multimedia Tools and Applications* .
**URL:** *https://doi.org/10.1007/s11042-021-11192-5*

Hryniewska, W., Bombiński, P., Szatkowski, P., Tomaszewska, P., Przelaskowski, A. and Biecek, P. (2020). Do not repeat these mistakes – a critical appraisal of applications of explainable artificial intelligence for image based covid-19 detection.

Irmak, E. (2020). A novel deep convolutional neural network model for covid-19 disease detection, *2020 Medical Technologies Congress (TIPTEKNO)*, pp. 1–4.

Liu, J., Zhang, Z., Zu, L., Wang, H. and Zhong, Y. (2020). Intelligent detection for ct image of covid-19 using deep learning, *2020 13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, pp. 76–81.

Maghdid, H. S., Asaad, A. T., Ghafoor, K. Z., Sadiq, A. S., Mirjalili, S. and Khan, M. K. (2021). Diagnosing covid-19 pneumonia from x-ray and ct images using deep learning and transfer learning algorithms, *Multimodal Image Exploitation and Learning 2021*, Vol. 11734, International Society for Optics and Photonics, p. 117340E.

Mei, X., Lee, H.-C., Diao, K.-y., Huang, M., Lin, B., Liu, C., Xie, Z., Ma, Y., Robson, P. M., Chung, M. et al. (2020). Artificial intelligence–enabled rapid diagnosis of patients with covid-19, *Nature medicine* **26**(8): 1224–1228.

Mohammadi, A., Wang, Y., Enshaei, N., Afshar, P., Naderkhani, F., Oikonomou, A., Rafiee, M. J., Oliveira, H. C. R., Yanushkevich, S. and Plataniotis, K. N. (2020). Diagnosis/prognosis of covid-19 images: Challenges, opportunities, and applications.

Musleh, A. A. A. and Maghari, A. Y. (2020). Covid-19 detection in x-ray images using cnn algorithm, *2020 International Conference on Promising Electronic Technologies (ICPET)*, pp. 5–9.

Nayak, S. R., Nayak, D. R., Sinha, U., Arora, V. and Pachori, R. B. (2021). Application of deep learning techniques for detection of covid-19 cases using chest x-ray images: A comprehensive study, *Biomedical Signal Processing and Control* **64**: 102365.
**URL:** *https://www.sciencedirect.com/science/article/pii/S1746809420304717*

Özlem POLAT (2021). Detection of covid-19 from chest CT images using xception architecture: A deep transfer learning based approach, *Sakarya University Journal of Science* **25**(3): 813–823.
**URL:** *https://doi.org/10.16984/saufenbilder.903886*

Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O. and Rajendra Acharya, U. (2020). Automated detection of covid-19 cases using deep neural networks with x-ray images, *Computers in Biology and Medicine* **121**: 103792.
**URL:** *https://www.sciencedirect.com/science/article/pii/S0010482520301621*

*Preventing the spread of the coronavirus* (2020). *Harvard Medical School* .
**URL:** *https://www.health.harvard.edu/diseases-and-conditions/preventing-the-spread-of-the-coronavirus*

Rahman, T., Khandakar, A., Qiblawey, Y., Tahir, A., Kiranyaz, S., Abul Kashem, S. B., Islam, M. T., Al Maadeed, S., Zughaier, S. M., Khan, M. S. and Chowdhury, M. E. (2021). Exploring the effect of image enhancement techniques on covid-19 detection using chest x-ray images, *Computers in Biology and Medicine* **132**: 104319.
**URL:** *https://www.sciencedirect.com/science/article/pii/S001048252100113X*

Reshi, A. A., Rustam, F., Mehmood, A., Alhossan, A., Alrabiah, Z., Ahmad, A., Alsuwailem, H. and Choi, G. S. (2021). An efficient CNN model for COVID-19 disease detection based on x-ray image classification, *Complexity* **2021**: 1–12.
**URL:** *https://doi.org/10.1155/2021/6621607*

Sahinbas, K. and Catak, F. O. (2021). Transfer learning-based convolutional neural network for COVID-19 detection with x-ray images, *Data Science for COVID-19*, Elsevier, pp. 451–466.
**URL:** *https://doi.org/10.1016/b978-0-12-824536-1.00003-4*

Shi, F., Wang, J., Shi, J., Wu, Z., Wang, Q., Tang, Z., He, K., Shi, Y. and Shen, D. (2021). Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for covid-19, *IEEE Reviews in Biomedical Engineering* **14**: 4–15.

Taresh, M. M., Zhu, N., Ali, T. A. A., Hameed, A. S. and Mutar, M. L. (2021). Transfer learning to detect COVID-19 automatically from x-ray images using convolutional neural networks, *International Journal of Biomedical Imaging* **2021**: 1–9.
**URL:** *https://doi.org/10.1155/2021/8828404*

Wang, D., Hu, B., Hu, C., Zhu, F., Liu, X., Zhang, J., Wang, B., Xiang, H., Cheng, Z., Xiong, Y., Zhao, Y., Li, Y., Wang, X. and Peng, Z. (2020). Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China, *JAMA* **323**(11): 1061–1069.
**URL:** *https://doi.org/10.1001/jama.2020.1585*

Zu, Z. Y., Jiang, M. D., Xu, P. P., Chen, W., Ni, Q. Q., Lu, G. M. and Zhang, L. J. (2020). Coronavirus disease 2019 (covid-19): a perspective from china, *Radiology* **296**(2): E15–E25.