Evaluation and Development of Artificial Intelligence tools to Assess COVID-19 Severe Acute Respiratory Syndrome from Chest Imaging

by

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A project report submitted in conformity with the requirements
for the degree of Master's of Science in Information Technology

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2021

Abstract

Chest CT is being more widely used as a diagnostic test for COVID-19 Severe Acute Respiratory Syndrome-related lung disease. Artificial intelligence (AI) has the ability to assist in the rapid assessment of CT scans for COVID-19 Severe Acute Respiratory Syndrome findings from other clinical entities. Here that a group of deep learning algorithms trained on a diverse multinational cohort of 1280 patients to localize parietal lung parenchyma followed by classification of COVID-19 Severe Acute Respiratory Syndrome can achieve up to 90.8 percent accuracy, with 84 percent sensitivity and 93 percent specificity, as measured in an independent test set (not included in training and validation) can achieve up to 90.8 percent accuracy, with 84 percent sensitivity and 93 percent specificity. Chest CTs from oncology, emergency, and pneumonia-related indications were used as normal controls. In 140 patients with laboratory reported other (non COVID-19) pneumonia, the false positive rate was 10 percent. In a variety of patient populations, AI-based algorithms can quickly differentiate CT scans with COVID-19 induced pneumonia, as well as distinguish non-COVID related Severe Acute Respiratory Syndrome from chest imaging with high specificity.

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Chapter 1

Introduction

Coronavirus Disease in the Year 2019 (COVID-19) Severe Acute Respiratory Syndrome has spread across the world at an alarming rate, with a propagation mechanism that is still unknown. The virus is most often carried with little to no symptoms, but in 2–8 of those infected, it can cause a rapidly progressive and often fatal pneumonia. Because of the particular challenges posed by SARS-CoV-2 infection, such as peak infectiousness at or just before symptom onset and a poorly understood multi-organ pathophysiology with dominant features and lethality in the lungs, the exact mortality, incidence, and transmission dynamics are still unknown. The rapid spread has put a strain on healthcare systems around the world, partly due to a lack of key protective equipment and skilled providers, and partly due to varying access to point-of-care testing methodologies, such as reverse transcription polymerase chain reaction (RT-PCR). As rapid RT-PCR testing becomes more widely available, challenges such as high false negative rates, processing delays, test technique variability, and sensitivity as low as 60–70 remain.

Computed tomography (CT) is a test that offers an insight into pathophysiology and can reveal information about disease diagnosis and progression at various stages. Although rapid diagnosis of COVID-19 Severe Acute Respiratory Syndrome continues to be a challenge, frontline radiologists confirm a pattern of infection that is quite common, with ground glass opacities in the lung periphery, rounded opacities, expanded intra-infiltrate vessels, and later more consolidations that are a sign of advancing critical illness.

Although CT and RT-PCR are always in agreement, CT can also detect early COVID-19 Severe Acute Respiratory Syndrome in patients who have a negative RT-PCR test, in patients who have no symptoms, or in patients who have symptoms before or after they develop. Multiple centers in Wuhan, China, and northern Italy have used CT scans as part of the initial assessment of patients with suspected or confirmed COVID-19 Severe Acute Respiratory Syndrome. A recent international expert consensus study recommends the use of chest CT for COVID-19 patients with deteriorating respiratory status or in resource-limited settings for medical triage of patients with moderate–serious clinical features and a high pretest risk of COVID-19 Severe Acute Respiratory Syndrome.

A recent international expert consensus study recommends the use of chest CT for COVID-19 patients with deteriorating respiratory status or in resource-limited settings for medical triage of patients with moderate–serious clinical features and a high pretest risk of COVID-19 Severe Acute Respiratory Syndrome. Artificial intelligence (AI) approaches for the identification or characterization of COVID-19 Severe Acute Respiratory Syndrome on imaging may have a role due to the rapid rise in the number of new and suspected COVID-19 Severe Acute Respiratory Syndrome cases.

CT provides a transparent and fast window into this method, and deep learning of broad multinational CT data could provide automated and repeatable biomarkers for COVID-19 Severe Acute Respiratory Syndrome disease classification and quantification. AI has previously been shown to be capable of detecting COVID-19 infection or even distinguishing it from community-acquired pneumonia in single-center studies. Due to the homogeneity of data sources, AI models are often constrained in their applicability to other cultures, demographics, or geographies. Using data from a globally diverse, multi-institution dataset, this research aims to build and test an AI algorithm for the detection of COVID-19 Severe Acute Respiratory Syndrome on chest CT. We show that robust models can achieve up to 90 accuracy in independent test populations, have high specificity in non-COVID-19 associated pneumonias, and have adequate generalizability to unknown patient populations/centers. [1]

1.1 Background

The COVID-19 epidemic continues to have a terrible impact on the global population's health and well-being. Effective screening of infected patients is a significant step in the fight against COVID-19, with radiology evaluation employing chest radiography being one of the primary screening modalities. Early research discovered that patients with COVID-19 infection have anomalies in chest radiography imaging. Motivated by this and inspired by the scientific community's open source efforts, we present COVID-Net, an open source and publicly available deep convolutional neural network architecture optimized for the detection of COVID-19 cases from chest X-ray (CXR) pictures. We also introduce COVIDx, an open-access benchmark dataset made up of 13,975 CXR images from 13,870 patient cases, with the biggest number of publicly available COVID-19 positive cases to the authors' knowledge. Furthermore, we use an explain ability method to investigate how COVID-Net makes predictions in order to not only gain deeper insights into critical factors associated with COVID cases, which can aid clinicians in better screening, but also to audit COVID-Net in a responsible and transparent manner to validate that it is making decisions based on relevant information from the CXR images. While the open access COVID-Net, as well as the description on how to build the open source COVIDx dataset, is far from a production-ready solution, the hope is that it will be leveraged and built upon by both researchers and citizen data scientists to speed the development of highly accurate yet practical deep learning solutions for detecting COVID-19 cases and accelerating treatment who need it the most.

1.2 Problem Statement

Because X-ray machines are widely available, scans are relatively inexpensive, and are ubiquitous in both emergency and rural hospital settings, the chest X-ray (CXR) has taken center stage as a frontline diagnostic test, despite being less sensitive to detect the lung pathology caused by the coronavirus. It may be placed on a mobile platform, is very simple to disinfect, and is one of the most cost-effective ways to deal with an epidemic. But through X-ray the results are not completely accurate.

1.3 State of the art

Tulin ozturk demonstrates the COVID-19 epidemic continues to have a dramatic effect on the worldwide population's health and well-being. Effective screening of infected individuals is a vital step in the battle against COVID-19, with radiology evaluation utilizing chest radiography being one of the major screening techniques. It is important to discover positive cases as soon as possible in order to prevent the pandemic from spreading further and to treat afflicted individuals as promptly as feasible. Because there are no accurate automated toolkits accessible, the demand for supplementary diagnostic tools has grown. According to recent results acquired utilizing radiological imaging methods, such pictures offer important information about the COVID-19 virus. Advanced artificial intelligence (AI) techniques combined with radiological imaging can aid with accurate illness identification and can also help address the problem of a shortage of specialist physicians in rural communities.

Md. Rezaul Karim explains humanity is seeing a significant increase in infection levels throughout the world as a result of the coronavirus illness (COVID-19) pandemic. The efficient screening of incoming patients is a challenge hospitals face in the battle against the virus. One technique is to examine chest radiography (CXR) pictures, which generally necessitates the expertise of a radiology specialist. In this study, we provide 'DeepCOVIDExplainer,' an explainable deep neural networks (DNN)-based approach for automated identification of COVID-19 symptoms from CXR pictures. We analyzed 15,959 CXR pictures from 15,854 individuals, with normal, pneumonia, and COVID-19 cases included. CXR pictures are first thoroughly preprocessed, then augmented and categorized using a neural ensemble approach, with gradient-guided class activation maps (Grad-CAM++) and layer-wise relevance propagation used to highlight class-discriminating areas (LRP). We also give human-friendly explanations for the forecasts. With a positive predictive value (PPV) of 91.6 percent, 92.45 percent, and 96.12 percent, respectively, for normal, pneumonia, and COVID-19 cases, and precision, recall, and F1 score of 94.6 percent, 94.3 percent, and 94.6 percent, respectively, for normal, pneumonia, and COVID-19 cases, our approach can confidently identify COVID-19.

Parnian Afshar illustrates COVID-19 diagnosis, reverse transcription-polymerase chain reaction (RT-PCR) is currently the gold standard. It can take days to get a diagnosis, and the risk of false negatives is rather significant. Imaging, namely chest computed tomography (CT), can aid in the diagnosis and evaluation of this illness. Nonetheless, it has been demonstrated that a conventional dosage CT scan exposes patients to a substantial amount of radiation, particularly those who require several scans. In this research, we look at low-dose and ultra-low-dose (LDCT and ULDCT) scan procedures that minimize radiation exposure to levels comparable to a single X-Ray while retaining a high enough resolution for diagnosis. We construct an Artificial Intelligence (AI)-based framework utilizing a gathered dataset of LDCT/ULDCT scans to test the hypothesis that the AI model can give human-level performance during the pandemic, because thoracic radiology knowledge may not be widely available during the pandemic. Utilizing LDCT/ULDCT images, the AI model can quickly classify COVID-19, community acquired pneumonia (CAP), and normal patients using a two-stage capsule network design.

Mohammad Rahimzadeh says that the COVID-19 is a serious worldwide issue that has crippled numerous businesses and killed a large number of people all over the world. One of the most important strategies to reduce casualties is to identify sick people at the right moment. AI can play a big part in these situations by monitoring and recognizing sick people early on, which can benefit a lot of companies. We want to offer a completely automated technique for detecting COVID-19 from a patient's CT scan without the requirement for a clinical technician in this article. We provide a new dataset of 48260 CT scan pictures from 282 healthy people and 15589 images from 95 COVID-19 patients. Our proposed network uses all of a patient's CT scan image sequences as input to assess whether or not the patient is infected with COVID-19. In the first level, this network employs an image processing technique to exclude CT pictures in which the interior of the lung is not clearly apparent. This helps to reduce the amount of pictures that need to be classified as normal or COVID-19, which cuts down on processing time. Additionally, using this method causes the deep network to evaluate just the correct pictures in the following step, reducing false detections. We present a modified version of ResNet50V2 that is augmented by a feature pyramid network for categorizing selected CT images into COVID-19 or normal in the following step. The network considers a patient infected with COVID-19 if a sufficient number of CT scan pictures of that patient are recognized as COVID-19. On more than 7996 validation pictures, the ResNet50V2 with feature pyramid network obtained 98.49 percent accuracy and successfully recognized almost 237 patients out of 245 patients.

1.4 Contribution of this thesis

The contribution of this thesis is as follows:

- This study implemented different deep learning algorithms such as Convolutional Neural Network, AlexNet, GoogleNet, Transfer Learning, VGG16, ResNet, MobileNet, InceptionV3, SegNet, Siamese and Generative adversarial network for COVID induced pneumonia detection from chest-Xray imaging.

- Experimental results demonstrated that severqal deep learning models can successfully (accuracy is greater than 90 percent) detect COVID induced pneumonia from chest-Xray imaging which is as close as Human expert.

- Chest-Xray imaging equipped with deep learning algorithms are as successful as chest CT scan for detecting COVID induced pneumonia. However CT scan is very expensive and it needs expert tecqnicians to process and radiologist to analyse which is rarely available in the rural hospital setting. On the other hand, Chest-Xray is very cheap and available in almost every hospital.

1.5 Organization of this thesis

This thesis is organized in five chapters. The chapter 1 provides an overview of general background, problem setting, state of art, contribution and organization of the thesis in chest Xray and CT scan. The chapter 2 describes the previous work and the major contributions in briefly about chestXray and CT scan using deep learning. The chapter 3 illustartes some of the models and its pros and cons of each and every model completely. The chapter 4 explains the results and discussions like about the dataset used for two class and three class. Fianlly chapter 5 is for conclusion and Future work of the research based on Evaluation and Development of Artificial Intelligence tools to Assess COVID-19 Severe Acute Respiratory Syndrome from Chest Imaging.

Chapter 2

Literature Review

2.1 ChestXray using deep learning

Matthew P.Cheng [2] explains the global pandemic of COVID-19, which began in late 2019, requires diagnostic testing to identify people infected with severe acute respiratory syndrome–related coronavirus 2 (SARS-CoV-2). Diagnostic testing on a large scale has been a cornerstone of successful containment methods in a few nations. In contrast, due to limited testing capacity, the United States has prioritised testing for specific groups of people. The reference standard for COVID-19 diagnostics is real-time reverse transcriptase polymerase chain reaction–based assays performed in a laboratory on respiratory specimens. Point-of-care technologies and serologic immunoassays, on the other hand, are fast gaining popularity. Although there are excellent tools for diagnosing symptomatic patients in well-equipped laboratories, there are significant gaps in screening asymptomatic people during the incubation phase, as well as accurately determining live viral shedding during convalescence to inform decisions about when to end isolation.Many wealthy countries have faced difficulties with test delivery and specimen collecting, preventing rapid expansion of testing capacity. In low-resource environments, these obstacles may be substantially larger.

Md. Mohaimenul Islam, Tahmina Nasrin Poly [3] discussed about the Artificial intelligence (AI) has showed tremendous promise in combating COVID-19 in a variety of methods. This research primarily focuses on AI's role in managing COVID-19 using digital imaging, clinical and laboratory data analysis, and a review of the most recent studies published in the previous year. Investigated the use of artificial intelligence (AI) for COVID-19 detection, screening, diagnosis, severity progression, mortality, drug repurposing, and other tasks. We began with a technical overview of all COVID-19 pandemic models and concluded with a quick statement of the present state-of-the-art, limitations, and problems.

Keelin Murphy, Henk Smits [4] explains about the background Particularly in low-resource settings, chest radiography (CXR) may play a key role in COVID-19 triage. Purpose The goal of this study was to see how well an artificial intelligence (AI) system could detect COVID-19 pneumonia on chest radiographs. Methods A machine learning system (CAD4COVID-Xray) was trained on 24,678 CXR images, with 1,540 utilised solely for validation. The test set comprised of 454 continuously acquired CXR pictures obtained in patients suspected of COVID-19 pneumonia in a single center between March 4th and April 6th 2020. (223 RT-PCR positive subjects, 231 RT-PCR negative subjects). Six readers and the AI system independently assessed the radiographs. Six readers and the AI system independently assessed the radiographs. Receiver operating characteristic curve analysis was used to assess diagnostic performance. With an AUC of 0.81, the AI system successfully identified CXR images as COVID-19 pneumonia using RT-PCR test findings as the reference standard. At their maximum sensitivities, the system considerably outperforms each reader (p 0.001 using McNemar test). Only one reader can significantly surpass the AI system at its lowest sensitivity (p=0.04). Conclusions Six independent readers were compared to an AI system for detecting COVID-19 on chest radiographs.

Seyed Hamid Safiabadi Tali, LeBlanc [5] explains about the coronavirus disease 2019 (COVID-19) pandemic, which was caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) virus, has resulted in millions of confirmed cases and deaths around the world. Rapid and large-scale testing is critical in patient management and slowing disease spread, hence efficient diagnostic instruments are in great demand. This study examines current SARS-CoV-2 detection technologies in clinical laboratories, as well as breakthroughs in molecular, antigen-based, and immunological point-of-care testing, as well as recent sensor and biosensor device developments. The importance of specimen collection time and kind, as well as issues such as illness prevalence, setting, and procedures, are methods. The mechanisms of action of the various approaches, as well as their application span and known performance characteristics, are given in detail. The use of diagnostic imaging tools and biomarkers for measuring COVID-19 or monitoring disease severity or consequences is also covered.

Yun Chen, Gongfa Jiang [6] explains that As of June 24, 2020, the coronavirus illness 2019 (COVID-19) had infected over 9.3 million individuals and killed over 0.47 million people over the world. COVID-19 diagnosis and management need the use of chest imaging techniques such as computed tomography and X-ray images. The disease's high infectiousness places a significant load on radiologists. Artificial intelligence (AI)-based imaging analysis technologies are being investigated in attempt to overcome the challenge and increase the accuracy of the diagnosis. The advancement of chest imaging analysis approaches based on AI for COVID-19 in the last few months is the topic of this survey. In this paper, the research begin by recalling the imaging analysis methods of two common viral pneumonias, which can be used as a guide while evaluating the disease on chest images. The research go on to detail the evolution of AI-assisted disease diagnosis and assessment, and we discover that AI approaches are extremely useful in this application.

Andrew A. Borkowski, MD; Narayan A [7] discussed about Coronavirus disease-19 (COVID-19) is a respiratory disease caused by an unique member of the coronavirus family that quickly spread to pandemic proportions with substantial morbidity and mortality. It has had a significant impact on society and global economies in just a few months. COVID-19 has posed a number of obstacles to many elements of health care, including the development of reliable diagnostic, treatment, and prevention strategies. The time it took to develop reliable diagnostic procedures impeded early efforts to stop the virus from spreading. Artificial intelligence (AI) is a fast expanding subject of computer science with numerous health-care applications. Deep learning and neural network methods are used in machine learning, which is a subset of AI. It is capable of recognising patterns and doing difficult computing operations significantly more quickly and precisely than humans.

Buddhisha Udugama, Pranav Kadhiresan [8] illustrates its discovery in Hubei Province, China, in December 2019, COVID-19 has spread throughout the world. SARS-CoV-2, the viral etiology of COVID-19, was first identified using a combination of computed tomography imaging, whole genome sequencing, and electron microscopy. The purpose of this review article is to provide information about SARS-CoV-2 diagnostic and surveillance technologies as well as their performance characteristics to the general public. We discuss upcoming point-of-care diagnostics and encourage academics to take their ideas beyond the prototype stage.To handle the SARS-CoV-2 outbreak, using plug-and-play diagnostics would be beneficial in averting future epidemics.

Ahmed T. Sahlol [9] stated the rapid spread of the new Corona virus, COVID-19, which causes deadly symptoms in humans and animals and can lead to death if complications are not addressed. Convolutional neural networks (CNNs) are the current state-of-the-art image classification approach, but they require a lot of computing power to deploy and train. The strengths of CNNs (using a powerful architecture called Inception) to extract features and a swarm-based feature selection algorithm (Marine Predators Algorithm) to select the most relevant features are combined in this paper to propose an improved hybrid classification approach for COVID-19 images. The integration of fractional-order and marine predators algorithms (FO-MPA) is regarded as a robust tool in mathematics known as fractional-order calculus (FO). The proposed method was tested on two public COVID-19 X-ray datasets and found to be effective in terms of both performance and computational complexity reduction. The two datasets are made up of X-ray COVID-19 images submitted on Kaggle by international cardiothoracic radiologist, researchers, and others. The suggested method effectively chose 130 and 86 out of 51 K features retrieved by inception from dataset 1 and dataset 2, respectively, while also boosting classification accuracy. When compared to a collection of contemporary feature selection methods, the results are the best on these datasets. The proposed approach beats multiple CNNs and all current research on COVID-19 pictures, attaining 98.7 percent, 98.2 percent, and 99.6 percent, 99 percent classification accuracy and F-Score for dataset 1 and dataset 2, respectively.

Caio B. S. Maior [10] discussed regarding SARS-CoV-2 has spread so swiftly over the world, scientists have focused their efforts on better understanding the virus's features and potential methods for preventing, diagnosing, and treating COVID-19. Using convolutional neural networks to construct an image-based method to enable COVID-19 diagnosis is a valid approach discussed in the literature (CNN). Due to the novelty of COVID-19, the availability of radiological data is limited. As a result, numerous techniques use reduced datasets, which may be inadequate and bias the model. We used chest X-ray pictures from free datasets to run an analysis using six distinct databases to distinguish images of infected individuals while distinguishing COVID-19 and pneumonia from 'no-findings'. We also presented binary classification with a precision of 91.0 percent for sick patient detection (i.e., COVID-19 or pneumonia) and 98.4 percent for COVID-19 detection (i.e., distinguishing from 'no-findings' or 'pneumonia'). As a result, this system appears to be promising for a low-cost, quick, and noninvasive method of supporting COVID-19 diagnosis.

2.2 CT using deep learning

Cheng Jin, Weixiang Chen, Yukun Cao [2] illustrates the COVID-19 diagnosis using chest CT allows patients to receive timely therapy and helps control the disease's spread. We devised an artificial intelligence (AI) method for quick COVID-19 detection and used the AI system to undertake extensive statistical analysis of COVID-19 CTs. We used a huge dataset of over 10,000 CT volumes from COVID-19, influenza-A/B, non-viral community acquired pneumonia (CAP), and non-pneumonia individiduals to build and test our approach. Our deep convolutional neural network-based system achieves an area under the receiver operating characteristic curve (AUC) of 97.81 percent for multi-way classification on a test cohort of 3,199 scans, and AUCs of 92.99 percent and 93.25 percent on two publicly available datasets, CC-CCII and MosMedData, respectively, in such a difficult multi-class diagnosis task. At a reader study including five radiologists, the AI system outperformed all of the radiologists in more difficult tasks by two orders of magnitude. The diagnostic performance of a chest x-ray (CXR) is compared to that of a computed tomography (CT). Deep network interpretation is also done in detail to correlate system outputs with CT presentations.

Stephanie A. Harmon, Thomas H. Sanford, Peng An, Bradford J. Wood, Baris Turkbey [1] explains that the chest CT is proving to be a useful diagnostic technique in the treatment of COVID-19-related lung illness. Artificial intelligence (AI) has the potential to help with the quick examination of CT scans for COVID-19 findings distinction from other clinical entities. We show here that a set of deep learning algorithms trained in a diverse multinational cohort of 1280 patients to localize parietal pleura/lung parenchyma followed by classification of COVID-19 pneumonia can achieve up to 90.8 percent accuracy, with 84 percent sensitivity and 93 percent specificity, as measured in an independent test set of 1337 patients. Chest CTs from oncology, emergency, and pneumonia-related causes were used as normal controls. In 140 patients with laboratory confirmed other (non COVID-19) pneumonias, the false positive rate was 10 percent. In a variety of patient demographics, AI-based algorithms can quickly detect CT scans with COVID-19 linked pneumonia, as well as discriminate non-COVID related pneumonias with high specificity.

María Dolores Corbacho Abelaira [11] determines the SARS-Cov-2-caused coronavirus disease is a global pandemic with millions of verified cases and a significant mortality toll. The real-time polymerase chain reaction (RT-PCR) is currently the gold standard for detecting COVID-19 infection. Several failures in the detection of the disease using laboratory samples have raised questions regarding the infection's characterization and transmission of contacts. Chest radiography (RT) and chest computed tomography (CT) are particularly useful in clinical practice and have been routinely utilised to detect and diagnose COVID-19. Although RT is the most popular and widely available diagnostic imaging technology, it is read by less qualified professionals, who are often overworked, resulting in a significant number of errors. Triage, diagnosis, and assessment of severity, progression, and response to treatment can all be done with a chest CT scan. Currently, artificial intelligence (AI) systems in image categorization have showed promise, demonstrating that they can reduce diagnostic errors by at least matching radiologists' diagnostic performance.

Ilker Ozsahin, Boran Sekeroglu [12] illustrates the COVID-19 diagnostic technique can be classified into two categories: laboratory-based and chest radiography-based. The number of research using artificial intelligence (AI) techniques to diagnose COVID-19 using chest computed tomography has exploded in recent months (CT). In this work, we look at how chest CT can be used to diagnose COVID-19 in the context of AI. We used the terms "deep learning," "neural networks," "COVID-19," and "chest CT" to search ArXiv, MedRxiv, and Google Scholar. There were over 100 studies at the time of writing (August 24, 2020), and 30 of them were chosen for this review. COVID-19/normal, COVID-19/non-COVID-19, COVID-19/non-COVID-19 pneumonia, and severity were the categories used to categorize the investigations. The findings were presented for sensitivity, specificity, precision, accuracy, area under the curve, and F1 score.

Shigao Huang, Jie Yang, Simon Fong and Qi Zhao [13] focussed on Artificial intelligence (AI) is being utilized to help with epidemiology, molecular research and medication development, medical diagnosis and therapy, and socioeconomics in the COVID-19 problem. The combination of AI and COVID-19 can help doctors diagnose positive patients more quickly. We searched the literature using various academic databases (PubMed, PubMed Central, Scopus, Google Scholar) and preprint sites to learn about the dynamics of a pandemic relevant to AI (bioRxiv, medRxiv, arXiv). The clinical applications of machine learning and deep learning in the COVID-19 diagnosis are discussed in this review, which includes clinical features, electronic medical records, and medical pictures (CT, X-ray, ultrasound images, and so on). This review's current issues and future perspectives can be utilised to guide an ideal deployment of AI technology in a pandemic.

Cheng Jin, Weixiang Chen [8] explains early identification of COVID-19 via a chest CT allows patients to receive timely therapy and h elps restrict the disease's spread. We devised an artificial intelligence (AI) method for quick COVID-19 detection and used the AI system to undertake extensive statistical analysis of COVID-19 CTs. We used a large dataset with over 10,000 CT volumes from COVID-19, influenza-A/B, non-viral community acquired pneumonia (CAP), and non-pneumonia individuals to build and test our approach.Our deep convolutional neural network-based system achieves an area under the receiver operating characteristic curve (AUC) of 97.81 percent for multi-way classification on a test cohort of 3,199 scans, and AUCs of 92.99 percent and 93.25 percent on two publicly available datasets, CC-CCII and MosMedData, respectively, in such a difficult multi-class diagnosis task. The diagnostic performance of a chest x-ray (CXR) is compared to that of (CT). Deep network interpretation is also done in detail to correlate system outputs with CT presentations.

Parnian Afshar [14] discussed about its discovery in late 2019, the novel Coronavirus (COVID-19) has ravaged more than 200 countries, infecting millions of people and taking nearly 2 million lives. This extremely contagious disease spreads quickly and, if not managed quickly, can render healthcare systems inoperable. The current gold standard for diagnosis, the Reverse Transcription Polymerase Chain Reaction (RT-PCR), is time-consuming and has a low sensitivity. The first imaging modality to be employed was the chest radiograph (CXR), which is widely available and provides quick results. The current gold standard for diagnosis, the Reverse Transcription Polymerase Chain Reaction (RT-PCR), is time-consuming and has a low sensitivity. The first imaging modality to be employed was the chest radiograph (CXR), which is widely available and provides quick results. Its sensitivity, on the other hand, is famously lower than that of computed tomography (CT), which can be used to supplement other diagnostic procedures effectively. This research introduces COVID-CT-MD, a novel COVID-19 CT scan dataset that includes not only COVID-19 cases, but also healthy and Community Acquired Pneumonia infected participants (CAP). The COVID-CT-MD dataset, which includes lobe-level, slice-level, and patient-level labels, has the potential to aid COVID-19 research. COVID-CT-MD, in particular, can aid in the development of advanced Machine Learning (ML) and Deep Neural Network (DNN) based solutions.

Chapter 3

Deep learning based models

3.1 CNN

Due to its relatively low radiation dose, ease of access, practicality, low pricing, and speedy imaging process, X-ray units have become one of the most beneficial alternatives for triaging the novel Coronavirus disease COVID-19 infected individuals. The goal of this study was to create a reliable convolutional neural network (CNN) model for COVID-19 classification from chest X-ray pictures. It also aims to avoid bias issues caused by the database. Pre-trained architectures, such as DenseNet-201, ResNet-18, and SqueezeNet, used a total of 1,218 chest X-ray images (CXIs) consisting of 368 COVID-19 pneumonia and 850 additional pneumonia cases to construct a transfer learning-based CNN model. The chest X-ray images were obtained from publically accessible databases, and each image was carefully chosen to avoid any potential bias.

To avoid overfitting concerns, a stratified 5-fold cross-validation strategy was adopted, with a ratio of 90 percent for training and 10 percent for testing (unseen folds), and 20 percent of training data was employed as a validation set. The suggested CNN models' binary classification performance was assessed using the testing data. The activation mapping method was used to improve the radiograph's causality and visuality. The results showed that the suggested CNN model based on the DenseNet-201 architecture beat the others, with accuracy, precision, recall, and F1-scores of 94.96 percent, 89.74 percent, 94.59 percent, and 92.11 percent, respectively, outperforming the others. The findings showed that using the CNN model to reliably diagnose COVID-19 pneumonia from CXIs opens the way to accelerating triage, saving important time, and prioritizing resources, in addition to supporting radiologists.

The key to controlling and avoiding the spread of COVID-19 is early and prompt diagnosis, as well as speedier triaging. As a result, the development of time-efficient diagnostic techniques appears to be critical for early disease identification, treatment, and pandemic isolation. Artificial intelligence-based smart models have risen to popularity among traditional methodologies due to their advantages in terms of accuracy, speed, and ease of application. Using the CXIs to categorize COVID-19 pneumonia has several important advantages, including a lower radiation dose than computer tomography, the ability to be practical and accessible, and the fact that it is cost-neutral. CXIs are also less expensive than CT scans and have convenient access. However, because CXIs include only a few distinctive symptoms ascribed to COVID-19 pneumonia, detecting COVID-19 via CXIs rather than chest CT scans is more difficult. As a result, using an artificial intelligence-based algorithm to classify COVID-19 from chest X-ray views is critical.

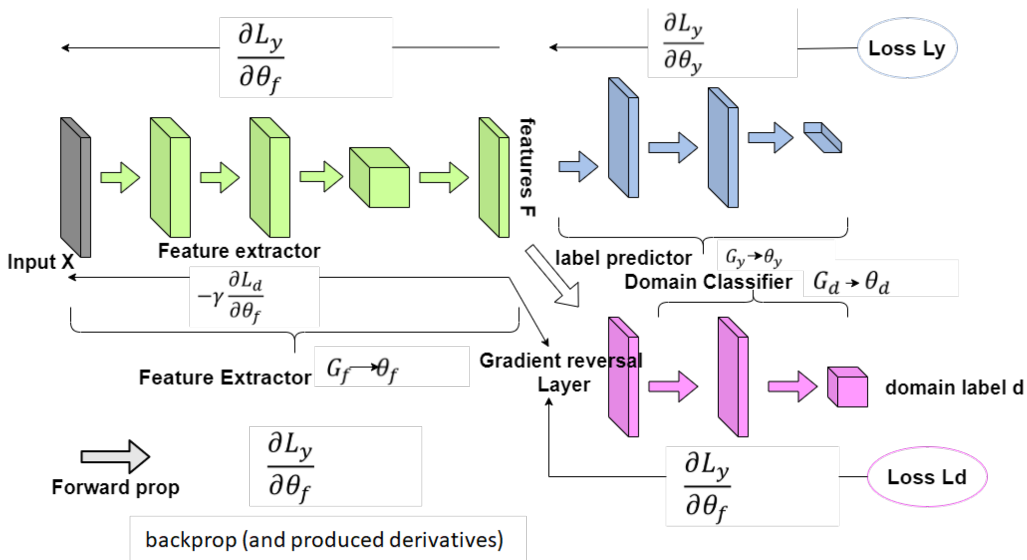

Figure 3.1: Evolvable Neural Turing Machines

By detecting pathognomonic characteristics like consolidation regions and nodular opacities, machine learning algorithms can accurately diagnosis COVID-19 pneumonia. The proposed deep learning-based models are critical for providing early and effective treatment as well as preventing the spread of disease. However, the most important point to note is that the majority of them employed identical publicly available information to train the model, resulting in a bias problem due to the small amount of COVID-19 cases. COVID-19 radiographic images acquired from the publications were used to construct chest radiographs in some datasets. They even contain lossy-images because the writers have previously altered image attributes such as brightness, contrast, sharpness, and so on. As a result, it's possible that the works based on these datasets are biassed, resulting in unreliable superb accuracy figures. The majority of the published CNN models have a classification accuracy of 93–99 percent. Furthermore, it was noted that some of the work employed radiological pictures from various age groups, such as children and the elderly. It can be predicted that it'll also generate a bias issue. [15]

3.2 VGG-16

The VGG is divided into two architectures: VGG-16, which has 16 layers, and VGG-19, which has 19 layers. VGG-16, which is made up of three parts: convolution, pooling, and fully connected layers. It begins with two convolution layers followed by pooling, then another two convolutions followed by pooling, then three convolutions followed by pooling, and finally three fully connected layers. The architecture of the VGG-16 model is depicted in the diagram below. The most intriguing aspect of the VGG model is that the model weights are available on a variety of platforms (for example, Keras) and may be utilised for additional analysis, as well as constructing models and applications. The concept of transfer learning is born from the idea of using model weights for future tasks.

One of the most suited models for CXR picture categorization is a deep learning model that combines the VGG-16 and the attention module. Our suggested model can capture more likely deteriorating regions in both local and global levels of CXR pictures because it combines attention and convolution module (4th pooling layer) on VGG-16.

We use the attention module to record the relationship between CXR picture ROIs for enhanced CXR image discrimination. Because we use the 4th pooling layer, our proposed approach requires less parameters. The suggested deep learning model can be trained from start to finish, eliminating the need for a separate classifier for training and testing. Three COVID-19 CXR datasets are used to test our model. We also use CXR pictures to conduct a qualitative and quantitative analysis of our method. Our model outperforms state-of-the-art approaches, according to the evaluation results. [16]

3.3 Pros and Cons

Pros of Convolutional Neural Network:

1.When orthology is important, or you're working with characters like emojis or bytes, this is the font to use.

2.ideal for brief texts (e.g., headlines)

3.By adding a linear layer after the pooling layer, you can most certainly improve your text classification model cnn. [17]

Cons of Convolutional Neural Network: High-dimensional data since convolutional neural networks are commonly employed for picture categorization (images). While the topology of a ConvNet is designed to prevent overfitting, a convolutional neural network requires a huge amount of input to perform properly. Of course, the amount of data you require is determined by the task's difficulty.

Training a convolutional neural network takes a long time, especially with huge datasets. To speed up the training process, you'll usually require specialised hardware (such as a GPU).

While CNNs are translation-invariant, they struggle with rotation and scale-invariance unless data is supplemented explicitly.[18]

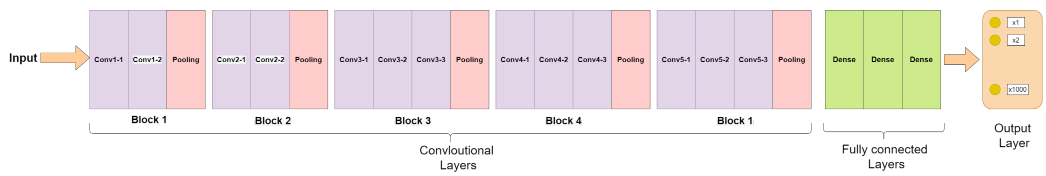

Figure 3.2: VGG16 model Architecture

3.4 Transfer Learning

A real-time polymerase chain reaction is the most extensively used new coronavirus (COVID-19) detection tool (RT-PCR). RT-PCR kits, on the other hand, are expensive and require 6-9 hours to confirm infection in a patient. Because RT-PCR has a low sensitivity, it produces a lot of false-negative results.

Radiological imaging techniques such as chest X-rays and computed tomography (CT) are utilized to detect and diagnose COVID-19 to tackle this problem. Chest X-rays are favoured over CT scans in this article. The reason for this is that X-ray machines can be found in almost all hospitals. X-ray machines are less expensive than CT scanners. Furthermore, X-rays emit fewer ionizing radiations than CT scans. COVID-19 identifies a number of radiological signatures that can be easily recognized using chest X-rays. This necessitates the use of radiologists to examine these signals. It is, however, a time-consuming and error-prone process. As a result, the analysis of chest X-rays must be automated. Deep learning-based algorithms can be used to automatically analyze chest X-rays, potentially reducing processing time. These methods can train network weights on big datasets as well as fine-tune pre-trained network weights on small datasets. These methods are, however, rather limited when it comes to chest X-rays. As a result, the major goal of this research is to use the extreme form of the Inception (Xception) model to construct an automated deep transfer learning-based strategy for detecting COVID-19 infection in chest X-rays. Extensive comparison analyses reveal that the proposed model outperforms existing models by a wide margin. [19]

3.5 Pros and Cons

pros: The reuse of a previously learned model on a new problem is known as transfer learning. It's particularly popular in deep learning right now since it can train deep neural networks with a small amount of data. This is particularly valuable in the field of data science, as most real-world situations do not require millions of labelled data points to train complicated models. [20] **Cons:** Your training data should have two alternatives whenever you apply transfer learning. To begin with, the distribution of the training data utilized by your pre-trained model should be similar to the data you will encounter during test time, or at the very least not fluctuate too much. Second, the number of training data for transfer learning should be calculated in such a way that the model is not overfit.

To limit the amount of parameters, can't eliminate layers with assurance. Because of the nature of the architecture, which detects low-level features, removing the convolutional layers from the first layers will result in poor learning. Furthermore, removing the first layers will cause issues with your dense layers because the amount of trainable parameters will change. Densely coupled layers and deep convolutional layers can be good places to cut, but it may take some effort to figure out how many layers and neurons to cut to avoid overfitting. [21]

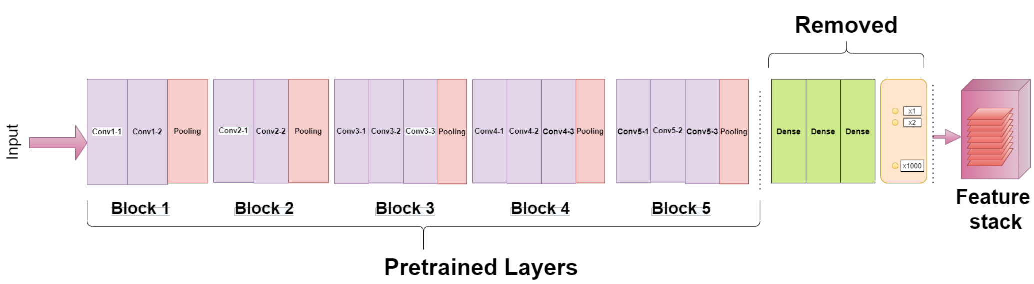

Figure 3.3: Transfer Learning

3.6 AlexNet

Eight layers make up the architecture: five convolutional layers and three fully linked layers. But that isn't what distinguishes AlexNet; here are some of the traits that are unique to convolutional neural networks:

ReLU Nonlinearity: Instead of the tanh function, which was typical at the time, AlexNet employs Rectified Linear Units (ReLU). The benefit of ReLU is in training time; using the CIFAR-10 dataset, a CNN using ReLU was able to reach a 25 percent error six times faster than a CNN using tanh.

Multiple GPUs: Back in the day, graphics processing units (GPUs) had 3 gigabytes of memory (nowadays those kinds of memory would be rookie numbers). This was made worse by the fact that the training set had 1.2 million images. By keeping half of the model's neurons on one GPU and the other half on another GPU, AlexNet enables for multi-GPU training. This not only allows for the training of a larger model, but it also reduces the training time.

Overlapping Pooling: The outputs of adjoining groups of neurons are generally "pooled" in CNNs. When the scientists added overlap, however, they detected a 0.5 percent drop in error and discovered that models with overlapping pooling are more difficult to overfit. [22]

3.7 Pros and Cons of AlexNet:

Pros of Alexnet: 1. AlexNet was the first large CNN model to train using GPUs. This resulted in models being trained more quickly. 2. AlexNet has a deeper architecture with eight layers, which implies it can extract more features than LeNet. It also worked well with colour photographs at the time. 3. There are two advantages to using the ReLu activation function in this network. Unlike other activation functions, it does not limit the output. This indicates that there isn't much of a loss of characteristics. 4. It is the summation of gradients' negative output that is negated, not the dataset itself. Because not all perceptrons are active, this will enhance model training speed even further. **Cons of AlexNet:** 1. This model has a low depth compared to the other models in this post, therefore it has a hard time learning features from image sets. 2. In comparison to future models, we can see that achieving higher accuracy results takes longer. [23]

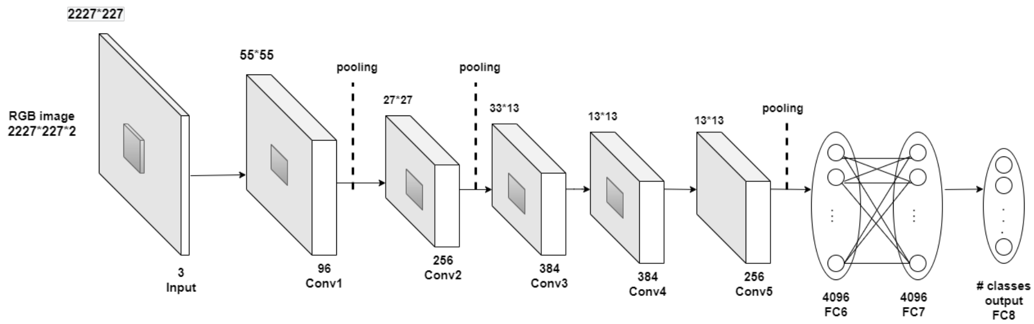

Figure 3.4: AlexNet

3.8 ResNet

ResNet, short for Residual Networks, is a well-known neural network that serves as the foundation for many computer vision tasks. In 2015, this model was the winner of the ImageNet challenge. ResNet was a game-changer because it allowed us to successfully train extraordinarily deep neural networks with 150+ layers. Due to the problem of vanishing gradients, training very deep neural networks was difficult before ResNet. AlexNet, the ImageNet 2012 victor and the model that appears to have sparked the interest in deep learning, had just eight convolutional layers, while the VGG network had 19, Inception or GoogleNet had 22, and ResNet 152 had 152. In this, code a ResNet-50, a smaller version of ResNet 152 that's widely used as a starting point for transfer learning, in this blog.[24]

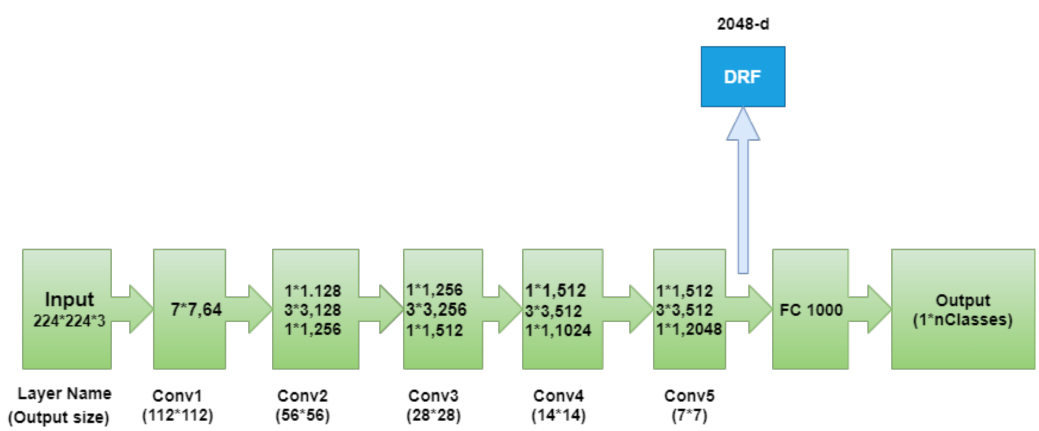

Figure 3.5: ResNet

3.9 Pros and Cons of ResNet:

Pros of ResNet: 1.Every epoch, the ResNet architecture does not need to fire all neurons. This cuts training time in half and enhances accuracy. It does not attempt to learn a feature again once it has been learned, instead focusing on learning fresh features. 2.The degradation problem was caused by the complexity of an identical VGG network, which was solved through residual learning. [23]

Cons of ResNet: Architecture has become more sophisticated. Batch normalisation layers must be implemented because ResNet relies significantly on them. Adding skip level connections, for which you must account for the dimensionality between the various layers, can be a headache. [25]

3.10 MobileNet

MobileNet is a CNN architecture that is both efficient and portable, and it is employed in real-world applications. To develop lighter models, MobileNets typically use depthwise separable convolutions instead of the usual convolutions used in previous architectures. MobileNets adds two new global hyperparameters (width multiplier and resolution multiplier) that let model creators trade off latency or accuracy for speed and small size, depending on their needs. Convolution layers that are depthwise separable are used to construct MobileNets. A depthwise convolution and a pointwise convolution make up each depthwise separable convolution layer. A MobileNet contains 28 layers if depthwise and pointwise convolutions are counted separately. [26]

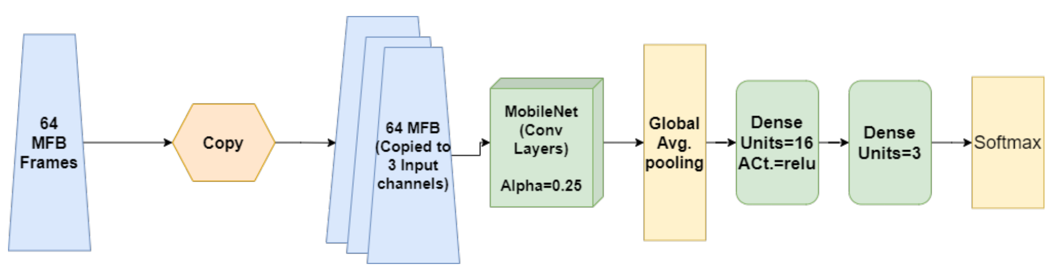

Figure 3.6: MobileNet

3.11 Pros and Cons of MobileNet:

Pros of MobileNet: Palmprint-based biometric technology has gotten a lot of interest because of its several benefits, including ease of use with low-resolution photos, low-cost hardware, and high identification accuracy.[27]

Cons of MobileNet: MobileNets are low-latency, low-power models that have been parameterized to match the resource restrictions of various use cases. [27]

3.12 Inception V3

Inception-v3 is a convolutional neural network design from the Inception family that includes Label Smoothing, Factorized 7 x 7 convolutions, and the inclusion of an auxiliary classifer to transport label information deeper down the network, among other improvements (along with the use of batch normalisation for layers in the sidehead). It's the third version of Google's Inception Convolutional Neural Network, which was first shown off at the ImageNet Recognition Challenge. [28]

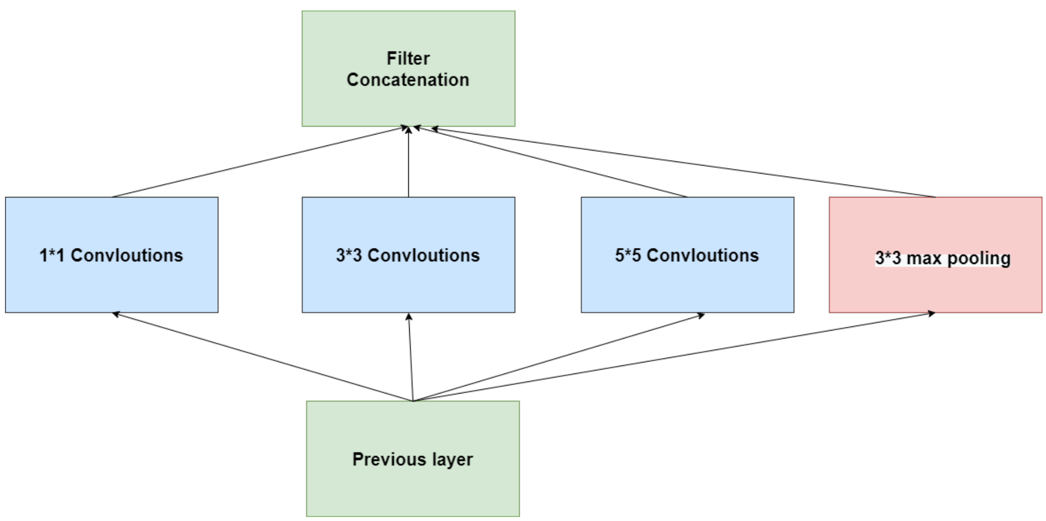

Figure 3.7: Inceptionv3

3.13 Pros and Cons InceptionV3:

Pros of InceptionV3: 1. The inception layer's purpose is to cover a larger area while maintaining a fine resolution for minute details on the photos. So the idea is to convolve several sizes in parallel, starting with the most precise (1x1) and progressing to a larger one (5x5). 2. The concept is that a succession of gabor filters of various sizes will handle varied object scales better. With the added benefit of being able to learn all of the filters on the conception layer. [19]

Cons of InceptionV3: The InceptionV3 has the disadvantage of being more expensive to analyse than shallow networks and requiring significantly more memory and parameters. The first completely linked layer is responsible for several of these factors. [29]

3.14 SegNet

SegNet is a model for semantic segmentation. An encoder network, a corresponding decoder network, and a pixel-wise classification layer make up the basic trainable segmentation architecture. The encoder network's design is topologically identical to the VGG16 network's 13 convolutional layers. The decoder network's job is to convert low-resolution encoder feature maps into full-resolution input feature maps for pixel-by-pixel classification. The unique aspect of SegNet is how the decoder upsamples the lower resolution input feature maps. To conduct non-linear upsampling, the decoder uses pooling indices obtained in the matching encoder's max-pooling step. [30]

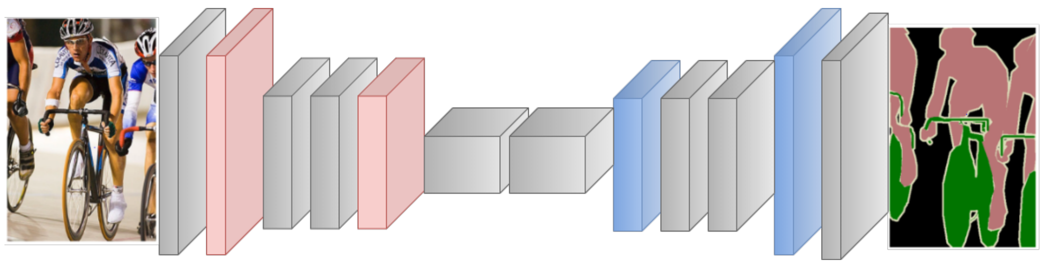

Figure 3.8: SegNet

3.15 Pros and Cons of SegNet

Pros of SegNet SegNet upsamples (without learning) the feature map(s) and convolves with a trainable decoder filter bank using the maximum pooling indices. FCN upsamples the decoder output by learning to deconvolve the input feature map and adding the equivalent encoder feature map. [30]

Cons of SegNet: Because SegNet comprises the decoder architecture, it runs slower than FCN and DeepLabv1. SegNet also requires less memory for training and testing. In comparison to FCN and DeconvNet, the model is substantially smaller. [31]

3.16 Simaese Network

A Siamese Neural Network is a type of neural network architecture that has two or more subnetworks that are identical. The term ”same” refers to the fact that they have the same setup, including the same parameters and weights. The updating of parameters is duplicated throughout both sub-networks. These networks are used in a variety of applications to determine the similarity of inputs by comparing feature vectors.

A neural network learns to predict many classes in the traditional way. When we need to add/remove new classes from the data, this causes an issue. We must update the neural network and retrain it on the entire dataset in this situation.Deep neural networks also require a vast amount of data to train on. In contrast, SNNs learn a similarity function. As a result, we can train it to detect if the two images are identical (which we will do here). This allows us to classify new types of data without having to retrain the network. [32]

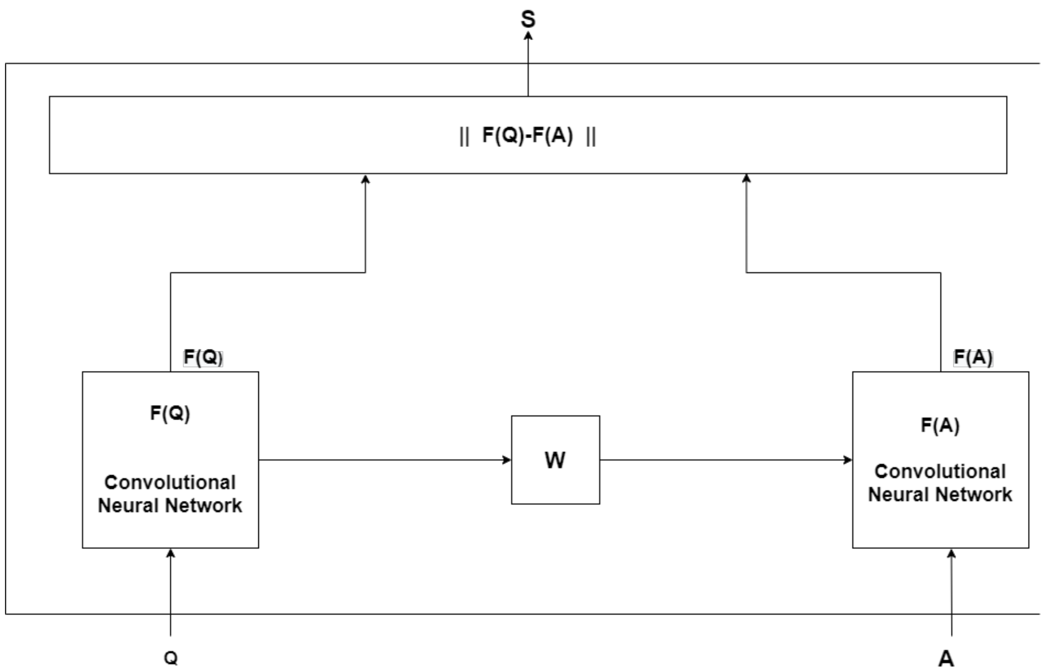

Figure 3.9: Siamese

3.17 Pros and Cons

Pros of Siamese Network 1. More resistant to class imbalance: With the help of One-shot learning, Siamese Networks can recognise a few images per class in the future with just a few photographs per class.

2. Nice to have the best classifier in an ensemble: Because its learning method differs from Classification, averaging it with a Classifier can provide considerably better results than averaging two associated Supervised models.

3. Siamese focuses on learning embeddings (at the deeper layer) that group together similar classes/concepts. Thus, semantic similarity can be learned.

Cons of Siamese Network: 1. Siamese Networks require longer training time than traditional networks since they use quadratic pairings to learn from (to view all available information), which makes them slower than traditional classification learning (pointwise learning).

2. Because paired learning is used in training, the probabilities of the prediction will not be output, but the distance from each class will. [32]

3.18 GAN

The deep convolutional generative adversarial network, or DCGAN for short, is an extension of the GAN architecture that uses deep convolutional neural networks for both the generator and discriminator models, as well as model and training configurations that result in robust generator training. The deep convolutional generative adversarial network is significant because it identified the model restrictions needed to construct high-quality generator models in practice. As a result of this architecture, a huge number of GAN extensions and applications have been developed quickly. [33]

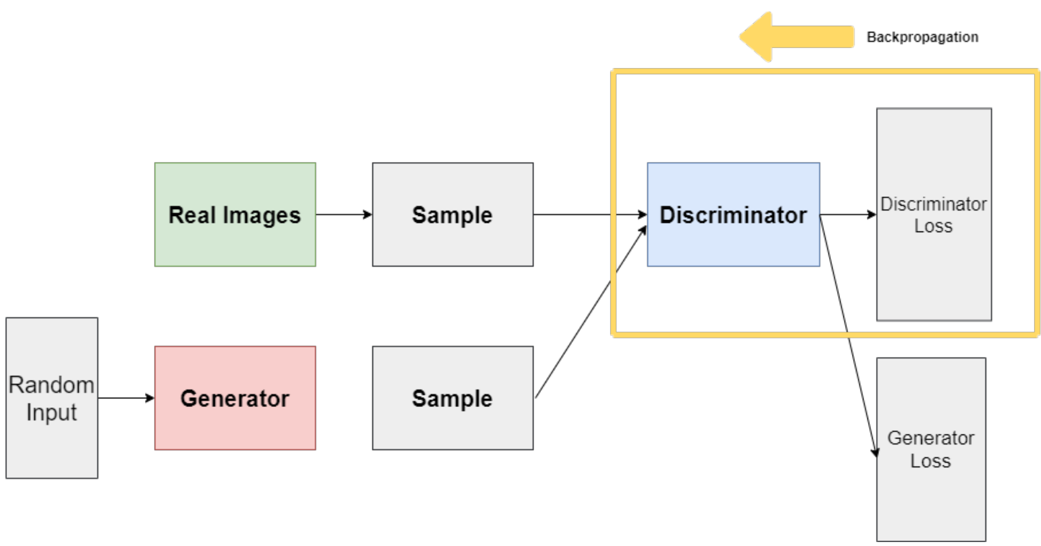

Figure 3.10: Generative adversarial network

3.19 GAN

Pros of Generative Adversarial Network

1. GANs produce data that resembles the original data. When you feed GAN an image, it will create a new version of the image that is similar to the original. It can also generate alternative versions of text, video, and audio.

2. GANs go into the minutiae of data and can quickly interpret it into many formats, making them useful in machine learning.

3. By using distinguish trees, streets, bicyclists, people, and parked automobiles using GANs and machine learning, and we can even measure the distance between different items.

Cons of Generative Adversarial Network

1. More difficult to train: You must continuously submit different sorts of data to see if it performs correctly.

2. Producing outcomes from text or speech is a difficult task. [34]

Chapter 4

Results and Discussions

As previously mentioned, there are two datasets used for every model in this research paper. The two class datatset has chest Xray images in that there are three sub divisions like train, test and validation. For every subdivison there is Normal and Pneumonia images. The three class datatset has COVID Data Gradient Cresent images in that there are all and two subdivisions. In all and two there are test, train images. The only difference between two class and three class is two class contains only normal and pneumonia images but three class have normal, pneumonia and COVID images.

4.1 Two class classification

We used the same transfer learning architecture to diagnose pediatric pneumonia to test the generalizability of our AI system in the diagnosis of common illnesses. According to the World Health Organization (WHO), pneumonia kills over 2 million children under the age of five every year, making it the top cause of childhood death (Rudan et al., 2008). It kills more children than HIV/AIDS, malaria, and measles combined (Adegbola, 2012). According to the World Health Organization, almost all instances of new-onset childhood clinical pneumonia (95 percent) occur in poor nations, notably in Southeast Asia and Africa. The two most common causes of pneumonia, bacterial and viral infections, need completely different treatments (Mcluckie, 2009). While bacterial pneumonia requires an early referral for antibiotic therapy, viral pneumonia is managed with supportive care. As a result, precise and prompt diagnosis is critical. Because chest X-rays are regularly acquired as standard of care and can assist discriminate between different forms of pneumonia, radiographic evidence is an important component of diagnosis in below figure.

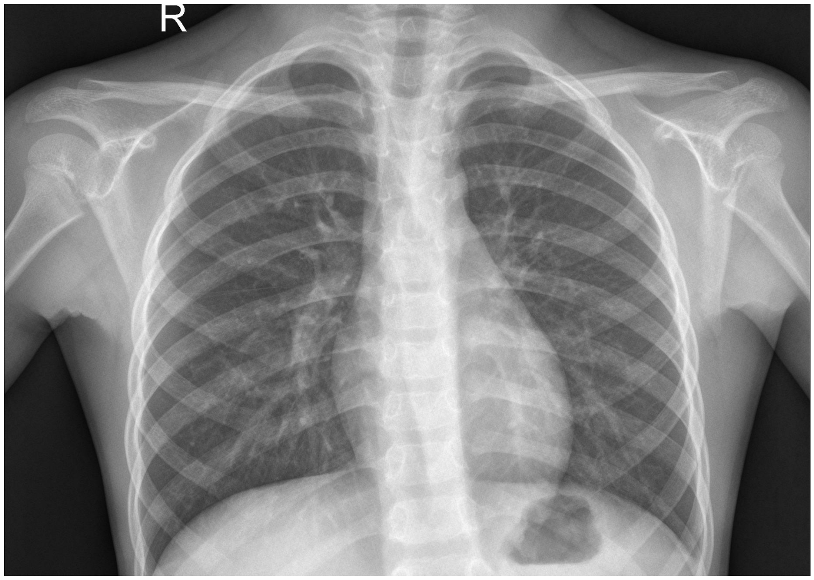

Figure 4.1: Two class Normal chestXray Image

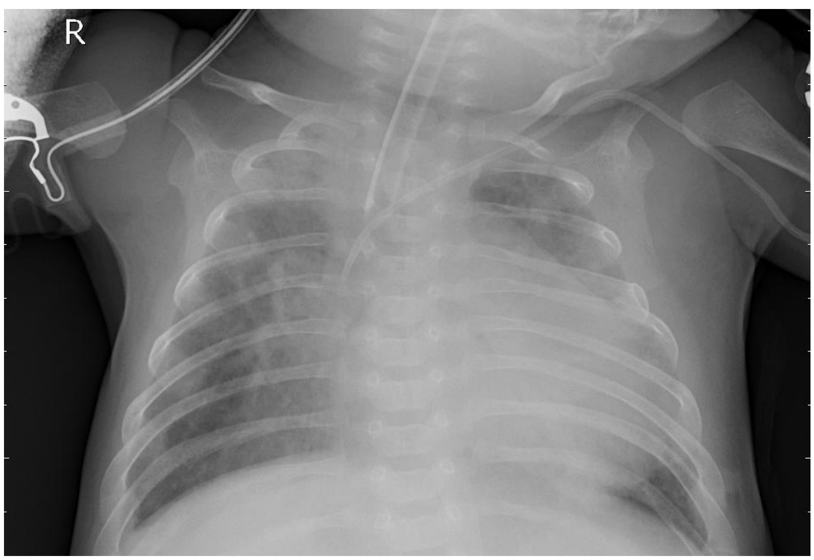

Figure 4.2: Two class Pneumonia chestXray Image

However, quick radiologic interpretation of images is not always possible, especially in low-resource settings where children pneumonia is most common and has the greatest death rates. To that aim, we looked at the efficiency of our transfer learning framework in classifying pediatric chest X-rays in order to diagnose pneumonia and distinguish between viral and bacterial pneumonia in order to speed up referrals for children in need of immediate help.

To train the AI system, we gathered and categorized a total of 5,232 chest X-ray pictures from children, including 3,883 defined as displaying pneumonia (2,538 bacterial and 1,345 viral) and 1,349 normal. The model was then put to the test with pictures from 624 patients, including 234 normal images and 390 pneumonia images (242 bacterial and 148 viral). We attained a 92.8 percent accuracy with a sensitivity of 93.2 percent and a specificity of 90.1 percent when comparing pneumonia-related chest X-rays to normal chest X-rays. For distinguishing pneumonia from normal, the area under the ROC curve was 96.8 percent. With a sensitivity of 88.6 percent and a specificity of 90.9 percent, a binary comparison of bacterial and viral pneumonia yielded a test accuracy of 90.7 percent. For discriminating between bacterial and viral pneumonia, the area under the ROC curve was 94.0 percent. [35]

4.2 Three class classification

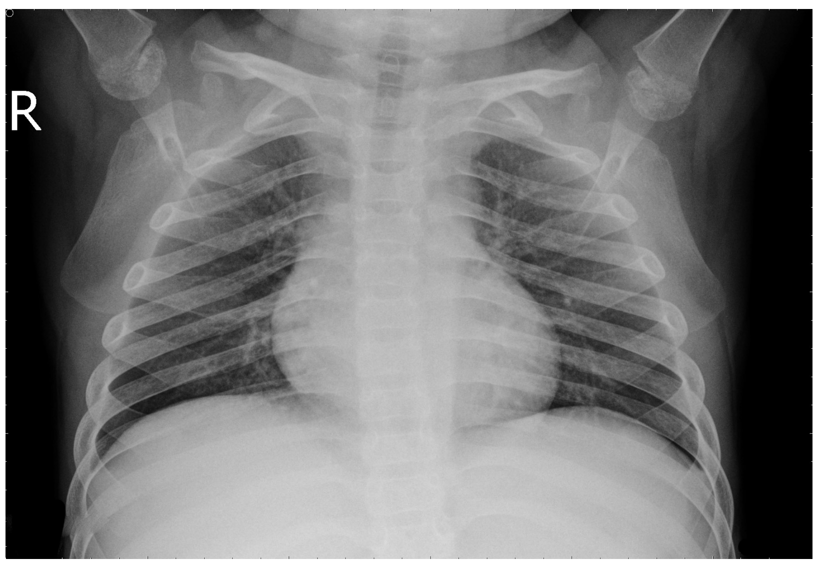

Figure 4.3: Three class Normal

To address the problem, we created our own dataset by merging the Kaggle Chest X-ray dataset with Dr. Joseph Paul Cohen's COVID19 Chest X-ray dataset from the University of Montreal. Both of these datasets are made up of posterior anterior chest pictures of pneumonia patients. We used the instance available on March 18, 2020, because the COVID19 dataset is updated everyday as additional instances are released. Our dataset is divided into three categories, each containing nine images as a test set.

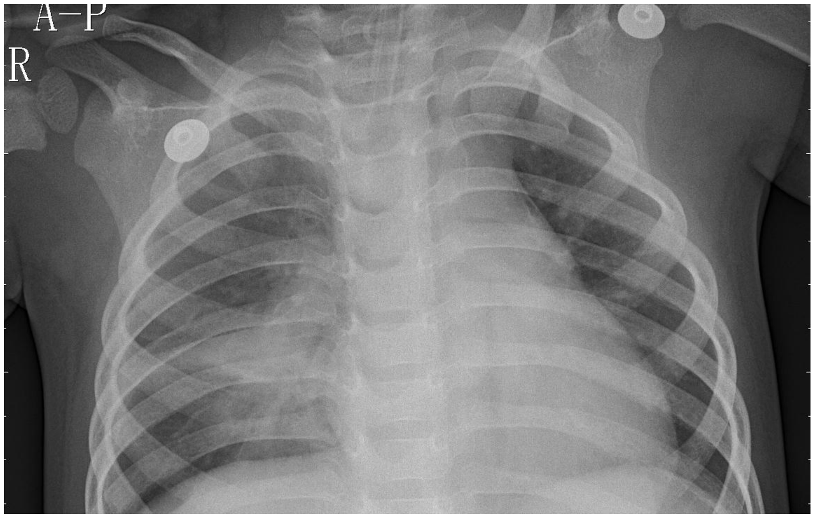

Figure 4.4: Three class Pneumonia Viral

Healthy: 79 images
Pneumonia (Viral) : 79 images
Pneumonia (COVID-19): 69 images

Our code was written in Keras and Tensorflow, and run in a Google Colaboratory GPU-enabled notebook instance. All code is available on the Gradient Crescent repository. **The Binary Case:** Let's start with the binary case: comparing healthy lungs versus those suffering from SARS-COV-2-related pneumonia. The Covid19 GradientCrescent Binary notebook goes through this in detail. Let's start by importing our dataset from GradientCrescent's Google Drive.

!gdown https://drive.google.com/uc?id=1coM7x3378f-Ou2l6Pg2wldaOI7Dntu1a

!unzip Covid Data GradientCrescent.zip

We'll then import some of the required libraries and establish our dataset paths as well as a few network settings. We'll keep our learning rate at 5e-4 because we're implementing transfer learning. Next, we'll use the ImageDataGenerator class to set up the training and validation preprocessing as well as batch picture preparation methods, with the class mode option set to "binary" in this example.

Let's finish off by defining our network, which will be shared by both of our notebooks. We're fitting a pre-trained models such as VGG16, AlexNet, GoogleNet, Simaese network, Inception, ResNet, DenseNet and Generative Adversarial Network to a sequence of densely-connected layers of our own, with a sigmoid activation function for the binary classification case in our output layer. We'll build our network and then connect it to the ADAM optimizer. With our network defined, let's begin training for 20 epochs. You should see that our validation accuracy soon converges to much over 80 percent.

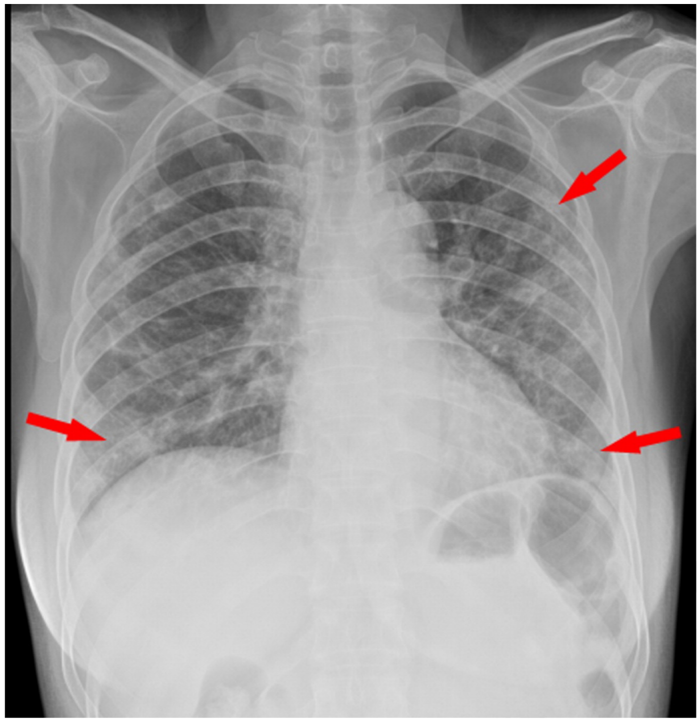

Figure 4.5: Three class COVID 19

We could input additional validation instances to decrease inter-epoch variance with a bigger dataset, but the results are adequate for demonstration purposes. Finally, we'll visualize our accuracy and loss parameters as a function of our training epochs using the matplotlib package. [36]

4.3 DL Model Evaluation

We evaluated the performance of different deep learning models in terms of accuracy, Precision, Recall and F1score which are demonstrated in Table 4.1 and Table 4.2 respectively for two class (Normal and Pneumonia) and Three class (Normal, Pneumonia and COVID pneumonia) respectively.

The below table for two class describes about models, We can detect best accuracy in MobileNetV2 for training as 96.8 percent, VGG16 for test accuracy as 90.2 percent, DenseNet201 for validation accuracy as 98.0 accuracy. The precision value is high in VGG16 as 87.6 percent, Recall value is better in AlexNet as 99.7 percent and Finally F1-score value is good in VGG16 as 92.6 percent.

Similarly for three class evaluates about AlexNet, AlexNet (Transfer Learning), MobileNetV2, ResNet50, InceptionV3, VGG16 and DenseNet201. In this research we can detect the best accuracy for training, test and validation. Firstly, the training accuracy is best in MobileNetV2 as 96.9 percent, the test accuracy is better in AlextNet (Transfer Learning) as 88.9 percent compare to AlexNet and the validation accuracy as 92.7 percent in AlexNet, Alexnet (Transfer Learning) and MobileNetV2. The precision value is high as 86.5 percent in AlexNet (Transfer Learning). The Recall value is also high in AlexNet (Transfer Learning) as 88.9 percent. The F1 score is good in AlexNet (Transfer Learning) as 87.3 percent. Finally, what we observe in this we can get better accuracy when we implement **Transfer Learning**

S.No	**Model name**	**Training Accuracy(%)**	**Test Accuracy (%)**	**Validation Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
1	**AlexNet**	0.951	0.819	0.969	0.766	**0.997**	0.873
2	**DenseNet201**	0.960	0.891	**0.980**	0.856	0.992	0.919
3	**MobileNetV2**	**0.968**	0.894	0.969	0.870	**0.977**	0.920
4	**InceptionV3**	0.950	0.835	0.954	0.800	0.982	0.881
5	**ResNet50**	0.918	0.843	0.954	0.811	0.977	0.886
6	**GAN+VGG16**	0.950	0.883	0.962	0.853	0.982	0.912
7	**VGG16**	0.961	**0.902**	0.968	**0.876**	0.982	**0.926**

Table 4.1: **Two class Using Pretrained Models**

S.No	**Model name**	**Training Accuracy (%)**	**Test Accuracy (%)**	**Validation Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
1	**AlexNet**	0.790	0.778	**0.927**	0.792	0.741	0.736
1	**AlexNet (TL)**	0.948	**0.889**	**0.927**	**0.865**	**0.889**	**0.873**
2	**MobileNetV2**	**0.969**	0.500	**0.927**	0.424	0.444	0.428
3	**ResNet50**	0.829	0.500	0.878	0.471	0.407	0.390
5	**InceptionV3**	0.912	0.444	0.926	0.410	0.407	0.407
6	**VGG16**	0.943	0.47	0.951	0.321	0.389	0.350
7	**DenseNet201**	0.960	0.444	1.000	0.379	0.389	0.383

Table 4.2: **Three class using Pretrained Models**

4.4 Discussion

Furthermore, our network is a generic platform that can be used to make clinical diagnostic decisions using a variety of medical imaging techniques (e.g., chest X-ray, MRI, computed tomography). We showed this by training our network on a dataset of pediatric pneumonia chest X-ray pictures. The relatively large number of varied objects on chest X-rays, particularly the imaged areas beyond the lungs that are unrelated to the diagnosis of pneumonia, makes categorization challenging. The high-accuracy model that resulted implies that this AI system has the ability to learn from more complex images with a high degree of generalization while using a limited input set. This transfer learning framework presents a compelling system for further exploration and analysis in biomedical imaging, as well as more generalized application to an automated community-based AI system for the diagnosis and triangle of common human diseases, by demonstrating efficiency with multiple imaging modalities and a wide range of pathology. We also anticipate that by making our data and scripts available in a publicly accessible database, other biomedical researchers will be able to use our work as a resource to enhance the performance of future models and advance the field. This may make screening programs and referral systems more efficient across the board in medicine, especially in rural or low-resource areas, with broad clinical and public-health implications. [35]

Chapter 5

Conclusion and Future work

When AI is used to analyze radiological images, it can help expedite and enhance diagnosis while also improving radiologists' workflow. Despite its lower sensitivity than CT, CXR is the most frequent and commonly utilized imaging technique, therefore attempts to enhance its diagnostic yield are of the highest importance. Because of its potential capacity to forecast the length of hospital stays, it may be used to track illness development, give an objective assessment based on quantitative data, decrease subjectivity and variability, and optimize resources. It might assist enhance efficiency in the management of the COVID-19 infection when used as a support in clinical practice and in conjunction with other diagnostic procedures.

Chest X-rays can reveal a few distinguishing features in the lungs of COVID-19 patients. As COVID-19 spreads across the world, the number of cases continues to grow at an exponential rate. To keep the healthcare system from collapsing, a technology that can assist patients identify diseases utilizing a low-cost, quick method is required. The use of data mining algorithms to categorize pneumonia illness in chest X-rays may aid diagnosis in this setting, according to the research. When we examine chest pictures of patients with pneumonia caused by many types of bacteria and try to predict a specific type of pneumonia, the problem becomes considerably more complex (COVID-19). In the actual world, there are many more people who do not have pneumonia than those who do. Furthermore, the number of individuals suffering from pneumonia caused by diverse infections is inherently unbalanced, and owing to the COVID-19 epidemic, measuring the precise imbalance between these numbers is becoming increasingly difficult. We proposed a classification method to identify and

describe COVID-19 as a pneumonia disease caused by different pathogens in chest X-rays in view of a feasible scenario.

5.1 Future Work

The suggested approach will be developed in future study to be abdicable for various COVID-19 datasets, including SARS-CoV-2 CT-scan, COVID-CT, and statistical datasets. However, in the case of COVID-19 illness, the accuracy of the prediction approach will be supplemented with optimization strategies based on classification and regression algorithms.

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