

Deep learning-based analysis and classification of COVID patient through CT images



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Declaration

I certify that this research work titled “*Deep learning-based analysis and classification of COVID patient through CT images*” is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical, and spelling mistakes. Thesis is also according to the format given by the university.

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Abstract

The world is facing a prodigious pandemic initiated through SARS-CoV-2. Corona Infection was first emerged and recognized in Wuhan China which became a global pandemic. Industries all around the world are crippled and many people are killed by this deadly virus. It is not viable to control the spread when this variant of the virus emerged. Therefore, effectively identifying and isolating the people who have symptoms of the disease plays a great role in preventing it. To test COVID 19, the Reverse transcription-polymerase chain reaction (RT-PCR) is the current methodology. Researchers are trying to find different other methods, all over the world, to diagnose coronavirus in affected people. Radiological equipment such as Radiographical images came up as potential alternatives for COVID-19 diagnosis.

New coronavirus caused pneumonia in the patients of COVID-19 and it is analyzed by the CT scans. So, CT scan is considered as an effective approach for screening and diagnosing COVID-19. An important role could be played by Artificial intelligence and machine learning, in this time of need, only if we can accumulate the available data that can help us pick out the infected patients from the healthy ones. In this research, we have presented technique for the analysis of lungs CT-scan images to classify and detect the infected patient. The proposed methodology is mainly consisted of two-part, classification on original dataset with different loss functions, followed by testing on other datasets and classification on color-mapped dataset followed by fine-tuned transfer learning on other datasets. The lightweight neural network, Efficient-Net B0 is utilized in proposed technique, for classification on publicly available dataset which has largest number of samples. It gives the accuracy of 90.35%. Efficient Net model is also trained using different loss functions, kullback leibler divergence and sparse cross entropy, which gives the accuracy of 99.97% and 99.67%. Different other datasets have also been tested on trained weights of Efficient-Net architecture and accuracy of 99.89% and 88.98% is achieved. We also have color-mapped the dataset into JET color-map and trained the Efficient-Net B0 model, which gives the accuracy of 99.90%, and fine-tuned the trained weights of color-mapped dataset on two different datasets and achieved accuracy of 99.18% and 86.62%, respectively. We have done a comparative analysis through specialized pre-processing techniques.

Key Words: *Deep Neural Network, CT scan, Radiology, Convolutions Neural Network, Artificial intelligence, EfficientNet*

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CHAPTER 1: INTRODUCTION

The Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) is an infectious disease because of which about 219 million infected cases arises , 4.55 million deaths happened and 209 million people recovers, from the infectious disease. Coronavirus encompasses the large number of viruses. They existed in both animals and humans, resulting in the form of the common cold in humans and other infections in bats, camels, and cattle. The cause of COVID-19 is Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), it is also from the family of these coronaviruses. It has been said by the experts that SARS-Cov-2 started from bats, same as MERS and SARS originated coronaviruses. COVID is named as 'co' for corona, 'vi' for virus and 'd' for disease, and 19 for the year it appeared. Since there was a lot of variety of animals so there was a lot of variety of viruses. Which cause the virus to change so that it started infecting and spreading among people. Workers caught coronavirus from the market, and it spread in Wuhan. On 1st December first case with coronavirus symptoms is reported, and then spread among the whole area. After whole research it has been found out that the virus is a novel Corona virus. On 31st December 2019 first case is reported at Wuhan as novel corona virus.

These individuals were linked to the nearby wildlife market showing the chance to transmit the virus from one to another human being [1]. A serious outbreak of the new COVID



Figure 1. 1: Corona Virus its effect on economy

quickly spread across China and later to various countries. It is declared as international concern for public health by WHO (World Health Organization), and the occurrence of a new viral disease is announced by WHO on January 30, 2020. WHO named the new viral disease as COVID-19 in n February and declared it as a global pandemic in March 2020.

The most concerning element of the new COVID is its fast and all over the palace capacity, it is highly contagious. The infection is primarily passed on to others openly from people with the virus; it is sent implicitly via the surfaces and air of the climate with which contaminated people interact. Therefore, effectively identifying and isolating the people who have symptoms of the disease plays a great role in preventing it. It causes several variations in the victim, one of the general indication of COVID include temperature, dry hack, and drowsiness. Indication or symptoms of this disease vary from individual to individual. Various manifestations for example loss of odor and taste, migraines, and pain in the neck may occur in some patients, but extreme side effects showing the continued movement of COVID-19 include shortness of breath, chest pain, and loss of ability to move or speak.

1.1 Motivation:

The new COVID causes viral pneumonia in the lungs which leads to serious respiratory illnesses. At the very start, there was not much diagnosis or research available to the doctors due to which they were not able to detect every COVID patient. Then the reverse transcription-polymerase chain reaction (RT-PCR) came into use by the doctors to identify the infected patient. Other than RT-PCR other techniques are also used for diagnosis of COVID as Antibody test, Serology test, medical imaging, and Isothermal nucleic amplification test. RT-PCR was a restricted method as it requires experts and experimentation for the assessment of the results. Also, RT-PCR kits became short on the peak time of the COVID outbreak, and every country could not get many RT-PCR kits to cope up with the number of patients that were increasing immensely. These issues resulted in the rapid spread of the virus by the suspected patients as they could not go through any test. To overcome this issue, researchers started looking for new and alternative methods to identify the COVID patients.



Figure 1. 2: Corona virus and lungs

Therefore, timely detection of a covid patient can save many lives and to facilitate it, is the motivation behind this research. Technology is aiming at the automated process, focus on reducing the manual work as much as possible and thus it is aiding the mankind in every field. Systems are being enabled which can follow a set of commands and take action accordingly. In this process of automation, Artificial intelligence concept is waved, , which tries to imitate the human brain learning capacity.

Researchers find out that in most patients of COVID 19, lungs are infected, so they suggested analyzing the CT- Scan, and X-rays to detect COVID-19. As medical imaging devices are almost available in every treatment center, so these tests are feasible as well as cheap. New coronavirus caused pneumonia in the patients of COVID, and it is analyzed by CT scans. So, a CT scan was considered as an effective approach for screening and diagnosing COVID-19. CT scan images provide subsequent evidence about chest abnormalities. Purpose of this research is to improvise the clinical diagnostic system through deep learning methods to identify COVID patient through Lung CT scan.

1.2 Problem Statement

For the diagnosis, complication detections, and coronavirus disease 2019 prognostication, the chest CT play the potential role. Lungs CT scan has been considered as the highly sensitive method. Different deep learning techniques are executed on the CT dataset to find out the respective results [1]. This research's purpose is to explore deep learning techniques to improve the classification accuracies for the exposure of COVID patient detection using Lungs CT scans.

1.3 Aims and Objectives

Major aims and objectives of the research are as follow:

- Utilization of deep learning in identification of the covid patient through CT scans of lungs to identify covid and normal patient.
- To explore effect of pre-trained weights of a large dataset in small datasets
- A Large dataset of CT scan is used in a neural network to get more accurate results
- Use of different loss function of multi-class problem.
- To utilize **color maps** for better classification

1.5 Structure of Thesis

This work is structured as follows:

Chapter 2 covers the importance of lungs in human body and their brief anatomy. It further discusses effect of Corona virus on lungs.

Chapter 3 gives review of the literature and the significant work done by researchers in past few years for the diagnosis of corona virus through radiographical images.

Chapter 4 the proposed methodology is discussed in detail with all the techniques used.

Chapter 5 introduces the databases used for evaluation purposes. The results of all the experimental are discussed in detail with all desired figures and tables.

Chapter 6 concludes the thesis and reveals future scope of this research.

CHAPTER 2: CORONAVIRUS AND HUMAN LUNGS

There are five vital organs crucial for human survival: brain, heart, kidney, liver and lungs. It has been allowed by the respiratory system along with lungs to flow the oxygen from the air to the body, and the excretion of carbon dioxide from the body to the lungs. This chapter will briefly cover the lungs anatomy, its imaging techniques. Also, why the CT images are preferred for the detection of diseases of lungs and the effect of coronavirus on lungs.

2.1 Structure of Lungs

Lungs are made up of sacks of tissues, located within the thoracic cavity of the chest between the rib cage and diaphragm. They extract oxygen from air which is transferred to the blood and finally to the cells of human body. Their structure is shown in Figure 2.1. Usually left lung is smaller than right lung because left lung shares a space within the heart in the chest. Nose and mouth are the two openings for the inhaling of air, then pharynx helps the air to travel down to trachea. Trachea then divided into two bronchi connected to the lungs. Left lung is smaller than the right one, as the former has two lobes and the later has three lobes or sections. There are many tiny airways known as bronchioles, which are further parts of bronchi, they increase the surface area. Alveoli is the air sack at the end of every bronchiole. The alveoli contain various capillary veins in their walls where gas exchange with the bloodstream occurs.

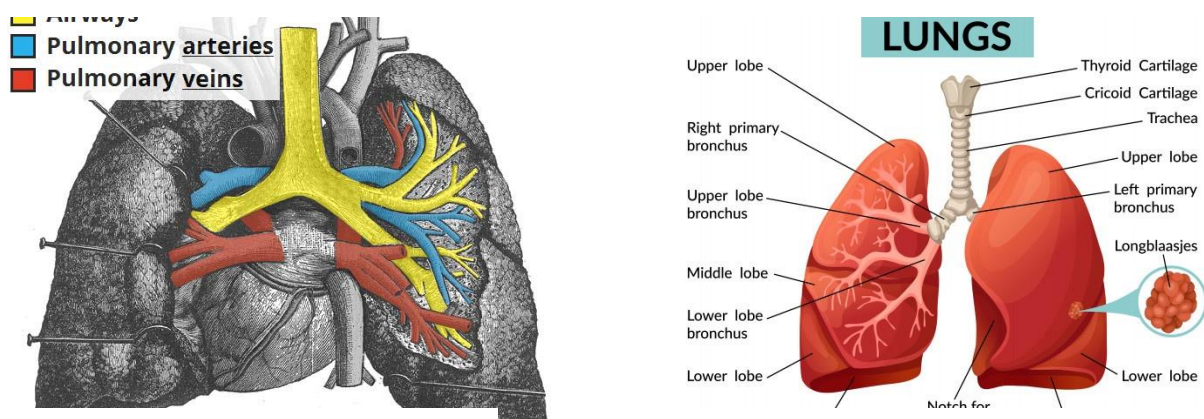


Figure 2. 1: The Lungs(left), The structure of lungs(right)

2.2 Imaging Techniques to Analyze Lungs

Medical imaging is a technique used for visual representation of body for medical analysis. The different types of medical imaging are X-rays, Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRI) and Ultrasound (Figure 2.2). X-rays are a kind of radiations which when pass through body, produce an image on the x-ray film according to the density of striking objects. The radiations that pass through the objects strike the film and burn it that makes the film black. Bones appear whitest as they are dense enough to absorb almost all the radiations so very few radiations pass through them and hit the film. Soft tissues such as muscles appear grey, and air/gas appears black. CT scan provides 360° cross sectional images of body using X-rays. MRI combines a powerful magnetic field with an advanced computer system and radio waves to produce details of body parts without use of radiations. Ultrasound gives the internal structure of different parts of body using sound waves of frequencies higher than human audible range. Mostly CT scan and x-rays images are used for analysis of lungs. Lung CT scan has been considered as the highly sensitive method to diagnose as it also could detect complications. Many researchers did a case study on Chest CT as more useful for the detection of lungs complications [17]

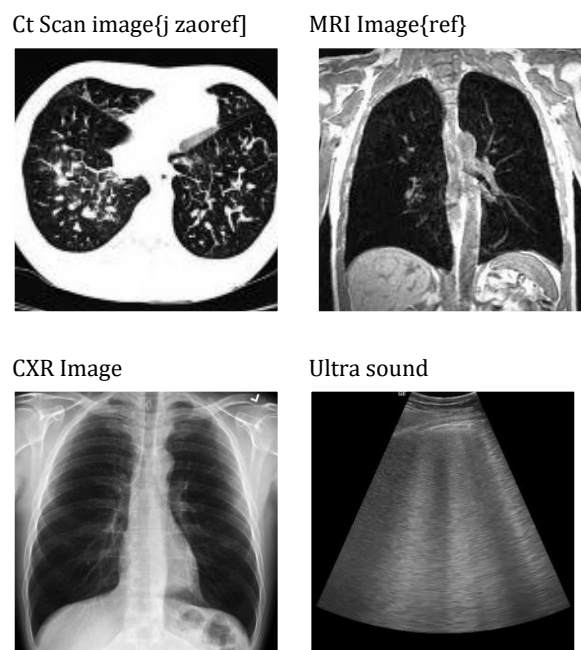


Figure 2. 2: Medical imaging techniques (a) CT scan (b) MRI (c) Ultra-sound (d) X-ray

2.3 SARS-CoV-2

Coronavirus encompasses many viruses. They existed in both animals and humans, resulting in the form of common cold in humans and other infections in bats, camels, and cattle. The Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), cause the COVID-19, it is also from the family of these corona viruses. It has been said by the experts that SARS-Cov-2 started from bats, same as MERS and SARS originated corona viruses. China's wet

market had fresh meat, fishes and the animals killed on spot. Some of them contained wild or banned species, like raccoon dogs, cobras, and wild boars. Most experts stated that at that time of year there were no export of bats in China's wet market, they suspected that it may be caused because of pangolins, as infected pangolins have been detected of same coronaviruses as SARS-CoV-2. Since there was a lot of variety of animals so there was a lot of variety of viruses. Which cause the virus to change so that it started infecting and spreading among people. Workers caught coronavirus from the market, and it spread in Wuhan in December 2019. These individuals were linked to the nearby wildlife market showing the chance to transmit the virus from one to another human being [1].

Coronavirus structure

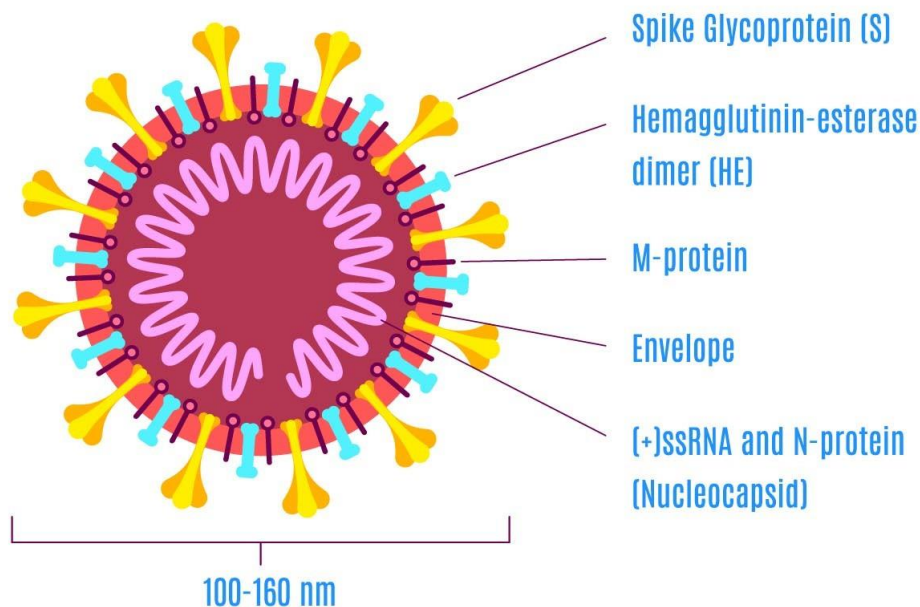


Figure 2. 3: Structure of corona virus

The first case is reported in December 2019, the symptoms were malaise, fever, dry cough, and dyspnea, but it has been declared as Wuhan Pneumonia, because of the pneumonia symptoms, also it was not a flu. Since there was a serious outbreak of the new virus quickly spread across China, and the lockdown is implemented. The researchers started to find about the contagious virus, they found out that the virus is from the family of coronaviruses, and it

is not a pneumonia, it was named as SARS-CoV-2. The virus evolved and spread among people of Wuhan, and then to various countries. On January 30, 2020, it is announced as international concern for public health. In February it named as COVID 19 and in March it is declared as global pandemic.

Effectively identifying and isolating the people who have symptoms of the disease have a great part in preventing it. With the passage of time the SARS-CoV-2 has been evolved and changed in into different variant in each layer. Till now there has been four variants of SARS-Cov-2, and four layers each with stronger variant. The Delta variant is most contagious, it can cause some serious illness and sometimes death. Also, it can transmit directly through air, as it stays for a long time in the air. Since for now the scientist have discovered some different types of vaccines, which have some promising effect in reducing the number of coronavirus infected cases. But there is need to do more research to make vaccines for different variants of. SARS-CoV-2.

2.3.1 Coronavirus and lungs

COVID-19 is a respiratory disease, one that especially reaches into your respiratory tract, which includes your lungs. It causes viral pneumonia in the lungs which leads to serious respiratory illnesses, it might be mixed up with the pneumonia. An array of breathing problems can be cause by COVID -19, from minor to critical. Some people may have more serious symptoms if they suffer any other health problems as heart disease, cancer, and diabetes.

Once the infection enters your body, it encounters the layers of mucus that link you're some body parts such as nose, mouth, and eyes. The infection invades a solid cell and these cell generate new parts of the infection. It increases and new infections contaminate neighboring cells. Reflect your airways as an upside-down tree. The trunk is your trachea, or windpipe. It splits into smaller and smaller branches to your lungs. Toward the end of every stop there are small air wallet known as alveoli. This is in which oxygen enters the blood and carbon dioxide escapes. The new COVID can harm the top or lower part of your airlines. It is going down the airlines. The lining can turn out to be irritated and infected Sometimes the contamination can get into your alveoli. [33]

The infection travels down the lungs causing the swelling and inflammation in the lungs, it might start from one part but with the passage of time it spread among whole lungs. There is

20%-30% evidences are present for developing of clots in lungs , heart , brain, and legs in analytically ill patients, and these clots are sometimes life threatening.

2.3.2 Transmission

The most concerned element of the new COVID is its fast and wide spreading capacity. The infection is primarily passed on to others straight from people with the disease; It is sent implicitly via the sides and air of the climate in which contaminated people interact with.

Infection is spread through direct contact with the respiratory system of an infected person (coughing and sneezing). [32] COVID-19 infection can survive on surfaces for a very long time, but basic disinfectants can kill them.

2.3.3 Precautions

It is not possible to be remain at safe side during the time of pandemic, but still there are some factors which could be decrease the risk to get infected:

- **Social distancing**
 - Prolonged, frequent, or close contact with a person having COVID-19, should be avoided. Also, it is better to keep a safe distance from the people who have direct contact with the covid patients such as health care workers
- **Immune system**
 - Weak immune system could be affected from coronavirus quickly
 - One should avoid the treatments that weaken the immune system e.g. chemotherapy, biological agents
 - Too young or too old age – the immune system of people who are young or elderly tend to be weaker as compared to those of healthy adults
 - Having other diseases such as diabetes, kidney disease, head or neck cancer can weaken the immune system.
- **Proper Hygiene**
 - One should keep his hands sanitized.
 - Washing the hands properly with an alcohol-based hand wash
 - Use if face masks, and gloves in crowded places
- **Medical Assistance**
 - One should properly take the medical assistance if they have any health issue, or there are any symptoms of flu or pneumonia.

2.3.4 Symptoms

It causes several variations in the victim, the best common symptoms of COVID includes temperature, dry hack, and drowsiness. Indication or symptoms of this disease vary from individual to individual. Various manifestations for example loss of odor and taste, migraines and some patients may suffer in pain Neck, but extreme side effects showing continued movement of COVID-19 includes shortness of breath, chest pain and loss of ability to move or speak.

2.3.5 Diagnosis

At the very start, there was not much diagnosis or research available to the doctors due to which they were not able to detect every COVID patient. Then the reverse transcription polymerase chain reaction (RT-PCR) came in use by the doctors to identify the infected patient. Other than RT-PCR other techniques are also used for diagnosis of COVID as Antibody test, Serology test, medical imaging, and Isothermal nucleic amplification test. RT PCR was a restricted method as it requires experts and experimentation for the assessment of the results. Researchers find out that in most patients of COVID 19, lungs are infected, so they suggested to analyze the Radiographical Images to detect COVID-19.

- **RT-PCR:**

Infections that caused virus diseases and are basically obtained by a respiratory path, for example SARS-CoV-2, are usually analyzed by direct detection of viral segments in respiratory samples. The two most common tools used to do this are tests to nucleic acid amplification tests by polymerase chain response (PCR) or antigen-based tests. On the beginning of COVID, RT-PCR tests was the first available methods established and widely deployed to diagnose the infected patients, until other methods discovered by researchers. Although antigen test could also be used but first not every country has facility to use this test secondly, they were not that reliable in comparison of the RT-PCR. Viral RNA is detected by SARS-CoV-2 RT-PCR; A positive result is deeply self-explanatory for the presence of an infection. The affectability of these tests is not uniform and is influenced by the examination itself, but also by the restriction of detection, the viral inoculum, the time of the test and the location of the test kit. Direct popular projections can be based on certain quality goals and differ in terms of affectability and clarity. Real time RT-PCR In pathogens, to detect the availability of any specific genes' material, any virus included, a nuclear derived method has been used names as, RT-PCR, reverse transcription polymerase chain reaction. at first the

specific genes were detected through radioactive isotopes markers, but with the passage of time it has been upgraded to fluorescent dyes. In this technique, scientist can predict the results during the ongoing test process. Real time RT-PCR has been widely used for diagnoses of other diseases too, like Ebola virus, Zika virus also other viral diseases. Adapting this method for detection of COVID 19 virus requires a lot of support as with the increase of national wide testing capacities. The main difference between RT-PCR and PCR itself is that the later works on the available DNA of pathogens, for example viruses and bacteria while the former first converts RNA to DNA. Coronavirus is the only virus available in RNA so RT-PCR has been developed for it, while swine flu, Ebola virus or any viral foot and mouth disease can be detected through PCR. First have a short look on what virus and genetic material actually is, the genetic material's microscopic package, which may comprise of two acids deoxyribonucleic acid (DNA) or ribonucleic acid (RNA). surrounded by envelop of molecules is known by virus. DNA and RNA have different structures and carry different information: former is two stranded with information like genetic code, blueprint, and other while later has one strand that performs operation like copying and transmission of genetic code to proteins. It helps synthesis of protein which carry out function that results in development and keep organism alive. Some infections, for example, the SARS-CoV-2 virus, which results COVID 19, just contain RNA, which implies that for survival and multiplication they depend on infiltrating healthy cells. Once inside the cell, the infection utilizes its own hereditary code — RNA on account of the Coronavirus infection — take responsibility and reprogram cells, transforming them into virus making manufacturing operations. Since RNA is one stranded and virus is also available in RNA, so scientist discovered that to perform PCR it has to be transformed into DNA, a process called reverse transcription. RT-PCR real part is to copy or amplify DNA in process of detecting viruses, that is why it has been changed from RNA to DNA.

Detection of Coronavirus through RT-PCR: Using reverse transcribed methods RNA is converted into DNA with help of a specific enzyme, in which additional fragments of DNA added by the scientist. These additional fragments get attached to the viral DNA section, it

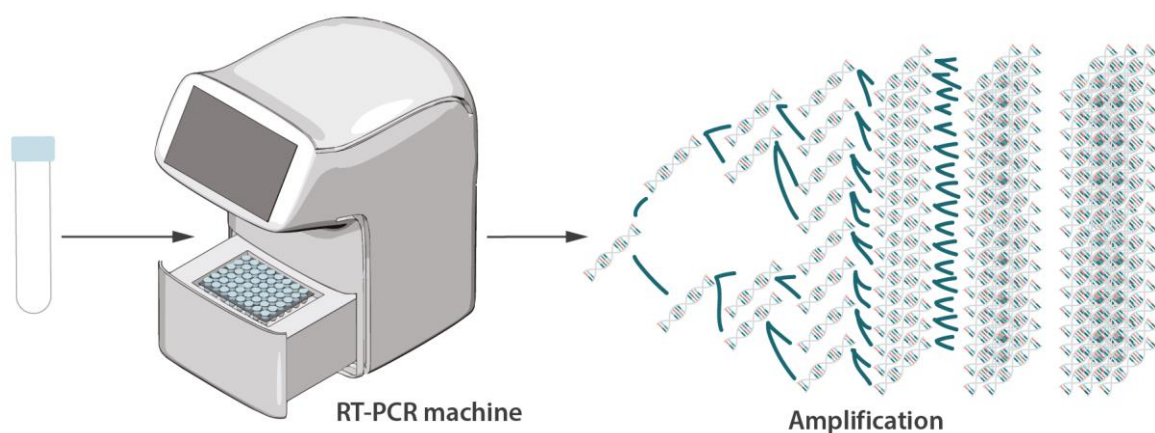


Figure 2. 4: RT-PCR amplification

there is any. Other functions of additions genetic fragments are in amplification and marking the DNA for detection of the Virus. Transcribe DNA along with the fragments the placed into the RT-PCR machine, which triggers specific chemical reactions on different heat and cold conditions, which results in multiplication of the sample and new identical copies are generated as shown in figure 2.4 Total of approximately 35 cycles has been repeated which dives many identical copies of DNA section of virus, created from each strand of virus [5]. The sign labels, attached to DNA strands, release a shining dye. RT-PCT machine measure the fluorescent dye after every cycle and keep checking the level. After a specific level it proves the presence of the virus in the DNA. It has also been monitored by the scientist that how many levels are required to reach a certain level and estimate the severity of the infection. They noticed that if the cycles are less, virus is more severe. RT-PCR method is a very sensitive and precise technique, the diagnosis can be delivered within 3 to 4 hours or 2 to 3 days, it depends on laboratory condition and national testing capacities. Studies shows how he specificity of RT-PCR has been improved over time.



Figure 2. 5: Testing of COVID through RT-PCR

Limitations: Since it was considered as the most accurate methods for COVID detection before the discovery of other methods, as it has less contamination error also it is implemented in a specific environment. But there are not 100 percent chances that the result is always right, there is a possibility of the error, and a infected person might be declared clear. The limitation factors also depend on the laboratory conditions and the staff working on the RT-PCR. Also, it might take 24 hours or more than that, so for a patient in emergency cannot rely on RT-PCR, in comparison of a patient already admitted. It has been noted that the results of continuous RT-PCR could be influenced by the change in the viral RNA arrangements. In different studies the diversity in heredity and rapid development of the novel coronavirus has been seen [6] [7]. The false negative results may cause by the diversity in the groundwork, and some targeted areas of SARS-CoV-2 genome in the test. Even though, the RT-PCR was performed on specific areas of viral genome for the better results, , with inconsistency causing disorder among preliminaries and testing and grouping goals can lead to this decrease in test execution and expected false negative results. In such manner, various objective quality enhancement goals are achieved to keep away from invalid outcomes. A few types of current SARS CoV-2 RT-PCR ongoing RT-PCR pack have been created and supported quickly, yet with various quality. False negative results could also be occurred due to insufficient organisms or inappropriate handling.

Radiographical Images:

With increasing cases of COVID, scientist could noy only reply on RT-PCR. They did research and found out that as COVID is a respiratory syndrome, it effects lungs, just as they are infected in pneumonia or other lung disease. Then researchers started their work on CT scan images of lungs and chest X-ray. In next two sections Ct scan and X-ray has been

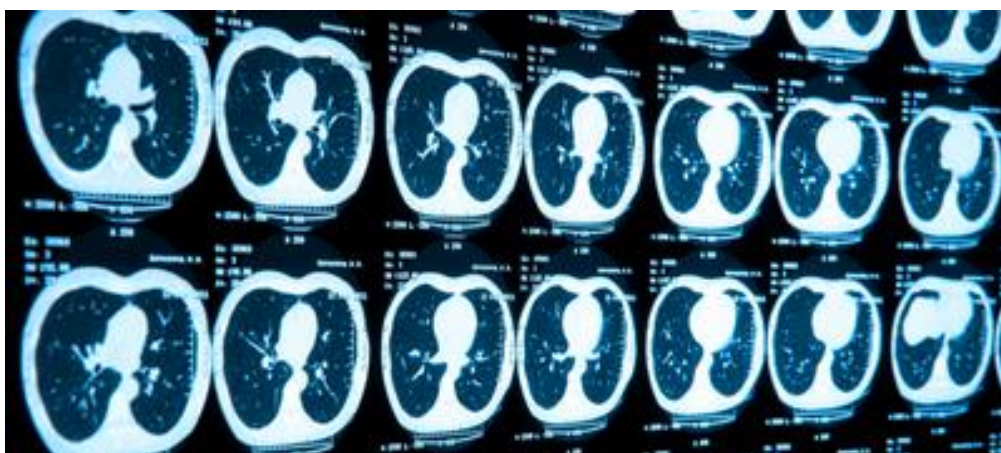


Figure 2. 6: COVID CT Scans

discussed along with the methods used to diagnose through radio graphical images.

Lungs Ct scan: With the evolution of pandemic, medical images became highly important in clinical findings along with some limitations of RT-PCR. Research started finding different other methods and came to know that CT scan could play a very significant role in testing of coronavirus. SARS-CoV-19 is a respiratory syndrome which directly affects the lungs, it might be mixed up with the pneumonia. Lungs CT scan has been considered as the highly sensitive method to diagnose the COVID virus as it also could detect the complications. Many researchers did case study on Chest CT as more useful for COVID detection [17] There might be possibility of false negative prediction from Ct scan diagnosis, the reason is that on early stage when the disease is just started it might not have affected lungs as much which can be shown in CT scan. This fact led the American college of radiology to issue the statement after research, that CT could only be used for the hospitalized patients which had specific clinical indications. Along with early-stage CT scan, another reason of false negative results could be abnormal CT scan.

CXR: In the examination and monitoring of different lung diseases, such as infiltration, pneumonia, tuberculosis, hernia and atelectasis, Chest X-rays play a significant role. Researchers found out that CXR images of infected patients could also help in diagnosing the COVID patient as it affects the upper respiratory tract and lungs. Since it has been a low cost, easy to operate method and it has low radiation dose. CXR of patients with lung diseases, such as lung opacity, pneumonia and COVID 19 has been collected, and researchers developed different ways to diagnose the infected COVID patient. Along with the detection of infected person, Chest X-ray could also be helpful to know the effect of the virus on lung tissue.

2.3.6 Treatment:

Tuberculosis, if diagnosed on time, is curable through proper treatment. But treating TB takes much more time as compared to other bacterial infections. It is because the TB bacteria grow very slowly and unfortunately, also die very slowly. Usually, antibiotics are taken for six to nine months. The exact time and dose depend upon patient's health, age, possible drug resistance, the type of TB (latent/active) and the location of infection in the body. Latent TB can be treated using only one type of drug while active TB treatment may require numerous drugs at once. Treatment must be modified in case of drug-resistant TB disease. Drug-resistant TB occurs when the microorganisms become tough to the drugs used to treat TB and thus, the drug can no longer kill the microorganisms. The most common regimens for

tuberculosis include Isoniazid, Rifampin (Rifadin, Rimactane), Ethambutol (Myambutol) and Pyrazinamide.

Completing the full course of treatment is very crucial. After few weeks of the medication, a patient may feel well and may not remain contagious. This might be tempting to stop the treatment but ceasing it too soon or skipping doses can make the bacteria (that are still alive) drugs resistant, leading to TB that is much more dangerous and tough to treat.

2.4 COVID 19 observation through CT scan of Lungs.

In January 2020, the COVID 19 first chest imaging findings were first published, which includes the involvement of bilateral lung and ground-glass opacities in most hospitalized patients. Respiratory inflammation signs through CXR or CT scan can be seen by doctors on a chest. Doctors may look at something like “ground glass opacity” on lung CT scan, because it has resemblance to the frosted glass on a shower door. Chest CT examinations may lead to both false-negative and false-positive results.



Figure 2. 7: Observation of COVID on the Lung CT scan: "frosted glass on shower door"

CHAPTER 3: LITERATURE REVIEW

This chapter consists of the literature work from journal articles, conference papers, case studies and books. The main objective of this paper is to collect, synthesize and organize the existing knowledge related to the usage of radio graphical images and the methods that are used to detect Coronavirus. The focus of this chapter is to review several papers in which work has been done to predict the COVID disease from Lungs CT-Scan, and to identify the gaps. From the end of 2019, the topic of COVID disease and different methods of diagnosis of the patient has attracted ample number of researchers towards it. The smart methods of COVID diagnosis have become a salient topic among researchers from all around the world since the COVID has been got worst. Significant amount of effort is spent by a lot of people in searching new and better ways to predict the COVID patient. Different works agree on different methods to provide best diagnosis results. In this section we will briefly discuss the work contribution by different researchers by utilizing different methods.

With increasing cases of COVID, the scientist could not only rely on RT-PCR. They did research and found out that as COVID is a respiratory syndrome, it affects the lungs, just as they are infected in pneumonia or other lung diseases. Then researchers started their work on CT scan images of lungs and chest X-rays. At early stage it has been considered work of a radiologist to read the images according to his knowledge and create a result of his findings. Since COVID outbreak was rapid and it became a hard task for the radiologist to do things this way, also not in every area or every country there are proper knowledge or experts of radiology, it brought research to find out some other methods and they started looking towards artificial intelligence and deep learning. Since this is an era of artificial intelligence. Proper availability of the data can lead to many significant findings without the involvement of a radiologist. for disease diagnosis. This chapter will summarize all the valuable research in this domain.

3.1 Classification:

In the analysis of medical images, the methods based on machine learning has shown groundbreaking success [18]. In a clinical setting it is reliable, automatic, and easy to implement the Machine learning techniques. Images with alike features are analyzed in any ML based application to classify. Basically, an image analysis approach works as to segment the image region which can be of interest, the image features are being identified which are extracted by the segmented region in spatial domain. After the features are identified, an

optimal Machine learning algorithm has been developed which works to allocate image sample to respective class. Many deep learning techniques have been implemented on radiographical images each one with different results of accuracy and specificity. Since deep learning has been considered best for CT images, many works have already been done on CT images because of which researchers decided to use deep learning model for detection of COVID too.

Previously, Grewal et al., [8] analyzed 77 brain Ct images by using DenseNet and recurrent neural network layers. Hemorrhage was predicted by Radnet with accuracy of 81%. Song et al. [9] used three deep neural networks to classify lung cancer. Chronic obstructive pulmonary disease has also been detected by deep neural network [10].

The important points to analyze in a CT image in order to detect COVID, was paving and regular pattern, consolidation and opacities at ground glass level. The relation between CT images and clinical finding of patient has been investigated by Zhao et al. [11]. They clinically observed 101 patients from different cities. All available clinical, research and epidemiological information was collected for all patients. As stated in the rule for COVID-19 (preliminary variant 5) [29] of the National Health Commission of China, the patients were isolated into four groups: those with mild infection, normal type, extreme type, and fatal type. They used four different types of scanners for CT scan images of all the patients using different parameters. The CT scan images are then evaluated by two different radiologists, they read the images by themselves. There are 25 features, some of them are ground-glass opacities (GGO), mixed GGO and consolidation, consolidation subpleural bands, pleural effusions etc. the statistical analysis has been done through these features.

Ai, Tao, et al. [12] done a comparative study on both methods, RT-PCR, and clinical findings of lung CT scans. Out of 1014 patients, 59% patients had RT-PCR positive and 88% had positive CT scans. Based on positive RT-PCR results, the ability of chest computed tomography to be influenced when recommending COVID-19 was 97%. While in case of RT-PCR negative out of 413 patients 308 had positive chest CT results. It has been shown by the comparative analysis that Chest CT scan could be a more accurate method for detection of COVID patient.

Another meta-analysis has done to compare the sensitivity and specificity of COVID which gives pooled sensitivity and specificity of chest CT as 94% and 37% for detection of COVID through Chest Ct, correspondingly, although RT-PCR pooled sensitivity was 89% [15].

It has been shown by Ai et al. [13] that sensitivity was 97% when he worked on a pre trained U net and a 3D deep neural network using Ct images of 1014 patients and compared his results with the results of RT-PCR, which has also been performed on same patients. CT scan of 51 patients has been collected and RT-PCR is also performed, and it has been confirmed that CT scan has more sensitivity, 98%, in comparison of RT-PCR, 71% [14].

Zheng et al. [22], developed a deep neural network software to detect COVID using 3D CT volumes. A CTnet-10 model was developed to differentiate COVID and Non-COVID images, which gave accuracy of 82.1% [16]. They compared other deep learning models such as VGG-16 and 19, ResNet-50, InceptionV3, and DenseNet-169, the result showed that VGG-19 is best of all which gave accuracy of 94.52%.

J Zhao et al [3]. build an open-sourced dataset contained 746 images. In the proposed methodology images are resized and augmented. Multi-task learning and self-supervised learning is developed as diagnosis methods and gives an AUC of 0.98, F1 of 0.90, and the 0.89 accuracy on the model. Cosine scheduling with a period of 10 is used to adjust the learning rate across the training process.

An infection-size-aware Random Forest (iSARF) method which can automatically categorize subjects into groups with different ranges of infected lesion sizes is proposed by Shen et al. [20].

Efficient-Net architecture came in researchers' site in 2019, the work has been done on a small dataset on Efficient-Net deep neural network with alternating learning rates techniques with 5 fold cross-validation strategy performed to predict the test data in each fold. Domain generic transfer learning is used. The test predictions of each fold are averaged and evaluated against the ground truth. The dataset is augmented to increase the number of images, along with transfer learning to avoid overfitting. Achieved F1-score of 0.9, cyclic learning rate and constant learning rate resulted in F1- score of 0.86 and 0.82 [20].

He, X., Yang, et al [22] proposed a self-trans approach which reduced the risk of over-fitting. eXplainable deep learning approach was used which gave F1 score of 97.31% [23]. The inter-observer variability inherent task is analyzed by [24], proposing solution with help of annotation procedure and noise modelling. The eXplainable approach is non-iterative and is entirely based on recursive calculations and use of prototypes. Therefore, it is

computationally very efficient. The advantages of the proposed method include: high precision as compared with the top state-of-the-art algorithms and high level of explainability.

The dataset is divided into 80% for training purposes and 20% for validation purposes. Rahimzadeh, M. et al [25] introduce a new dataset that contains 68849 CT scan images, the proposed network takes all the CT scan image sequences of a patient as the input and determines if the patient is infected with COVID-19. At first, the network runs an image processing algorithm to discard those CT images that inside the lung is not properly visible in them. This helps to reduce the number of images, so it reduces the processing time. Less chance of reduces false detections. Modified version of ResNet50V2 that is enhanced by a feature pyramid network is proposed. The ResNet50V2 with feature pyramid network achieved 98.49% accuracy on more than 7996 validation images and correctly identified almost 237 patients from 245 patients.

Eight different CNN models are employed by Chowdhury et al. for identification of COVID-19 patients based on chest and Xray images [19]. The classification is mainly based on transfer learning on the dataset of three classes, with normal, covid and pneumonia patients CXR images. They achieved 99.7% classification accuracy, 99.7% precision, 97.9% sensitivity, and 99.95% specificity on normal and COVID-19 images, while 99.9% classification accuracy, 97.95% precision, 97.9% sensitivity, and 98.8% specificity for normal, COVID-19 and viral pneumonia.

Ter-Sarkisov, et al[30] proposed a method which has two parts, detection and prediction, for three classes COVID< Common pneumonia and normal. It detects the ground glass opacity from CT scan images and the predict on the base of bounding boxes. The dataset is derived from China national center for bioinformatics named as COVIDx-CT. R-CNN final and mask are used in this approach for segmentation. The final accuracy on the 5% train test split was 91.66%, with 90.80% COVID sensitivity, 91.62% common pneumonia sensitivity and 92.10% normal sensitivity.

The extensive summary of the literature review is shown in the table (number)

Table 1: Summary of Literature Review

Paper	Year	Author	Method(s)	Database	Accuracy
[1]	2020	Rahimzadeh et al.*	ResNet50V2	New And Large Lung CT Scan Dataset	Accuracy 98.49%
[2]	2019	Angelov et al.*	eXplainable Deep Learning approach (xDNN)	SARS-CoV-2 CT-scan dataset	F1 score of 97.31%
[3]	2020	Anwar, et al*	EfficientNet and 5 fold cross validation	COVID-CT-Dataset	Accuracy 89.7%, F1 score 89.6% AUC 89.5%
[4]	2020	J Zhao et al.*	multi-task learning and self-supervised learning	COVID-CT-Dataset	Accuracy: 89% F1 score 90% AUC 98%
[5]	2020	Xuehai He* et al.*	Sample-efficient	They built their own CT'scans dataset	Accuracy 94.00%
[6]	2020	Keegan Lensink et al.*	Pixel wise segmentation UNet [18] a DeepLabv3Plus with a ResNet50 backbone and a PSPNet with an InceptionResNetv2	Self created CT Dataset	Opacity Intersection-Over-Union score of 0.76 on trained data
[30]	2020	Ter-Sarkisov, et al	Segmentaion of Lesion in chest CT scan: Used Faster R-CNN and MASK CNN	Images of patients from China center of bioinformatics	Accuracy: 91.66%, sensitivity 90.80% COVID, 91.62% common pneumonia\92.10% Normal
[7]	2020	Hoda Asefi*	Meta-Analysis	General images of patients	Sensitivity: 94 Specificity: 37%, pooled sensitivity of RT-PCR: 89%
[8]	2021	Parnian Afshar*	statistical analysis to collect CT images	COVID-CT-MD dataset	-----
[9]	2020	Eric D. Tenda1	Case Study	-----	-----

3.2 Research Gaps

Reviewing the literature, we have come to know the methods and techniques use for diagnosis of Covid patient through CT images, we have also come across some of the research gaps. Generally, a small CT image datasets (maximum of 5000) have been used for COVID analysis, there is only one largest publicly available dataset and there is no other work have done on it, except the ones who introduced the dataset. None of the researcher have done any specialized preprocessing, except the augmentation, to support the network. Most studies have utilized transfer learning only. No study has analyzed effect of different loss function using CT images.

CHAPTER 4: MATERIALS AND METHODOLOGY

In this section first the material available for the chest CT scan is discussed followed by the proposed methodology.

4.1 Materials

Since corona was unexpectedly spreading rapidly, radiologist was highly occupied, and some of them do not have much experience to detect COVID from CT scan, to address this issue several deep learning techniques were used to screen COVID from CT scans [2], but the CT scans used in this research kept hidden from public which in results delays other researcher to develop more methods. Some of the publicly available datasets have been discussed below:

4.1.1 COVID-CT-Dataset

To resolve this issue J Zhao et al. [3] collected the CT-scan images both for COVID and non-COVID patients. He built CT dataset of 346 COVID Positive CT scans of 216 patients and 397 COVID negative CT scans, some of the sample's images have been shown in figure 4.1. He extracted reported CT images by reading the captions, from COVID19 760 medRxiv and BioRxiv preprints. after the release of this dataset, several feedbacks have been received to the concerning researchers about the usage of the dataset. The significant concerns are summed up as follows. To begin with, when the first CT pictures are placed into papers, it resulted into the degradation of the image quality, which may predict the conclusion choices less exact. The degradation of quality comprises: the Hounsfield unit (HU) values are lost;

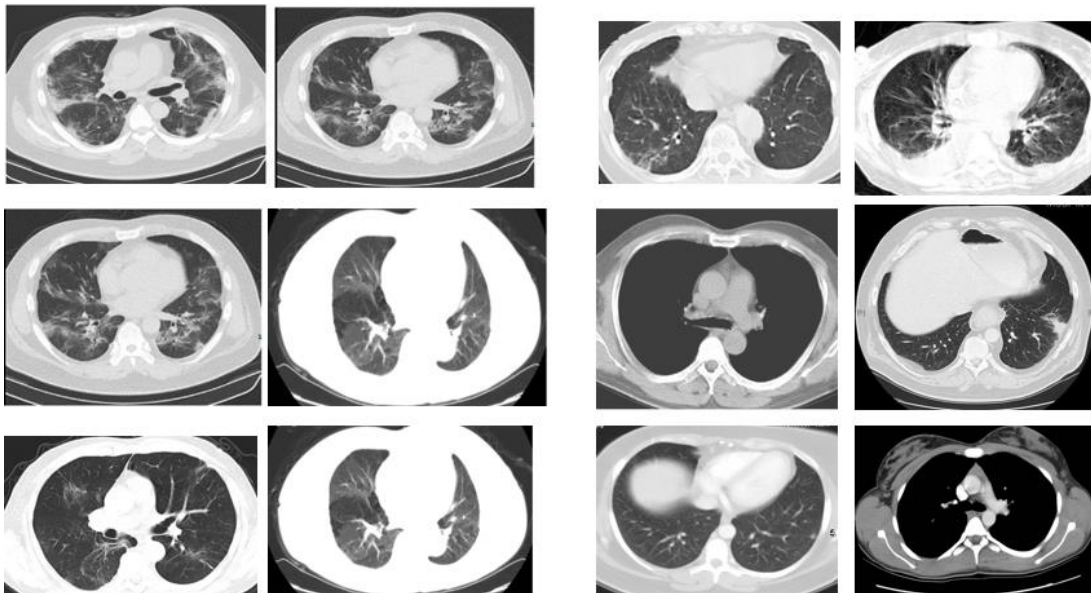


Figure 4. 1: Sample images of COVID CT dataset [3]

the number of pieces per pixel is decreased; because of which image resolution is reduced.

Second, the first CT exam contains a group of CT slices. However, when you put in paper, certain key cuts are selected, which can also have a negative effect on the results. When these concerns are discussed with the radiologist, they did not take it as some significant issues, as they were already tried working on low quality images, with a good accuracy. Also, in some cases a single slice of CT image is enough for detection. So, both of the concerns were not of much significant and that is proved by other methods, like training and testing on low quality images and CT image slices.

4.1.2 SARS-CoV-2 CT-scan dataset

After the dataset proposed by J Zhao, other researchers also started looking for new and vast dataset with more CT scan images. Angelov, P. et al. [4] proposed dataset (sample images shown in figure 4.2, which has been collected from Sao Paulo hospital Brazil, composed of 2483 images, with 1252 CT scans of 60 Covid patients, which 32 are male and 28 are female, and 1230 Ct scan images of 60 Non-Covid patients, with 30 males and 30 females. The 1230 images of no covid patients have some other pulmonary diseases. Patient's details have been shown in figure 4.3.

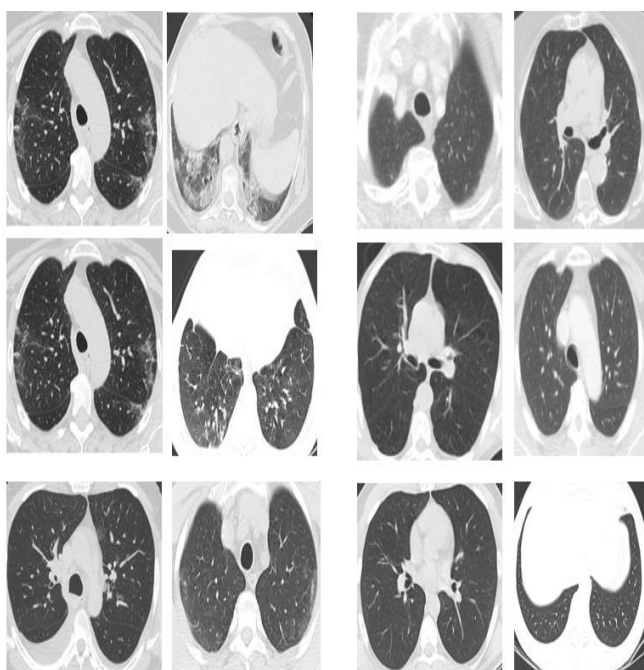


Figure 4. 2: SARS-CoV-2 CT-scan dataset Sample images [4]

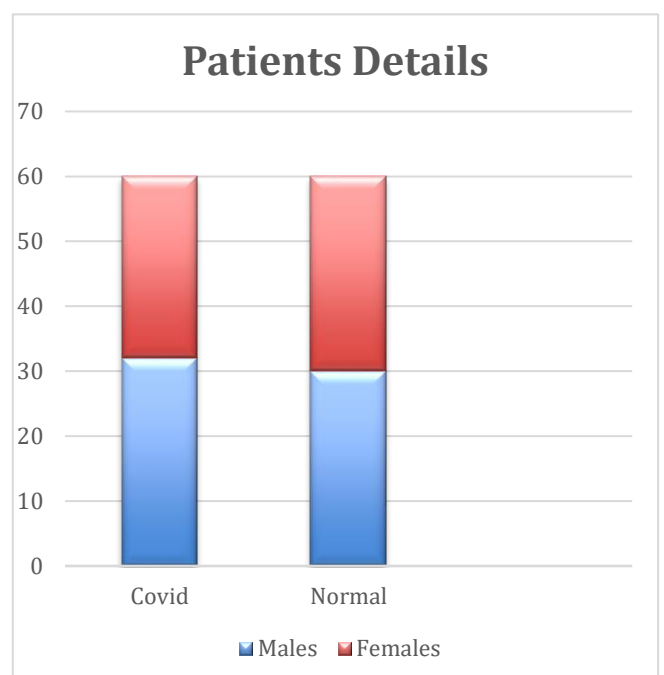


Figure 4. 3: Patients details [4]

4.1.3 New And Large Lung CT Scan Dataset

The data gathered from an Iran's medical center Negin [25]. To capture and visualize Lungs CT images, SOMATOM scope model is used in that center, which gave resultant CT images in format of DICOM with size 512*512. Rahimzadeh et. al [25] changed the DICOM format into TIFF format, the difference between two is that the former included the patient's private information but in tiff format only 16-bit gray scale data is available excluding the person's private information. It could have been converted to 8-bit images instead of 16. but it would result in some data lose.

Data of 95 Covid and 282 normal patients have been collected, the total CT scan images was 63,849, out of which 15,589 was COVID images and 48,260 was normal images. Since this was a huge dataset, which might have some images which was not worthy. To discard those images, researchers found a way in which they divided the whole dataset into three

categories, infection-visible, no-infection, and lung-closed. They performed an image selection algorithm, in which a region of the lung is selected, which might have more information, then a threshold value of dark pixels has been defined, which discarded all the

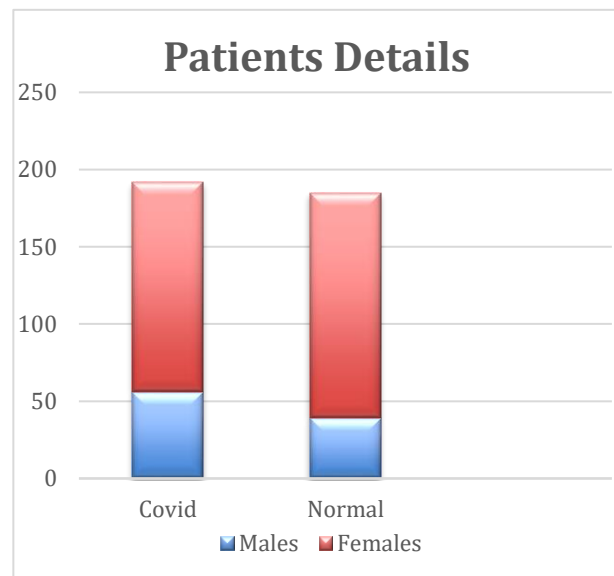


Figure 4. 4: Patients Details for COVID-CTset: A Large COVID-19 CT Scans dataset [25]

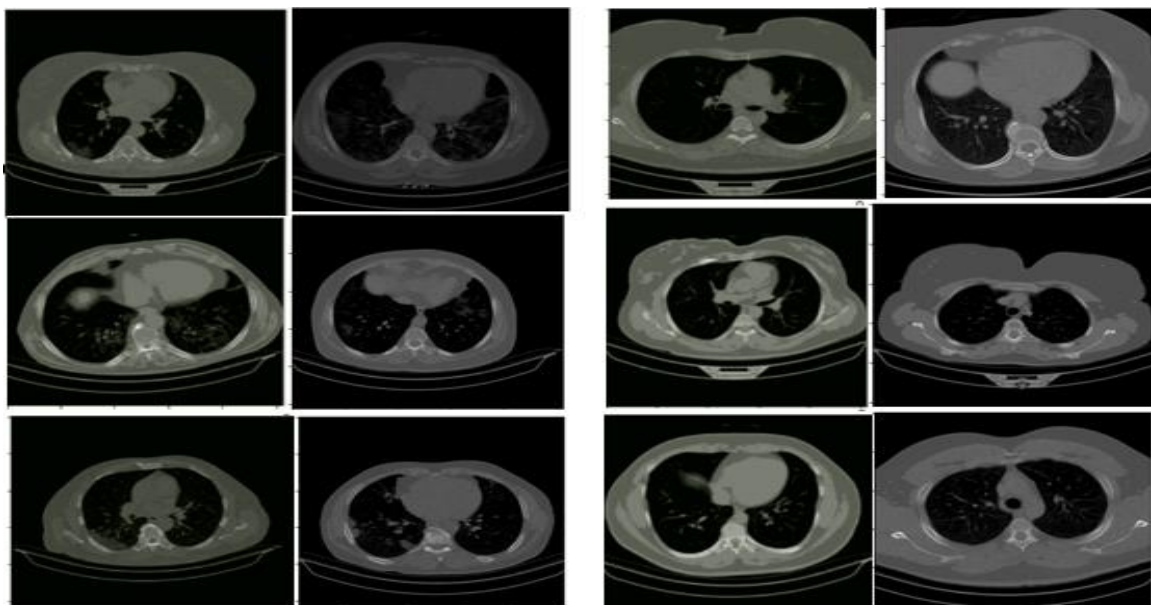


Figure 4. 5: COVID-CTset: A Large COVID-19 CT Scans dataset sample images[25]

images who does not reach the threshold, have less counted dark pixels. The resultant images have more dark pixels than the threshold, some samples have been shown in figure 4.5. It defined the final dataset of 12059 CT scan images which had more information, 2272 images of COVID, 9777 normal. Patients' details have been shown in figure 4.4. Another large classification and segmentation dataset with 144,167 CT images has been constructed [26]. This dataset has been collected from 400 infected patients and 350 un-infected patients.

4.1.4 Afshar, P., et.

Afshar, P., et. al [27] collected CT image data from Babak Imaging Center, Tehran, Iran. Ct scan images of 169 infected patients, created during february to august 2020, 60 Community acquired pneumonia (CAP) patients and Ct scans of 76 normal patients, collected from April 2018 to December 2019 duration. Different criterias are considered to detect the covid Ct scan image with help of radiologist, such as RT-PCR test report and other clinical findings, different image findings, area from where patient belonged, either high ratio of cases or less ratio of cases.

4.1.5 Sun, L et. al

Sun, L et. al [28] extracted dataset from China-Japan Union Hospital of Jilin University, Ruijin hospital of Shanghai Jiao Tong University, Tongji Hospital of Huazhong University of Science and Technology, Shanghai Public Health Clinical Center of Fudan University, Hangzhou First People's Hospital of Zhejiang University, and Sichuan University West China Hospital. Total of 2522 Ct images, 1495 CT images of infected cases, 1027 community accuried pneumonia.

4.1.5 COVID CT scan with mask

There is another dataset available on Kaggle [31] for the segmentation of COVID infection. The dataset consists of CT scan images of covid patient, three different types of masks, one is lungs mask, infection mask and third is lungs and infection mask.

- **Lungs images:** It consists of 3520 CT scan of COVID patients, there is no CT scan available for normal class.
- **Lungs Mask:** It consists of 3520 black and white images with only the Lungs showing.

- **Lungs Infection Mask:** In this folder there are 3520 masks showing only the infection part.
- **Lungs and infection mask:** 3520 mask images showing lungs and the infection.

Some sample images have been shown in figure 4.6.

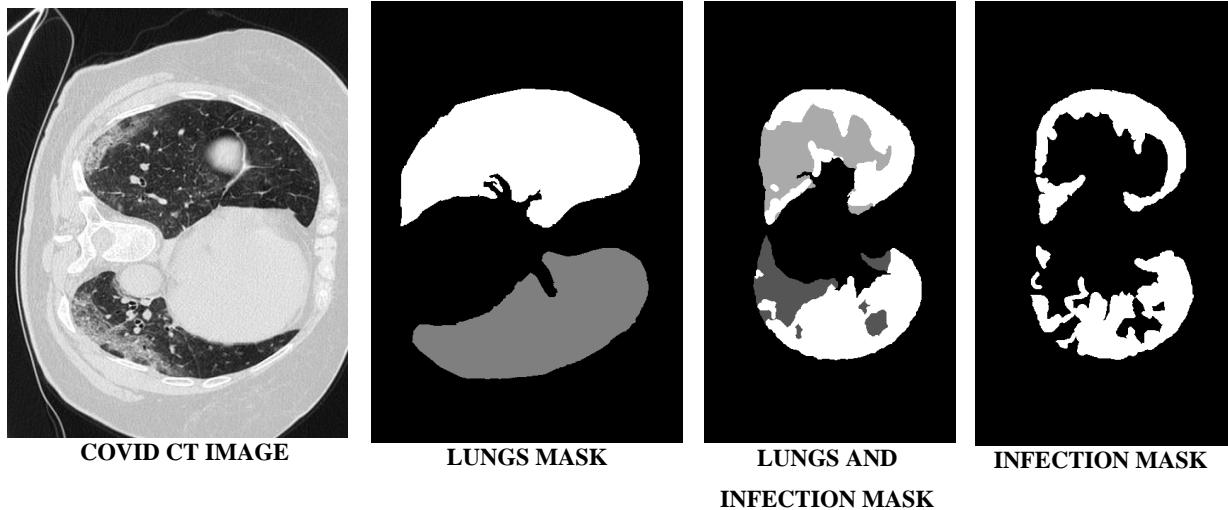


Figure 4. 6: Sample images for COVID CT mask dataset

4.2 Training Phase

In Training phase there are different steps like, data pre-processing. The preprocessing steps depends on the nature of the data. It could be normalized, augmented, resizes or many techniques could be applied according to the nature of the problem and neural network. The data is arranged in accordance with the respective labels of the classes. One reason behind making the data consistent is to predict the exact and required results, as the neural network will only focus on the required features.

Our final proposed methodology shown in figure 4.7, it consist mainly of two experiments.

- Training on the original dataset, we first pre-processed the dataset images. The steps of pre-processing included image normalization, resizing and image augmentation. The augmented dataset is then split into train test with the ratio of 0.3. The total dataset of 18k dataset is divided into 70% train with 13212 total images, and 30% test with 5667 total images. Efficient net Bo model is trained on the trained dataset. The Efficient Net b0 model with batch normalization, drop out dense layer and soft max as

output layer. The final result gives the accuracy of 98.00 percent. We have two other datasets with 756 and 2245 samples. Both datasets are then tested on the pre trained weights of the Efficient-net b0. It has been found out through testing result that the dataset with the smaller number of samples could give good results when tested on the pre trained weight of a larger dataset.

- The second experiment comprises of the specialized preprocessing, whole dataset is colormapped on colormap JET, normalized and then augmented. The dataset is splitted with the ratio fo 0.3 the efficinet net B0 model is then trained with same layers and parameters used in the first experiment. Our model achieved the accuracy of 99.90%. the pre trained model is then fine tuned on two other datasets which gives very promising results for both of the datasets.

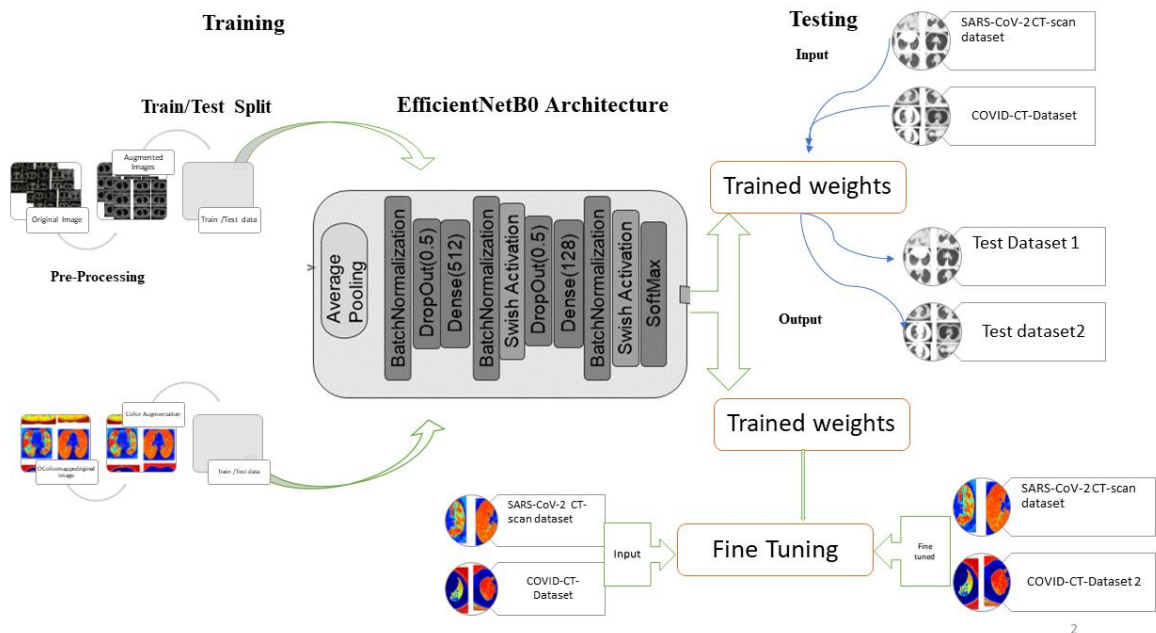


Figure 4. 7: Proposed methodology

4.2.1 Image Pre-Processing

Since the CT images in the dataset are in TIFF format, which are not visible by naked eye, or without any processing on monitor. To visualize the CT images of Covid and non-Covid cases, they are converted from 16-bit TIFF format to 32bit float type, to be visualized by regular monitor.

To make them visual, each 16-bit Tiff image (black) pixel value is divided by the maximum pixel's value, so that the output image is visualized by regular monitors and analyzed by the network. As shown in figure 4.8, left image is a TIFF image and right image is converted image.

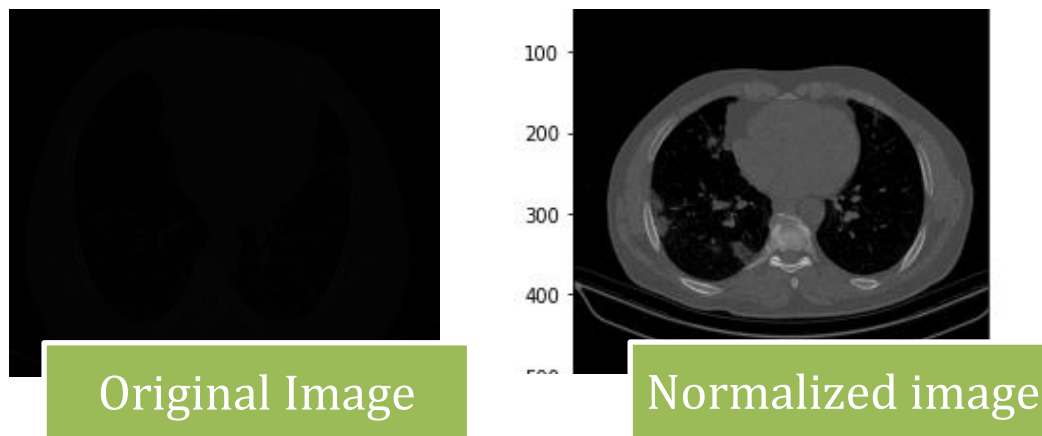


Figure 4. 8: Image Normalization

In training, to define the labels for categorical cross-entropy as error metric, it should be in the one-hot encoding. The representation of one hot coding is as follows, each label is represented as a series which has a single high,1, while the rest of the classes are represented by zeros.

4.2.2 Data Augmentation

Overfitting is a public problem which arises when a CNN model is being trained on a small dataset [36]. Overfitting generally results for poor generalization, it trains accurately but in testing the accuracy drops and the model classify all the samples as one class, high training accuracy but considerably very low validation accuracy. To overcome this issue scientist come up with the idea of data augmentation, it augments the data using different techniques to make it enough for a good training. Data augmentation modifies the data and enable to increase the samples of data. The augmentation techniques could be many, some of the are listed below.

- Cropping: Image is cropped according to specific dimension
- Flipping: Image is either flipped Vertically or horizontally
- Rotating: Image is rotated right or left
- Zooming: Image could be zoomed in or out, using scaling factor
- Rescaling: Image could be rescaled on new dimensions
- brightness changing: the contrast or brightness could be decreased or enhanced.
- Shifting: The image pixels could be shifted right or left

After visualizing the images, since Covid CT images have 75% less number of samples in comparison of non-COVID CT images. So the Covid images are augmented with three different techniques mentioned below with respective parameters;

1. Scaling: COVID CT images are zoomed in with the factor of 1.5 and 1.0, independently.
2. Flipping: COVID CT dataset have been flipped horizontally.
3. Brightness: Brightness enhancement or decrease depends on the Gamma Contrast factor. We have used gamma contrast as 2.0 for COVID CT data samples.

After applying the three image augmentation techniques, images shown in figure 4.9 we achieved the desired number of data samples as shown in the table. Which after concatenation gives total of 9100 CT images of Covid Ct scans. The figure 4.9 below shows all the three different augmented image.



Figure 4. 9: Augmented images (a) Scaled (b) brightness enhanced (c) flipped horizontally

Table 4. 1: Augmentation on Datasets

Dataset	Original Data		Augmentation Type	Augmented data	Total data
COVID-CTset : A Large COVID-19 CT Scans dataset	12058	9776	-----	-----	18875
		2275	Scaling	2275	
	Brightness		2275		
	Horizontal Flip		2275		
	Total		9100		

4.1.3 Color Mapping

Gray scale or binary images are not able to show small details sometimes, which may affect the training results. Color mapping is a technique which maps the pixels on the assigned colors, which makes the smaller features more visible, some of the intensity information could also preserved or removed using pseudo color techniques. There are mainly four categories of pseudo coloring, Sequential, cyclic, diverging, and qualitative. Each one has its own properties, some vary in saturation, lightning, starting and ending color, same color with various intensities, or miscellaneous colors. Data perception efficiency and effectiveness is improved by color mapping which play an important role in visualization therefore allow more insights into the data.

There are 12 basic colormaps that can be applied on gray scale images defined by OpenCV using the function applyColorMap() to produce pseudo colored image. Figure 4.10 shows the visual representation of colormaps.

We have trained our model by using different colormaps, resulting in varying efficiency of the neural network. The used colormaps are as follows:

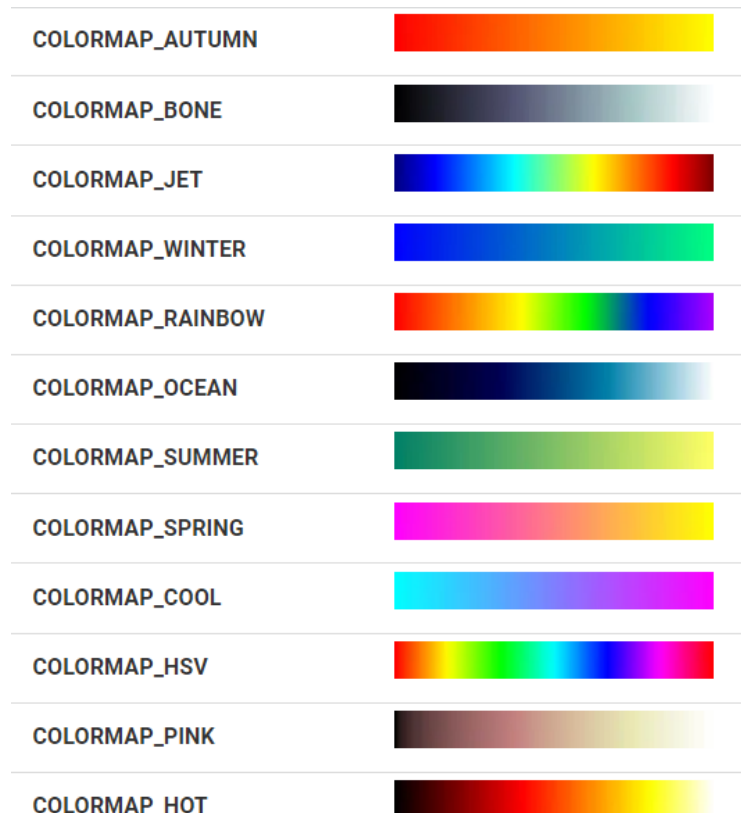


Figure 4. 10: Color maps OpenCV

- Pink: Pink pseudo code is used on the dataset, in pink pseudo code there is the variation of intensities of same color.
- Ocean: Ocean pseudo code is the distribution of blue color with varying intensities.
- Hot: Hot is also a sequential pseudo code, it varies in red and yellow.
- Jet: Jet is a miscellaneous pseudo code, it varies in colors of all the intensities.

The sample images for each colormap are shown below, along with the original image.



Figure 4. 11: : Sample image for each colormap

4.3 Classification

We have described extensively in this section, how we use latest CNN-based deep learning architecture to categorize COVID patient through CT scan images.

4.3.1 EfficientNet

Tan et al.[34] studied the detailed model of convolution neural network in three dimensions, width, depth and height. By studying the model scaling, there are many options to scale a convolution network, individually in term of width, or height or depth. Tan et al [34] comes up with an idea to combine all these dimensions to create a compound scaled convolution network. The compound convolution network become the one with less parameters which makes it efficient. The compound scaled coefficient is then used in a mobile sized baseline model, named as EfficientNet convolution neural network. The EfficientNet neural model uses FLOPS instead of latency, as it must be made hardware generic. There are seven models of EfficientNEt starting from B0 to B7, each with varying input parameters and total number of trainable parameters. Tan et al [34], tried scaling other models such as Resnet and mobile net on the same methods but the results was not promising. Compared to other models achieving similar ImageNet accuracy, Efficient-Net is much smaller. For example, the ResNet50 model as you can see in Keras application has 23,534,592 parameters in total, and

yet, it still underperforms the smallest Efficient-Net (called EfficientNet-B0), which only has 5,330,564 parameters in total.

EfficientNet B0:

The Efficient-Net family is based on a new method for scaling up CNN models. It uses a simple greatly effective compound coefficient. Efficient-Net scales each dimension with a fixed set of scaling coefficients, such as depth, width, and height uniformly. Practically, scaling individual dimensions improves model performance, however balancing all dimensions of the network with respect to the available resources effectively improves the whole performance.

Activation Function: Swish activation function is used in EfficientNet B0, this is a new activation function, most of the CNN models use the ReLU activation function. Swish activation is similar in architecture as of ReLU and LeakyReLU, and hence shares some of their good performance advantages. However, unlike these two, it is a smoother activation function.

$$f_{swish}(x) = \frac{x}{1+e^{-\beta x}} \dots\dots\dots (4.1)$$

Where $\beta \geq 0$ is a parameter that can be learned during training of the CNN model. β is the only parameter which can affect the activation function, changing the β parameter can change the swish activation function into linear or ReLU-like the ReLU function except it is smoother.

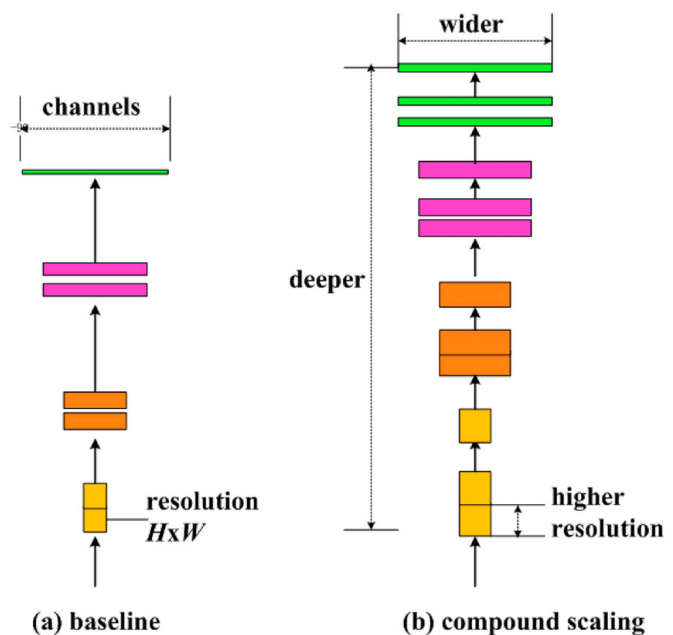


Figure 4. 12: EfficientNet Neural Network

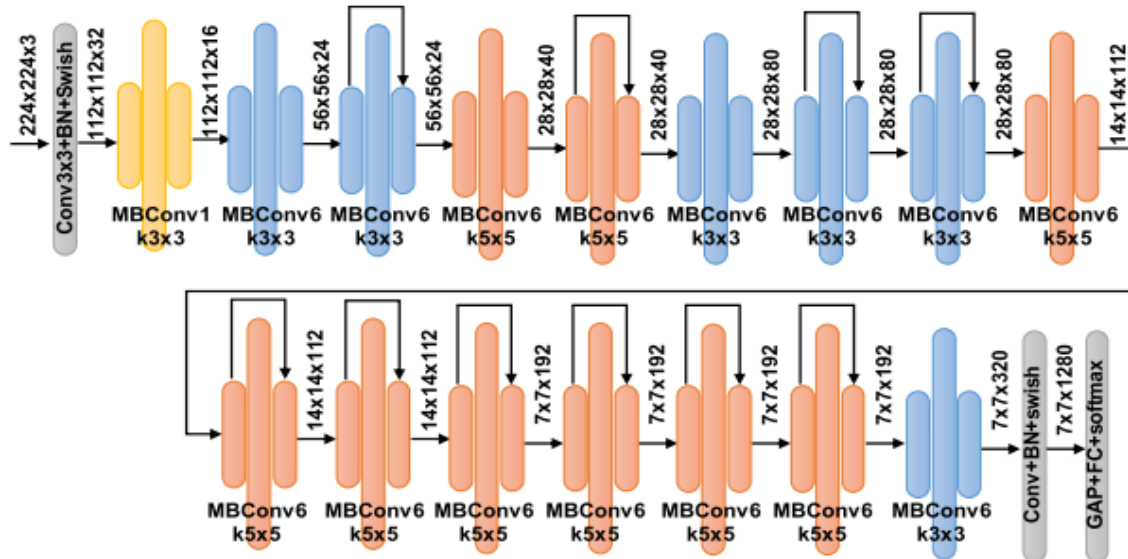


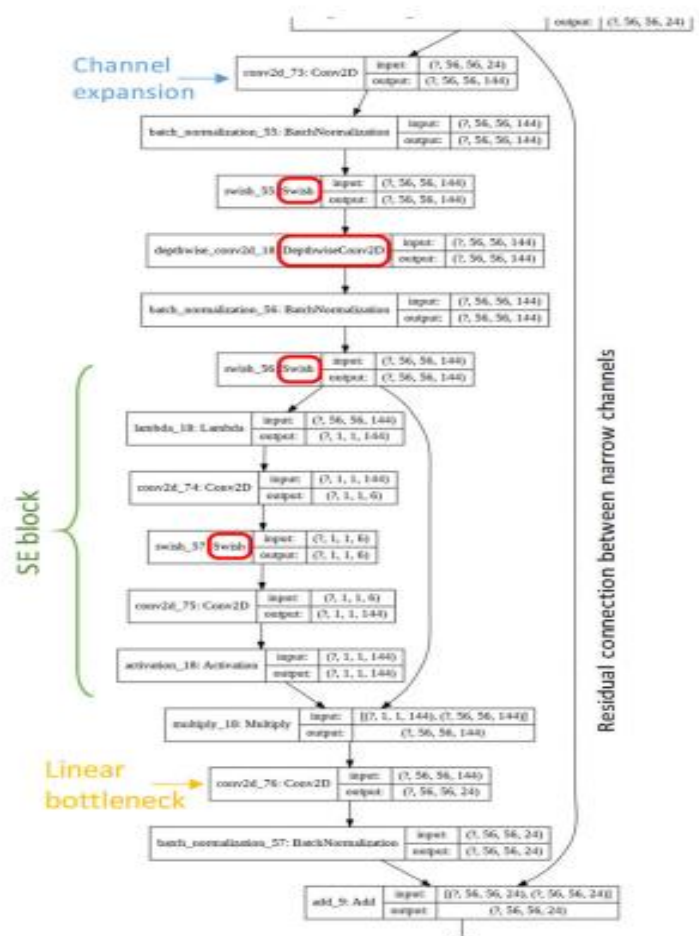
Figure 4.13: Basic EfficientNetB0 Architecture

It has been shown in figure 4.13 that there are multiple MBConv blocks, MBConv1, MBConv3, and MBConv6 blocks, in the baseline network. The filter size varies in each MBConv used in the convolutional layers inside the block (which can be 3×3 or 5×5) and depending on whether the block contains an inverted residual connection or not.

Also, the number of channels is increased or expanded with help of a larger number of filters inside each block. The third observation is the inverted residual connections which are taking place between the narrow layers of the model.

Mobile inverted bottleneck convolution (MB-Conv) block

Mobile inverted bottleneck convolution (MB-Conv) is the main building block of Efficient-Net model family. MB convolution blocks mainly used in Mobile-Net architecture first.



Using MBConv here is to utilize the idea of point wise convolution and dept wise convolution.

Then two more ideas are borrowed from MobileNet-V2, inverted residual connections, and Linear bottlenecks. The MBConv6 is shown in figure 4.14

There is only one block of MBConv1 is used in the Efficient-Net B0 architecture. As shown in figure 4.15.

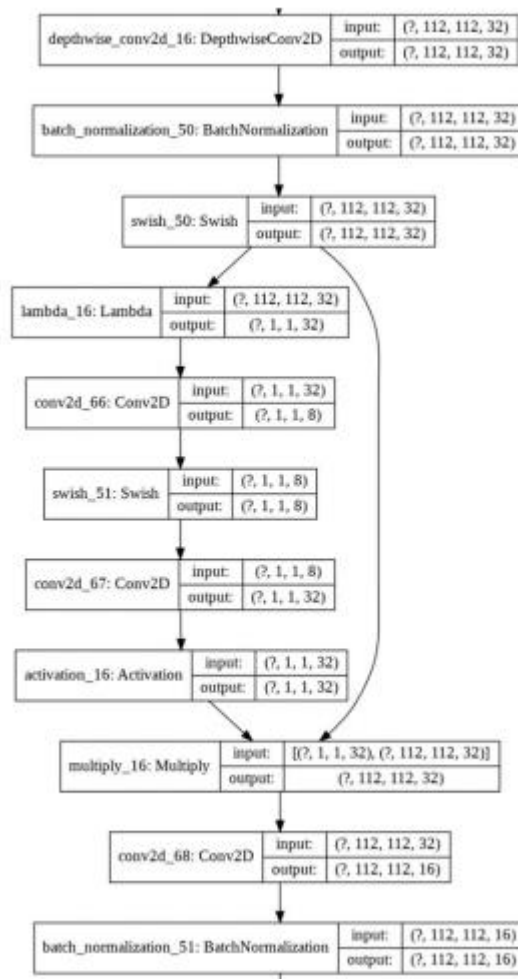


Figure 4. 15: MBConv1 Architecture [103]

4.3.2 Modification in EfficientNetB0

We modified the Efficient-Net by adding some more operator blocks on below of it, as shown in figure 4.16. In

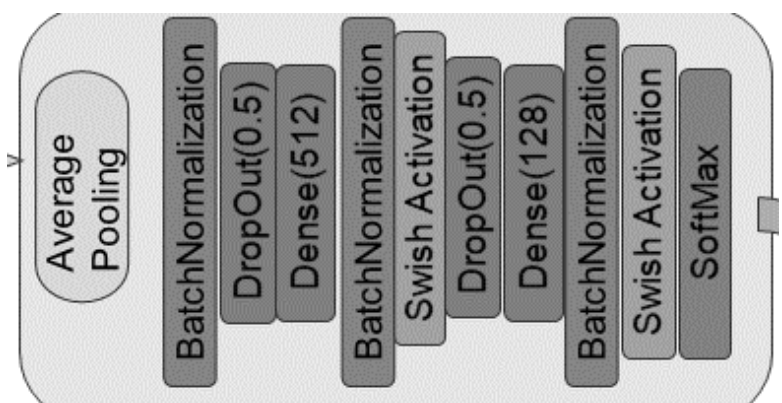


Figure 4. 16: Efficient-Net B0 layers

the proposed architecture, we used some different layers from the traditional mode to make it efficient according to the dataset. Figure 4.16 illustrates our proposed layers for the EfficientNetB0 composed of Average Pooling, two batch normalization layers, two dropout layers and two dense layers, swish activation as activation function and softmax as output layer. Pooling layers is added to prevent instances of severe overfitting from the sophisticated feature handling. The average pooling layer further reduced the number of parameters by rescaling the height, width, and depth of the incoming tensor from the base model into a 1x1x3 dimension, respectively. Batch normalization helps the data flow from one layer to another easily, then a drop out layer with 0.5 parameter is used which randomly set the outgoing edges of hidden units. Dense is used with different parameters at two layers. SoftMax is used as output layer which assign the probabilities in multiclass problems.

4.3.3 Training and Inference

EfficientNetB0 baseline model with some additional layers network is used in the proposed architecture. The dataset samples of 512*512 are scaled to 224*224 and normalized in the range of 0 to 1. For COVID-CTset: A Large COVID-19 CT Scans dataset, we follow the data augmentation technique for training: the image is zoom out with scaling property, and augmented scale image is brightened by gamma=2 and final images are flipped horizontally. COVID-CTset: A Large COVID-19 CT Scans dataset, data is split into test and train split. The model is trained with different batch size, the mini-batch size is 50 and totally 30 epochs. **Learning rate** plays an important role in model training, helps a network to perform better. The model is trained on different learning rate, varies from 0.1 to 0.00001, but the one which gives the best result is 0.00001 on 30 epochs and batch size of 50.

Loss function to minimize the error, multi class loss functions are used instead of binary cross-entropy, for binary class. We used three different loss function to evaluate the performance of our neural network and find the best loss function.

- Cross entropy calculates the difference in two probability distributions, it is often used for multiclass problems, since we can use binary cross-entropy, but the binary loss function does not give any significant results. Also, it used the labels in one hot form.
- Kullback leibler divergence helps in measurement of data loss on using different approximation.
- Sparse categorical cross entropy: the sparse categorical cross entropy does not use the labels in one hot form, the labels are in binary

4.4 Fine Tuning

The concept of fine tuning comes up from the idea of transfer learning. In fine tuning the network surgery is performed using different methods. A pre trained network is further fine-tuned to achieve the good results. Transfer learning is the base of fine tuning, a model trained on the large number of samples could be further used on other samples of same features.

There are many methods to fine tune a network, either to only freeze some layers, or to freeze some layers and add some extra layers from another base model to reduce the trainable parameters. Most of the time the FC layers of the pre trained model is replaced with the FC layers of a new model. The reason of freezing only the FC layers is that the early layers extract features that are relevant to diverse image recognition tasks. Figure 4.17 shows that which layer should be fine tune to achieve better accuracy. Therefore, fine-tuning idea have several choices of deep networks in practice.

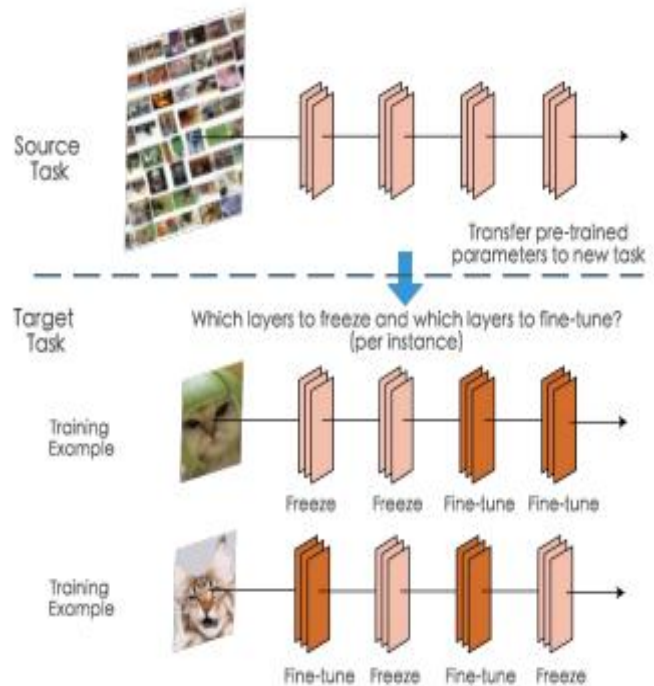


Figure 4. 17: CNN Model Fine Tuning [104]

In our proposed methodology, we froze some layers of the Efficient-Net mode. The proposed architecture may have a huge possibility to confront the problem of overfitting since we have unbalance and a smaller number of samples. For the efficient results we experimented different fine-tuning After applying fine tuning mechanism, the total number of parameters are 5,915,565 including trainable parameter: 1,281,000, and non-trainable parameters: 4,634,565. The model summary is shown in figure 4.18

batch_normalization_1 (BatchNor	(None, 512)	2048	dense[0][0]
activation (Activation)	(None, 512)	0	batch_normalization_1[0][0]
dropout_1 (Dropout)	(None, 512)	0	activation[0][0]
dense_1 (Dense)	(None, 128)	65664	dropout_1[0][0]
batch_normalization_2 (BatchNor	(None, 128)	512	dense_1[0][0]
activation_1 (Activation)	(None, 128)	0	batch_normalization_2[0][0]
dense_2 (Dense)	(None, 2)	258	activation_1[0][0]
=====			
Total params: 5,915,565			
Trainable params: 1,281,000			
Non-trainable params: 4,634,565			

Figure 4. 18: Summary of fine-tuned model

4.4.1 Training and Inference for fine tuning model

Above describe fine tuning model is train on two different color-mapped augmented datasets. Our model has been experimented with varying learning rate, different epochs and batch size. But the best results are achieved with the same parameter which are used for the training of the above-mentioned model. Technique of data augmentation is only applied on the COVID samples.

Table 4.2: Parameters

Parameter for Training	Value
Batch Size	50
Optimizer	Adam
Learning Rate	0.00001
EPOCHS	30
Loss function	Categorical Cross entropy
	Kullback Leibler divergence
	Sparse categorical entropy

4.5 Testing Phase

For training and testing purpose, the COVID-CTset: A Large COVID-19 CT Scans dataset, has been divided into the split of 0.3. The 30% of the dataset is used for the testing on the trained Efficient-NetB0 model. Other than COVID-CTset: A Large COVID-19 CT Scans dataset, two other datasets have been also tested on the trained models.

CHAPTER 5: EXPERIMENTAL RESULTS

5.1 Databases

Performance on different datasets is achieved using different experiments. We have used one large dataset, COVID-CTset: A Large COVID-19 CT Scans dataset for the training of our network, while the other dataset SARS-CoV-2 CT-scan dataset and COVID-CT-Dataset have been used for testing and for fine-tuned network

5.2 Performance Measures

As for now, accuracy and AUC are used as evaluation criteria. The total number of correct predictions out of all is considered as accuracy. The area under the ROC curve is known as AUC, which provides an aggregate measure of performance across all possible classification

The best results achieved in terms of

- Accuracy
- Loss
- Confusion matrix
- Training and testing results for both experiments has been achieved
- Blind testing is performed on two different datasets using pre trained weights
- The promising results of fine tuning are achieved on two different datasets.

5.3 Results

The Efficient-Net architecture is trained on 9100 COVID (2275 original and 6825 augmented) and 9777 Normal images, Total of 18875 images, split by 0.3%, 70% train and 30% test images. The network gives accuracy of 98.00%.

Table 5.1: Summary of train and test data.

Dataset	Count	Resolution	Accuracy	Loss
Train Data	13212	224x224x3	99.61%	0.06
Test Data	7664	224x224x3	98.00%	0.18

Extracted observation and Results are represented through Confusion matrices. COVID-CT set: A Large COVID-19 CT Scans dataset test data result in confusion matrix is given below in Figure. 5.3.

The trained weights are then tested on two other datasets, one is **COVID-CT-Dataset** with the 746 samples of 349 Covid Ct images 397 Normal Ct images.

And **SARS-CoV-2 CT-scan dataset** with total 2480 samples out of which 1252 Covid CT image 1230 Normal CT images. Predicted accuracy results are highly accurate and inspirational. The table 5.2 shows the accuracy of three datasets along with the confusion matrixes.

Table 5.2: Accuracy of different datasets with confusion matrix.

Dataset	New And Large Lung CT Scan Dataset		COVID-CT-Dataset		SARS-CoV-2 CT-scan dataset	
Count	5336(test)		746		2480	
Accuracy	98.00%		88.98%		99.89%	
True class	2358	346	309	108	1251	11
	44	2887	40	289	1	1218
Predicted class						

Loss function: The model is then trained on two different loss functions; loss function mainly measures the estimated value of the true value from the expected value. Below table shows the results with the kullback leibler divergence.

Classification with Kullback Leibler divergence:

Table 5.3: Kullback Leibler divergence results

Dataset	Count	Resolution	Accuracy	Loss
Train Data	13212	224x224x3	99.97%	0.01
Test Data	5663	224x224x3	99.88%	0.02

Trained Model Classification Testing Results

Classification with Sparse cross entropy:

Table 5.4: Classification with sparse cross entropy

Dataset	Count	Resolution	Sparse Accuracy	Loss
Train Data	13212	224x224x3	99.67	0.03
Test Data	5663	224x224x3		

Loss Function	Categorical cross entropy		Kullback Leibler divergence		Sparse cross entropy	
New And Large Lung CT Scan Dataset	5336(test)		5336(test)		5336(test)	
Accuracy	98.00%		99.88%		99.67%	
True class	2358	346	2718	37	2699	44
	44	2887	10	2898	20	2886
Predicted class						

Table 5.5: Results for all three loss function.

Color-Mapping Results

The dataset is color mapped, normalized, and augmented. It is trained on Efficient Net B0 Model. The trained weights are then fine-tuned on two different datasets.

- **COVID-CT-Dataset** with the 746 samples of 349 Covid Ct images 397 Normal CT images.
- **SARS-CoV-2 CT-scan dataset** with total 2480 samples out of which 1252 Covid CT image 1230 Normal CT images

The table below shows the classifications results of color mapped dataset.

Table 5.6: Classification results

Dataset	Count	Resolution	Accuracy	Loss
Train Data	13212	224x224x3	100%	0.001
Test Data	5663	224x224x3	99.90%	0.021

We have also tried different colormap for the analysis of finding the best colormap. The table below shows the comparison of different color-mapped applied on the dataset along with the original dataset.

Color-Mapps	Count		Train		Test	
			Accuracy	Loss	Accuracy	Loss
JET	18875	9776 normal	100%	0.005	99.90%	0.021
PINK			99.92%	0.005	99.81%	0.02
HOT+OCEAN		Covid: 2275(6825	99.01%	0.008	99.26%	1.16e ⁻⁰⁴
ORIGINAL DATASET		augmented)	99.61%	0.06	98.00%	0.18

Table 5.7: Comparison results of color mapped applied on dataset

Fine Tuning Results:

The table below shows the fine-tuning results on two different datasets:

Table 5.8: Fine tuning results on two datasets.

Dataset	Count	Resolution	Train Accuracy	Test accuracy	Train Loss	Test Loss
COVID-CT-Dataset	746	224x224x3	99.97%	99.18%	0.024	0.089
SARS-CoV-2 CT-scan dataset	2480	224x224x3	83.66%	86.62%	0.467	0.418

This table shows the results of color-mapped on all three datasets.

Table 5.9: Color mapped results on three datasets.

Color mapped Dataset	New And Large Lung CT Scan Dataset		COVID-CT-Dataset		SARS-CoV-2 CT-scan dataset	
Count	5336(test)		746		2480	
Accuracy	99.90%		99.97%		86.62%	
True class	2358	346	349	0	1159	93
	44	2887	17	380	454	775
Predicted class						

Comparison:

The table below shows the comparison results of all the experiments performed above:

Table 5.10: Comparison of same dataset with different loss function

	Experiment	Train test split	Loss Function	Accuracy	Loss
1	Classification on original dataset	13212/5663	Categorical cross entropy	90.35%	0.23
2	Classification on original dataset	13212/5663	Kullback leiber divergence	99.88%	0.02
3	Classification on original dataset	13212/5663	Sparse cross entropy	99.67%	0.03
4	Classification on colormapped dataset	13212/5663	Categorical Cross entropy	99.90%	0.02

The classification results with different loss function and with the color mapped dataset has been shown in the table. The kullback leibler divergence is giving the best results on original dataset. And the color mapped dataset is giving the best results out of all the experiments.

Comparison with the same dataset:

The table below shows the results of previous work on COVID-CTset : A Large COVID-19 CT Scans dataset, along with the results of proposed model. It has been shown in the table that what are the techniques used by Rahimzadeh et al [25] and the techniques used in the proposed methodology. Training on a CNN network is giving the results approximately same as the one proposed before. But with kullback leibler divergence the accuracy improves, and it becomes more than that of proposed before.

Applying the specialized pre-processing technique, color mapping, we have achieved the best accuracy out of all the other techniques.

The table below shows the comparison of all our technique and the technique proposed before.

Table 5.11: Comparison with another researcher.

	Dataset	Model		Accuracy
Rahimzadeh[25]	Normal: 9776 Covid: 2282 Total: 12058	ResNet50V2 with FPN		98.42%
		Xception		96.55%
Our Proposed Methodology	Normal: 9776 Covid: 2282(6817 augmented) Total: 18875	EfficientNet-B0 model	Categorical cross entropy:	98.00%
			Kullback Leiber divergene	99.88%
			Sparse cross entropy	99.67%
			Color-mapped dataset:	99.90%

CHAPTER 6: CONCLUSION & FUTURE WORK

6.1 Conclusion

In this paper, an Efficient-Net convolutional network architecture is utilized to detect the COVID infected patient, from the lungs CT scans. Since the Datasets was limited and are still emerging, so to effectively train the deep neural network, image augmentation techniques are used which helped in the training of the network as it enhanced the number of COVID images from 2275 to 9100. Testing of the trained neural network was performed on different Lungs CT scans dataset, to evaluate the performance of the neural network. Our results give 98.00% accuracy on the largest dataset, 99.89% on a comparatively small dataset, and 88.98% on a small dataset. We have also applied a specialized pre-processing technique which improves the results from 98.00% to 99.90% for the largest dataset. the pre trained model is further fine tuned to improve results on other datasets.

6.2 Contribution

- Balancing the samples of both classes
- Efficient-net B0 for training on largest dataset (with different loss functions)
- Blind testing on trained weights
- Color-mapping on original dataset
- Fine tuning on trained weights of color-mapped dataset

6.3 Future Work

In conventional ML algorithms, different features are manually selected and then a classifier is trained on them. On the other hand, deep models being one step ahead extract the features themselves. As there is no headache of extracting and choosing the optimum feature set according to the problem, the proposed architectures can be used for any other classification or medical image segmentation problem with little modifications. Also, any other ensemble can be implemented using combination of new architectures.

- The proposed method could be further extended in analysis of other lungs diseases through CT scan Images.
- The larger and more diverse datasets are needed to evaluate the methods.

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