



**IJIRCCCE**

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

**Volume 10, Issue 5, May 2022**

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

**Impact Factor: 8.165**



9940 572 462



6381 907 438



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# Covid-19 Detection and Visualization using CNN

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**ABSTRACT:** Deep Learning techniques in general and convolutional neural networks (CNNs) in particular have gained successful results in medical picture analysis and categorization. A deep CNN architecture has been developed in this work for the diagnosis of COVID-19 based on the chest X-ray image categorization. Due to the nonavailability of sufficient-size and good-quality chest X-ray image dataset, an effective and reliable CNN classification was a challenge. To deal with these complexities such as the availability of a very-small-sized and imbalanced dataset with image-quality issues, the dataset has been pre-processed in different phases using different techniques to achieve an effective training dataset for the proposed CNN model to attain its best performance. The testing results have showed the overall accuracy as high as 99.5 percent which illustrates the good capability of the suggested CNN model in the current application area. The CNN model has been evaluated in two scenarios. In the first scenario, the model has been tested using the 100 X-ray pictures of the original processed dataset which achieved an accuracy of 100 percent . In the second case, the model has been tested using an independent dataset of COVID-19 X-ray pictures. The performance in this test scenario was as high as 99.5 percent . To further prove that the suggested model outperforms existing models, a comparative analysis has been done with some of the machine learning methods. The proposed model has outperformed all the models generally and specifically when the model testing was done using an independent testing set. However, a larger dataset of COVID-19 X-ray images is necessary for a more accurate and trustworthy detection of COVID-19 infections when utilising deep transfer learning. This would be highly advantageous in this pandemic when the illness burden and the demand for preventative actions are in contradiction with the existing available resources.

**KEYWORDS:** Deep Learning, Convolutional Neural Networks, Activation Function.

## I. INTRODUCTION

SARS coronavirus 2 is the virus that causes Coronavirus disease 2019 (COVID-19), an infectious respiratory illness (SARS-CoV-2). Chinese authorities found the first instance in Wuhan in December of this year. COVID-19 became a pandemic as the disease spread across the globe.

Cough, fever, headache, exhaustion, difficulty breathing and loss of smell and taste are all common symptoms of COVID 19. One to fourteen days after being exposed to the virus, symptoms may appear. A third or more of those infected show no symptoms at all. Many (81 percent) of individuals who show signs that might be considered patients suffer mild to moderate symptoms, whereas 14 percent experience severe symptoms (dyspnea, hypoxia, or more than 50% lung involvement on imaging), and 5 percent experience life-threatening symptoms (dyspnea plus hypoxia) (respiratory failure, shock, or multiorgan dysfunction). People over the age of 65 are more likely to experience severe symptoms. After recovery, some patients continue to have a wide range of consequences (long COVID) and organs have been damaged. The disease's long-term repercussions are the subject of multi-year investigations.

Airborne particles and droplets containing COVID 19 can infect humans when they come into contact with them. These particles can be breathed over longer distances, even if people are far apart, especially if they are in close quarters. When contaminated fluids are splashed or sprayed into the eyes, nose, or mouth of an infected person, the virus can be transmitted. Even if a person does not show any symptoms, they are still contagious for up to 20 days and can spread the virus.

The condition can now be diagnosed using a variety of COVID-19 testing procedures. Nucleic acid of the virus can be detected through real-time reverse transcription polymerase chain reaction (rRT-PCR), transcription-mediated amplification (TMA), or reverse transcription loop-mediated isothermal amplification (RT-LAMP) from nasopharyngeal sample swabs.

Countries around the world have begun mass vaccination efforts for COVID-19 vaccines that have been approved and distributed. Additionally, quarantine, ventilation, concealing cough and sneezes, hand washing, and keeping dirty hands away from the face are other protective strategies. In public places, face masks or other covers have been recommended to reduce the chance of transmission. The primary therapy for the virus is symptomatic, but research is undertaken to create antiviral medications. Treatment of symptoms, supportive care, seclusion, and experimental methods all fall under the umbrella of management.

## 1. SYMPTOMS

The signs and symptoms of COVID-19 can range from moderate to life-threatening. If you're experiencing any of the following: coughing; fever; loss of smell and taste; nasal congestion and runny nose; muscle discomfort; sore throat; diarrhoea; eye irritation; toe swelling or turning purple; and in moderate to severe instances breathing issues, you may have a viral illness. Symptoms of the COVID-19 infection might vary from person to person, and they can alter over time. A respiratory symptom cluster with cough, sputum, shortness of breath, and fever has been discovered; a musculoskeletal symptom cluster with muscle and joint pain, headache, and exhaustion; and a digestive symptom cluster with abdominal discomfort, vomiting, and diarrhoea. COVID-19 is related with a loss of taste and smell in up to 88 percent of symptomatic cases in patients without antecedent ear, nose, and throat diseases.

Eighty-one percent develop mild to moderate signs, while 14 percent have severe symptoms (dyspnea, hypoxia, or more than 50% lung involvement on imaging) that require hospitalisation, and five percent have critical symptoms (respiration failure, septic shock, or multi-organ dysfunction) that require intensive care admission. Around a third of those who are infected with the virus never show any signs of illness. Even though they may not show any symptoms, asymptomatic carriers are nevertheless contagious. While some infected individuals may not show any symptoms at all, known as "pre-symptomatic" or "mildly symptomatic," they can still transmit the virus.

As is the case with most illnesses, there is a period of time before the first symptoms begin to develop. COVID-19 has a median latency of four to five days, with the virus potentially contagious on one to four of those days. Two to seven days following exposure is typical, and almost everyone will develop at least one symptom during the first 12 days.

Most people are able to return to their normal lives after a brief illness. However, a syndrome known as protracted COVID, which causes organ damage over the long run, affects more than half of a cohort of young adults who were home-isolated throughout treatment. The disease's possible long-term repercussions are the subject of multi-year investigations.

## II. RELATED WORK

### 2.1 Cascaded deep learning classifiers for computer-aided diagnosis of COVID-19 and pneumonia diseases in X-ray scan

Human coronaviruses (HCoVs) have long been considered inconsequential pathogens, causing the "common cold" in otherwise healthy people. However, in the 21st century, 2 highly pathogenic HCoVs—severe acute respiratory syndrome coronavirus (SARS-CoV) and Middle East respiratory syndrome coronavirus (MERS-CoV)—emerged from animal reservoirs to cause global epidemics with alarming morbidity and mortality. In December 2019, yet another pathogenic HCoV, 2019 novel coronavirus (2019-nCoV), was recognized in Wuhan, China, and has caused serious illness and death. The ultimate scope and effect of this outbreak is unclear at present as the situation is rapidly evolving. Coronaviruses are large, enveloped, positive-strand RNA viruses that can be divided into 4 genera: alpha, beta, delta, and gamma, of which alpha and beta CoVs are known to infect humans.<sup>1</sup> Four HCoVs (HCoV 229E, NL63, OC43, and HKU1) are endemic globally and account for 10% to 30% of upper respiratory tract infections in adults. Coronaviruses are ecologically diverse with the greatest variety seen in bats, suggesting that they are the reservoirs for many of these viruses.<sup>2</sup> Peridomestic mammals may serve as intermediate hosts, facilitating recombination and mutation events with expansion of genetic diversity. The surface spike (S) glycoprotein is critical for binding of host cell receptors and is believed to represent a key determinant of host range restriction.<sup>1</sup> Until recently, HCoVs received relatively little attention due to their mild phenotypes in humans. This changed in 2002, when cases of severe atypical pneumonia were described in Guangdong Province, China, causing worldwide concern as disease spread via international travel to more than 2 dozen countries.<sup>2</sup> The new disease became known as severe acute respiratory syndrome (SARS), and a beta-HCoV, named SARS-CoV, was identified as the causative agent.



Because early cases shared a history of human-animal contact at live game markets, zoonotic transmission of the virus was strongly suspected.<sup>3</sup> Palm civets and raccoon dogs were initially thought to be the animal reservoir(s); however, as more viral sequence data became available, consensus emerged that bats were the natural hosts. Common symptoms of SARS included fever, cough, dyspnea, and occasionally watery diarrhea.<sup>2</sup> Of infected patients, 20% to 30% required mechanical ventilation and 10% died, with higher fatality rates in older patients and those with medical comorbidities. Human-to-human transmission was documented, mostly in health care settings. This nosocomial spread may be explained by basic virology: the predominant human receptor for the SARS S glycoprotein, human angiotensin-converting enzyme 2 (ACE2), is found primarily in the lower respiratory tract, rather than in the upper airway. Receptor distribution may account for both the dearth of upper respiratory tract symptoms and the finding that peak viral shedding occurred late ( $\approx 10$  days) in illness when individuals were already hospitalized. SARS care often necessitated aerosol-generating procedures such as intubation, which also may have contributed to the prominent nosocomial spread. Several important transmission events did occur in the community, such as the well-characterized mini-outbreak in the Hotel Metropole in Hong Kong from where infected patrons traveled and spread SARS internationally. Another outbreak occurred at the Amoy Gardens housing complex where more than 300 residents were infected, providing evidence that airborne transmission of SARS-CoV can sometimes occur.<sup>4</sup> Nearly 20 years later, the factors associated with transmission of SARS-CoV, ranging from self-limited animal-to-human transmission to human superspreader events, remain poorly understood. Ultimately, classic public health measures brought the SARS pandemic to an end, but not before 8098 individuals were infected and 774 died.<sup>2</sup> The pandemic cost the global economy an estimated \$30 billion to \$100 billion.<sup>1</sup> SARS-CoV demonstrated that animal CoVs could jump the species barrier, thereby expanding perception of pandemic threats. In 2012, another highly pathogenic beta-CoV made the species jump when Middle East respiratory syndrome (MERS) was recognized and MERS-CoV was identified in the sputum of a Saudi man who died from respiratory failure.<sup>3</sup> Unlike SARS-CoV, which rapidly spread across the globe and was contained and eliminated in relatively short order.

**2.2 World Health Organization (WHO), Coronavirus disease 2019 (COVID-19) Situation Report-74.**  
<https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200403-sitrep-74-covid-19-mp.pdf>. Accessed 1 Sept 2020

An unprecedented outbreak of pneumonia of unknown aetiology in Wuhan City, Hubei province in China emerged in December 2019. A novel coronavirus was identified as the causative agent and was subsequently termed COVID-19 by the World Health Organization (WHO). Considered a relative of severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS), COVID-19 is caused by a betacoronavirus named SARS-CoV-2 that affects the lower respiratory tract and manifests as pneumonia in humans. Despite rigorous global containment and quarantine efforts, the incidence of COVID-19 continues to rise, with 90,870 laboratory-confirmed cases and over 3,000 deaths worldwide. In response to this global outbreak, we summarise the current state of knowledge surrounding COVID-19.

**2.3 Reyad O (2020) Novel Coronavirus COVID-19 Strike on Arab Countries and Territories: A Situation Report I. arXiv:2003.09501 [cs.CY]**

The novel Coronavirus (COVID-19) is an infectious disease caused by a new virus called COVID-19 or 2019-nCoV that first identified in Wuhan, China. The disease causes respiratory illness (such as the flu) with other symptoms such as a cough, fever, and in more severe cases, difficulty breathing. This new Coronavirus seems to be very infectious and has spread quickly and globally. In this work, information about COVID-19 is provided and the situation in Arab countries and territories regarding the COVID-19 strike is presented. The next few weeks main expectations is also given. Index Terms—Coronavirus, COVID-19, Arab Countries. I. INTRODUCTION The well known Coronaviruses such as MERS-CoV, SARSCoV and COVID-19 are a group of viruses that infects both birds and mammals which meaning that they are transmitted between people and animals. These set of Coronaviruses cause infections that are related to the common cold and flu in humans where symptoms vary according to the infected species [1], [2]. The COVID-19 has reported being a novel Coronavirus of a typical pneumonia since the date 31/12/2019. The COVID-19 started in Wuhan city in China and then spread around the world very fast. Covid-19 is considered as the second Coronavirus outbreak that affects the Middle East region, following the MERS-CoV which was reported in Saudi Arabia in the year 2012. United Arab Emirates (UAE) was the first Middle East Arab country to report a Coronavirus positive case, following the Wuhan city Coronavirus outbreak in China. Recently, on 11/03/2020, the World Health Organization (WHO) stated that the global COVID-19 outbreak is a pandemic because of the speed and scale of transmission of the virus. From the 195 countries in the world today, there are more than 266,100 Coronavirus total cases reported to Coronavirus resource center until now [3]. Moreover, the number of total deaths are more than

11,200 cases and the number of total recovered are more than 87,300 cases. Figure 1 shows the Coronavirus COVID-19 global cases presented by the center for systems science and engineering (CSSE) at Johns Hopkins University (JHU) up-to-the-date 20/03/2020 [4].

### III. PROPOSED ALGORITHM

Complexities such as a small and imbalanced dataset with picture quality difficulties necessitated the pre-processing of the dataset in multiple stages using multiple strategies so that the suggested CNN model could obtain its optimum results. For this application, the proposed CNN model has an overall accuracy of 98.6 percent, which indicates its capacity to perform well. Both of these instances have been evaluated with the CNN model. In the first case, the model was validated using the original processed dataset's 94 X-ray pictures, and it was found to be 100 percent accurate. An independent dataset of COVID-19 X-ray pictures has been used in the second scenario to test the model's performance. In this case, the system's performance reached a whopping 98.6%. A comparison with different machine learning methods has been performed to show that the suggested model outperforms them all. When tested on a different set of data, the proposed model outperformed all others in both general and specific ways. In order to accurately and reliably identify COVID-19 infections using deep transfer learning, a larger dataset of COVID-19 X-ray images is needed. This would be especially helpful during this epidemic, when illness burden and the need for preventative actions collide with the resources that are currently available.

#### 3.1 IMPLEMENTATION

Every module in this project is discussed in this section. There are a number of different modules involved in this process, including data collection, model creation, model summary, model fitting and training, visualisation of the CNN layers, saving and loading of models and weights, and storing precision and precision in a pickle.

##### 3.1.1 DATA COLLETION

The dataset used to train the system is equally as valuable as the system itself. In order for the system to work for everyone, gesture attributes like as hand size, orientation, and colour can vary from person to person. As a result, creating a hard dataset is essential for model training. However, the current lockdown makes it impossible to collect data from a large number of people. In order to make the images more challenging for a model to train on, the data was first produced using photos of covid X-rays and normal X-rays, and then enriched with additional images. Kaggle provided the data. For training and testing machine learning models, it's a well-known dataset. Access to the Dataset: <https://www.kaggle.com/alifrahman/covid19-chest-xray-image-dataset>

##### 3.1.2 MODEL CREATION

Initially, we need to prepare the data set as stated in Dataset Preparation. In this model the basic Convolution Neural Networks structure had used as Input layer -> Convolution Layer -> Max pooling layer -> Convolution layer -> ..... -> Fully Connected Layer -> Output Layer .

##### 3.1.3 MODEL SUMMARY

Keras provides a way to summarize the model which gives the detailed data of the model architecture. The summary is textual and includes information about:

- The layers and their order in the model.
- The output shape of each layer.
- The number of parameters (weights) in each layer.
- The total number of parameters (weights) in the model.

#### Model Fitting and Training

Model fitting is a step of feeding the model with large train data we have already made ready in the data pre-processing step. In this step, we feed data phase wise(epochs) according to batch size that we have discussed in the CNN concept.

```
#Compile defines the loss function, the optimizer and the metrics
model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',metrics=['accuracy'])
```

**Fig 1: Model Fitting**

The output of this phase will be accuracy and loss incurred during the training and validation phase as shown below. We can also know the several statistics of the model that are associated in the history object of the model.

```
#fit() is for training the model with the given inputs (and corresponding training labels)
classifier=model.fit_generator(
    training_data,
    epochs=50,
    validation_data=Validation_data,
    callbacks =[cp_callback])
```

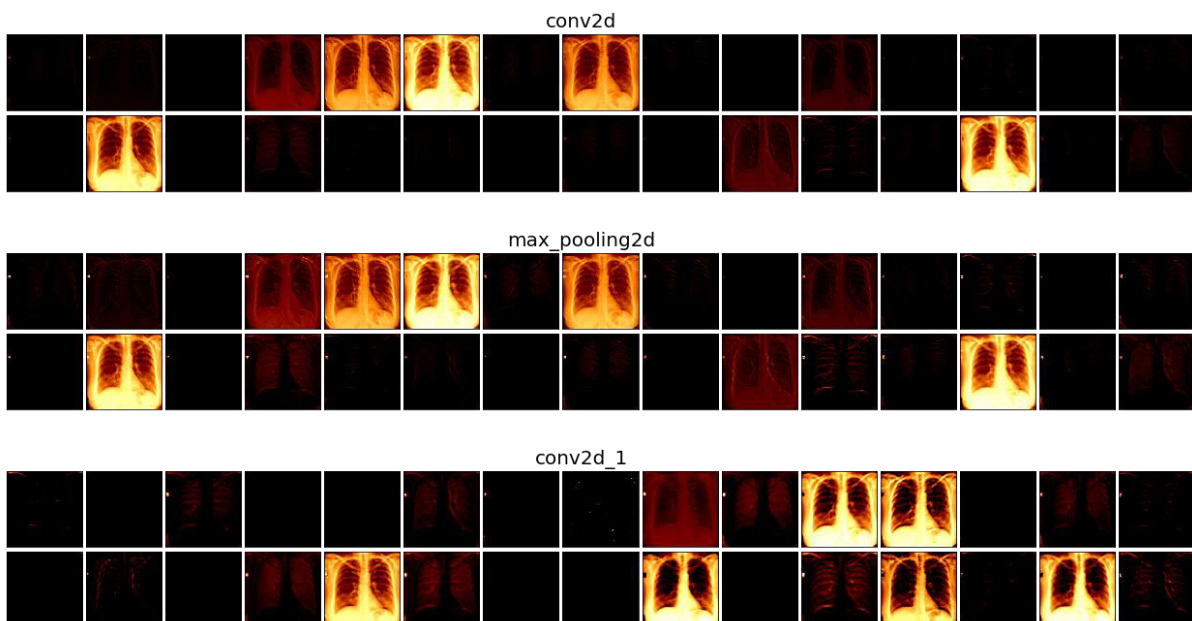
**Fig 2:Model Training**

Results will be disucces in Results and Discussion Section.

### Visualizing the CNN Layers

When it comes to picture categorization and recognition, convolutional neural networks are unbeatable. Filters are applied to each layer of CNN models to learn the features of the training images. At each convolutional layer, the features learned are dramatically different. Low-level information, such as edges, orientation, and colour, are often captured by the first layer of processing. Expanding CNN's number of layers allows for the acquisition of more detailed features that aid in the classification of images.

Different features gathered at each layer can be visualised in the following fashion to show how convolutional neural networks learn spatial and temporal dependencies of an image.



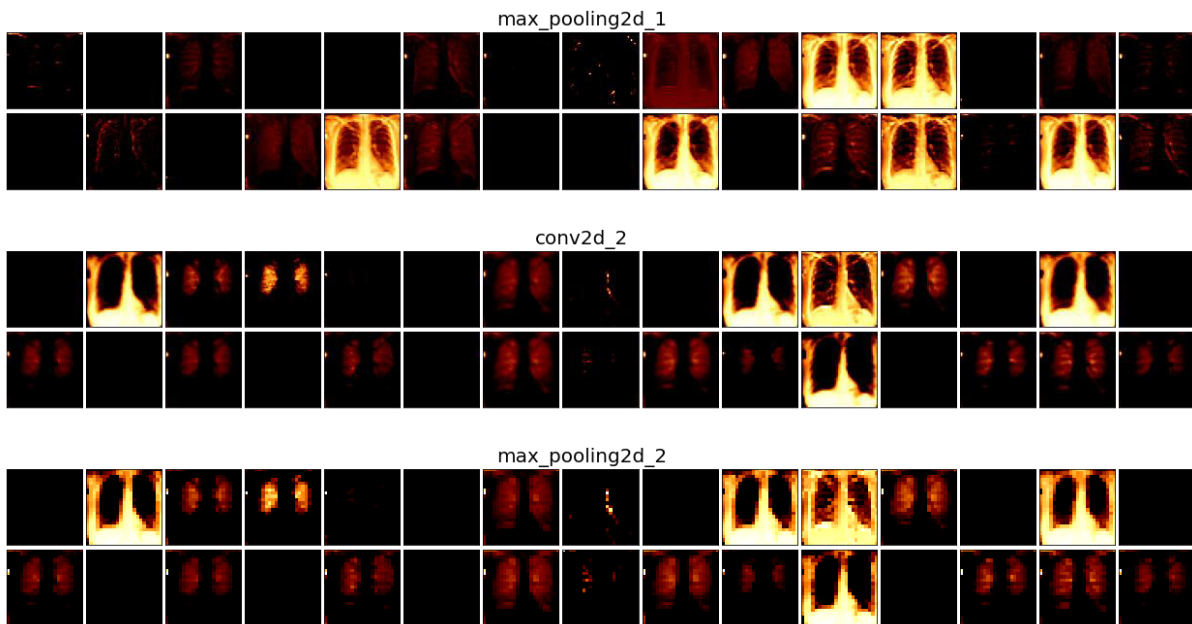


Fig 3: Visualizing CNN Layers

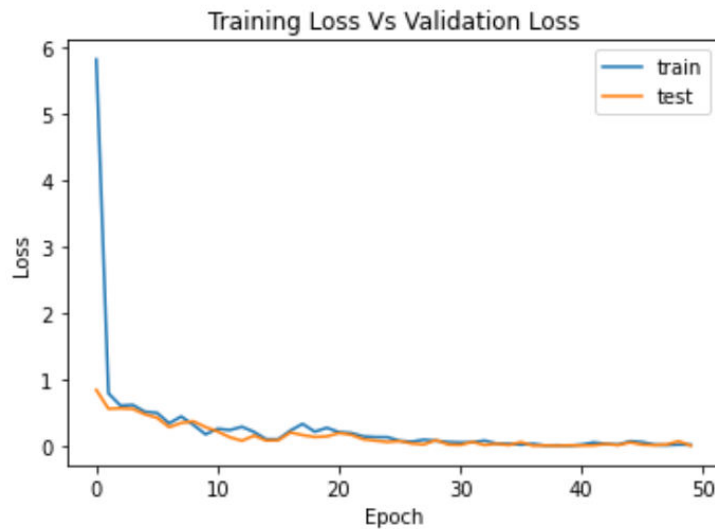
#### IV. RESULTS AND DISCUSSION

In this section, the Accuracy metrics of Convolutional Neural Networks (CNNs) are discussed. As in the above section we successfully trained and tested the model.

Epoch 40/50	3/3 [=====]	- 13s 3s/step	- loss: 0.0054	- accuracy: 1.0000	- val_loss: 0.0096	- val_accuracy: 1.0000
Epoch 41/50	3/3 [=====]	- 12s 4s/step	- loss: 0.0208	- accuracy: 0.9868	- val_loss: 0.0072	- val_accuracy: 1.0000
Epoch 42/50	3/3 [=====]	- 12s 5s/step	- loss: 0.0523	- accuracy: 0.9868	- val_loss: 0.0084	- val_accuracy: 1.0000
Epoch 43/50	3/3 [=====]	- 12s 3s/step	- loss: 0.0314	- accuracy: 0.9868	- val_loss: 0.0299	- val_accuracy: 1.0000
Epoch 44/50	3/3 [=====]	- 14s 4s/step	- loss: 0.0198	- accuracy: 1.0000	- val_loss: 0.0130	- val_accuracy: 1.0000
Epoch 45/50	3/3 [=====]	- 11s 5s/step	- loss: 0.0719	- accuracy: 0.9868	- val_loss: 0.0530	- val_accuracy: 0.9444
Epoch 46/50	3/3 [=====]	- 12s 4s/step	- loss: 0.0574	- accuracy: 0.9737	- val_loss: 0.0197	- val_accuracy: 1.0000
Epoch 47/50	3/3 [=====]	- 13s 5s/step	- loss: 0.0197	- accuracy: 1.0000	- val_loss: 0.0124	- val_accuracy: 1.0000
Epoch 48/50	3/3 [=====]	- 13s 4s/step	- loss: 0.0125	- accuracy: 0.9868	- val_loss: 0.0227	- val_accuracy: 1.0000
Epoch 49/50	3/3 [=====]	- 13s 4s/step	- loss: 0.0209	- accuracy: 1.0000	- val_loss: 0.0705	- val_accuracy: 0.9444
Epoch 50/50	3/3 [=====]	- 11s 3s/step	- loss: 0.0175	- accuracy: 0.9868	- val_loss: 0.0048	- val_accuracy: 1.0000

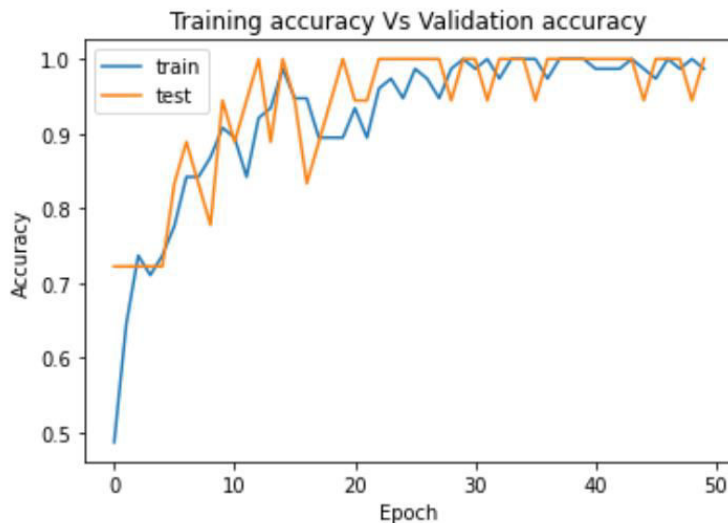
Fig 4: Test loss, test accuracy, train loss, train accuracy obtained after testing

After validation/test we got the validation accuracy of 100% from the starting to ending of training the validation accuracy was improved. The loss percentage decreased gradually.



**Fig 5: Graph of training loss vs validation loss**

The above Figure 5 indicates a gradual decrease in loss per step in validation. The blue line indicates the training Loss and the Orange line indicates validation loss.



**Fig 6: Training Accuracy vs Validation Accuracy**

The above Figure 6 shows the Accuracy of our mode. Which shows the best results. The blue lines indicate the training accuracy and the orange line indicates validation accuracy. were the best validation accuracy being 100% and the best training accuracy was 98.6%. This happens after you use Dropout, since the behavior once training and testing is completely different.

## V. CONCLUSION AND FUTURE WORK

The pandemic of Covid-19 is rapidly spreading. Bulk testing of cases quickly may be required due to the increasing quantity of instances. Multiple CNN models were used to classify Covid-19 patients based on their chest X-ray scans in this study. Out of these three models, we found that only the Xception net delivered the greatest results and should be employed. We were able to correctly classify covid-19 images, demonstrating the potential of such systems for automating diagnostic activities in the near future. Because of the possibility of overfitting, the high degree of accuracy obtained should raise some red flags. By comparing it to new data that will be made public soon, this can be confirmed.





In the future, we can use the huge chest X-ray dataset to test our model's predictions. Also, medical experts should be consulted for any practical use of this idea. Not only are we not attempting to create a perfect detection system, but we are also simply looking into possible, economically viable methods of combating this disease. Further research into the efficacy of these techniques can be pursued.

Convolutional Neural Networks (CNNs) have been shown to be excellent at detecting COVID images in this model. Despite the need for a significant number of photos, Convolutional Neural Networks are able to diagnose respiratory disorders with 95 percent train accuracy and 98 percent validation accuracy, according to research findings. Our networks can be improved so that we can get to 100% accuracy. This model's future work will involve creating a web page or mobile app that the general public may utilise. Additionally, we can employ a variety of approaches to better visualise COVID affected areas. Even in the medical field, this model illustrates that Convolutional Neural Networks can be used to their fullest potential.

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**Impact Factor: 8.165**

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**ISSN** INTERNATIONAL  
STANDARD  
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