DETECTION OF COVID-19 IN X-RAY IMAGES USING DEEP LEARNING

A DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF

THE REQUIREMENTS FOR THE AWARD OF THE DEGREE

OF

MASTER OF TECHNOLOGY IN

INFORMATION SYSTEMS

Submitted By

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(2020-2022)

CANDIDATE'S DECLARATION

I hereby declare that the work presented in this report entitled "**Detection of Covid-19 in X-ray images using Deep Learning**", in partial fulfillment of the requirements for the award of the MASTER OF TECHNOLOGY degree in Information Systems submitted in Information Technology Department at DELHI TECHNOLOGICAL UNIVERSITY, New Delhi, is an authentic record of my own work carried out during my degree under the guidance of Dr Dinesh Kumar Vishwakarma.

Patil.

Place: Delhi

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Date: 30th May, 22

(2K20/ISY/08)

CERTIFICATE

I hereby certify that the Project Dissertation "**Detection of Covid-19 in X-ray images using Deep Learning**" which is submitted by Hardik Patil, Roll No 2K20/ISY/08, Information Technology, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi

Date: 30.05.2022

Dr. Dinesh K.Vishwakarma

(SUPERVISOR)

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I humbly extend my words of gratitude to other faculty members of this department for providing their valuable help and time whenever it was required.

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ABSTRACT

The COVID19 outbreak has had such a negative impact on people's health and well-being all around the world. The pandemic has developed into one of the major humanitarian catastrophes in modern human history due to its devastating consequences on lives and livelihood. As a result, a comprehensive strategy to battle the pandemic is required. Due to the limitation of reverse transcription-polymerase chain reaction (RT-PCR) kits, it was impossible to test every patient with a respiratory disease. In the fight against COVID-19, rapid testing of infected patients is critical, and radiological evaluation utilizing chest Xrays is one of the most effective and successful screening procedures. The patient's chest X-ray scans revealed various abnormalities that are characteristic of a COVID19 infection.

In this study, we have used a publicly available dataset from Kaggle. The 9034 chest Xrays utilized in this study was categorized into five categories (Pneumonia, Normal, COVID19, Tuberculosis and Pneumothorax). To perform COVID19 diagnosis based on chest Xray pictures, we suggest combining convolutional processes CNN and dilated CNN and building a unique deep neural network with two inputs and one output. To extract features from the chest x-rays, we used two deep neural networks in parallel. The proposed neural network has an 82.53% accuracy rate in detecting Covid19 or Pneumonia or Normal cases or Tuberculosis or Pneumothorax. The x-ray scans of covid-19 patients can be utilized to diagnosis in areas where expert radiologists are not present, led to advances AI algorithms.

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CHAPTER 1

INTRODUCTION

Covid19 is an infection caused by SARS-CoV-2, a novel corona virus. The World Health Organization (WHO) initially informed the people about this new virus on 31 December 2019, after receiving a report of a cluster of patients of 'Viral Pneumonia' in Wuhan, China. On 30 January 2020, the World Health Organization(WHO) declared it a pandemic.[1]. On April 12th, 2022, there were around 500 million diagnoses and 6.18 million deaths reported.

It is a very dangerous disease that is rapidly spreading. COVID-19 symptoms in general Flu-like patients, such as cough, fever, dyspnea, as well as breathing problems, as well as the viral pneumonia epidemic[2]. However, these indicators are insufficient on their own. People can sometimes be asymptomatic but still have a positive CT scan of the chest and a positive diagnostic test for COVID-19 on multiple times. Most widely used approach for diagnosing Covid19 Chain reaction (RT-PCR) to transcriptase-polymerase. It's highly precise, but it is also costly, sluggish, and Currently, it's at an all-time high. X-rays of a chest are usually accessible, and they are both easier and less costly. COVID-19 related signals in the lungs, on the other hand, could be difficult to detect. Worldwide, healthcare systems are attempting to expand COVID-19 research facilities. More testing will be done to confirm the diagnosis and isolate those who are infected, reducing the spread of sickness across society. Due to its high sensitivity, COVID-19 victims' chest X-rays have proven to be an effective alternative method for diagnosing COVID19 in this scenario. But the accuracy of X-Ray diagnosis relies heavily on radiological knowledge. And when the number of patients is high, it becomes a tedious task. Deep neural networks (DNNs) were successful in detecting X-ray pneumonia, performing better than radiologists. To identify Covid-19 on such a xray images, we are examining the various deep neural network architectures[3].

Deep learning, which takes inspiration from the number of hidden layers it has, has carved out a niche for itself in the field of AI by producing good outcomes both to image based classification and regression tasks during the last decade[4]. Thanks to the extensive use of convolutional neural networks (cnn), image-based applications have reached their peak over the recent 7-8 years. In general, CNNs that attempt to imitate biological characteristics of humans on computers requires preprocessing of images or data before using them to such networks[4].

An alternative approach for testing is required for the following reasons:

- Standard tests are costly: Standard tool for covid19 testing is Antigen and realtime polymerase chain reaction(RT-PCR) test. These tests cost around 2000INR. The cost of an X-ray is 500INR and easily available everywhere.

- Time Consuming: These blood tests take 12 hours to 1 day to detect Covid19. If we use a deep neural network model, it will take only a few minutes to detect Covid19.

- Rapid Testing: Testing will be done as rapidly as feasible if these deep neural network models only take a few minutes for one individual to detect Covid19.

- The extent of spread can be detected: The level of spreading can be easily detected if the testing is done quickly.

1.1 Motivation

Patient care and screening are extremely important during an outbreak of Covid19. The need for medication is prioritized based on the severity of the disease[5]. Screening is used to diagnose disease in people who are asymptomatic. These precautions are extremely beneficial and helpful in stopping virus in patients and hospital staff.

The main foundations of diseases testing are patient awareness and education. It is considerably more advantageous for the health professional to recognize and treat the problem if the community is more aware of the condition. The patient's diagnosis should be accomplished at a distance of 1 meter from the patient. The Covid-19 patients clinical severity shown in following table1.1.1.

Table1. 1:The Covid-19 patients clinical severity

Clinical Severity	**Covid-19 infected patients (%)**	**Symptoms**	**Remark**
Mild Disease	81%	fever cold, tiredness and Ageusia	Hospital or Isolation at home
Severe Disease	14%	fever cold, tiredness and ageusia, pharyngitis, headache, diarrhea, dermatitis, irritated eyes	Hospital is in charge of it.
Critical Disease	5%	fever cold, ageusia and tiredness, pharyngitis, headache, diarrhea, dermatitis, irritated eyes, difficulty breathing, confusion, chest pain	Hospital is in charge of it.
The overall case fatality rate	2.30%		

1.2 Objective:

The Covid19 epidemic in chest xray radiographs is examined and diagnosed in precise detail in this research. The core objective of this research is to realistically enhance the speed of the Covid19 suspicious patients test. As per the organization monitoring the Covid19 issue, India has already suffered three waves of the virus, and the situation is expected to worsen. As a result, testing is the first line of protection, and the patient would be segregated as soon as the testing is completed. So, our first goal is to test suspect individuals as rapidly as possible, and we have seen in the past that results on Covid19 took three to five days to arrive due to the load on testing laboratories, and the doubtful patient was able to travel freely around during that duration. Other ways of diagnosing Covid19 in patients should be investigated to minimize these problems[6]. This study presents a novel method for detecting covid19 that is much faster.

The data for the top 10 nations is listed in Table 1.2, which includes reported cases and the number of patient deaths per region[1].

Table 1.2: Statistics of top 10 regions confirmed cases and number of deaths as of April 2022

S.No.	Country	Confirmed Cases	Deaths(In lakhs)
1	USA	8.04 Cr	9.85
2	India	4.3 Cr	5.22
3	Brazil	3.02 Cr	6.62
4	France	2.64 Cr	1.14
5	Germany	2.3 Cr	1.32
6	UK	2.17 Cr	1.71
7	Russia	1.78 Cr	3.65
8	South Korea	1.58 Cr	1.1
9	Italy	1.54 Cr	1.61
10	Turkey	1.5 Cr	1.09

1.3 Organization of Dissertation:

In the second chapter, we will look at the topic in general and how it came to be so important, highlighting how useful it may have been. We will also look at pertinent research on Covid19 diagnostic content. The second chapter will go into the fundamentals of the deep neural network model. We will also discuss related research work related to this study.

The architecture proposed convolutional neural network model for various diseases diagnosis based on chest xray images and the approach of the convolutional neural network model is discussed in the third chapter.

In chapter 4, we will discuss the experimental approach. We will also look at the data analysis and dataset used in this study and the training, testing, and validation data split.

The model's experimental approach will be discussed in the chapter 5. In this chapter, we will also discuss performance metrics in detail and calculate performance metrics by an obtained confusion matrix. The thesis's sixth chapter is geared toward a conclusion, with more research possibilities.

CHAPTER 2

BACKGROUND AND RELATED WORK

2.1 LITERATURE REVIEW

Deep learning (DL) as well as Machine learning (ML) are 2 kinds of computational learning that strive to automatically find significant patterns in data and solve problems. CNN is a pattern recognition model with superior feature learning capabilities that is well adapted to dealing with picture data. CNN has already proven effective in surgical subspecialties like as retinal detection, pneumonia diagnosis, and cancer diagnosis[7]. CNN can be used to detect Covid19 in patients using chest xray or CT scans because of its capacity to extract information from visual cues[8].

We have studied different Deep Neural Network models for Covid19 diagnosis based on chest xray images using a Deep Neural Network.

- **Covid19 xray images by using Convolutional Neural Networks with Transfer Learning Tuning Optimized** [9]

First this model established a new classification system which has been adapted that is capable of distinguishing patients with COVID19 was predicated on a xray, and then introduced a framework local interpretable approach to provide insights[10]. In order to optimize hyperparameters values used for a CNN's transfer-learning adjusting, the classification process utilizes a algorithm of the grey wolf optimizer[9].The results obtained demonstrated the methods efficiency, achieving an average accuracy of 94.76%.

Transfer learning with fine-tuning is a regularly utilized method that allows us to adapt a pre-trained network to any domain problem without having a large dataset[9].

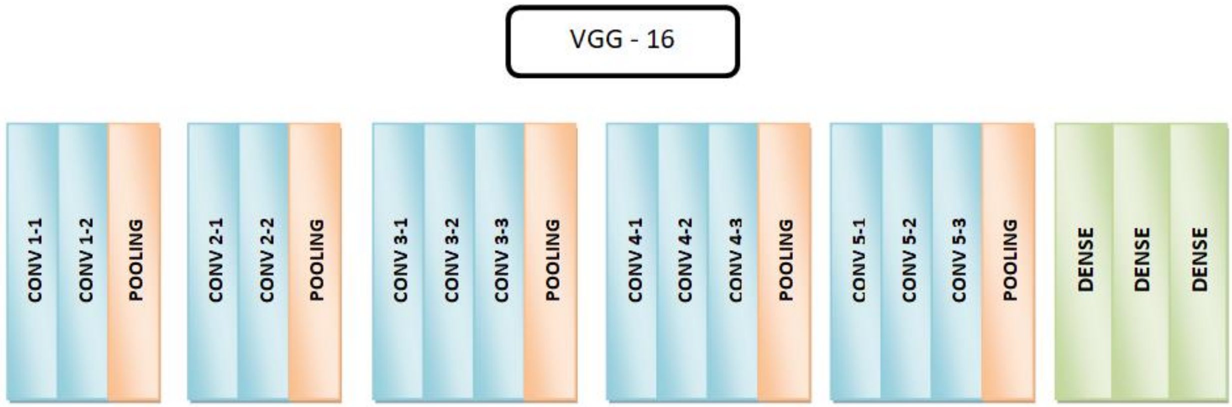


Figure 2. 1: VGG16 architecture adapted as base model

- **De-Tra-C deep convolutional neural network**[11]

DeTraC architecture overview: There are 3 stages of the DeTraC model. In the first step, they train De-Tra-C's & pretrained CNN model as the foundation for obtaining deep local information from each picture. To simplify the data distribution on a local scale, apply the class-decomposition layer of DeTraC. In the 2nd phase, the training is performed by applying a powerful gradient descent optimization method Lastly, they refine the images' final classification using De-Tra-C's class composition layer Detecting COVID19 Xray photos in patients of normal and severe respiratory conditions syndrome, De-Tra-C achieved a high precision of 95.20 percent[11].

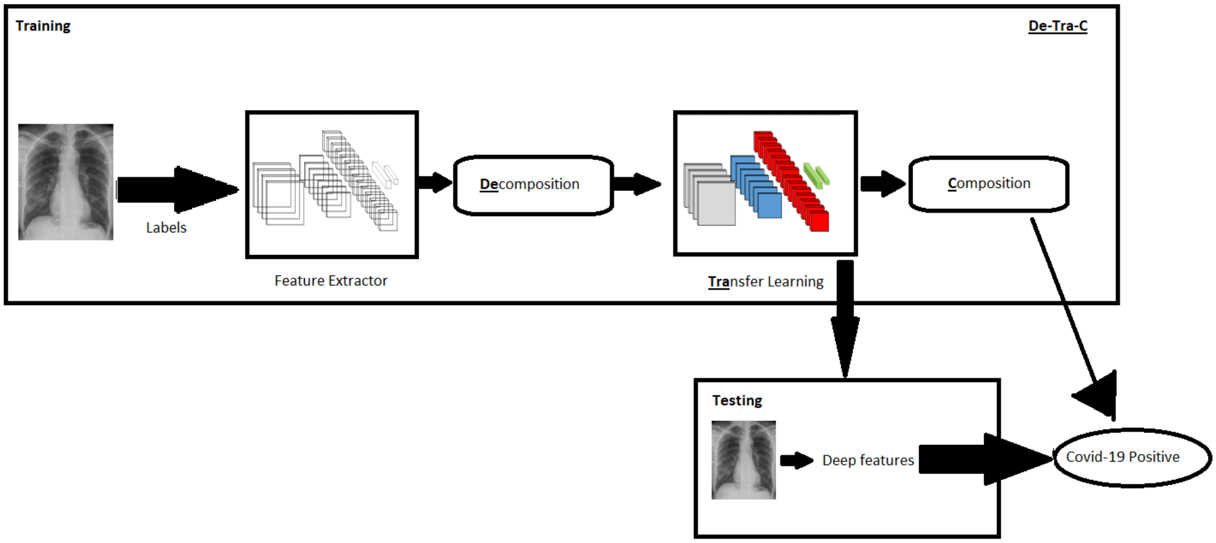


Figure 2. 2: De-Tra-C CNN architecture

- **PDCOVIDNet**[12]

For recognizing COVID-19 from chest xray pictures, a parallel dilated CNN system was proposed[12]. They proposed a COVID-19-based parallel dilated convolution neural network (CNN) detection methodology named Parallel Dilated COVIDNet based on xray of the chest (PDCOVIDNet).

PDCOVIDNet architecture: The architecture of PDCOVIDNet has three primary detection, extraction and visualization are examples of components[12]. PDCOVIDNet is a concurrent stack of convolution layers and a max pooling layer. Parallel layers are then injected at the feature level, and a convolution is performed afterwards, with activation on the extracted features that resulted. Subsequently, the fattened characteristics include Multi-Layer Perceptrons (MLP) into two layers, however to avoid overflow, an adjustment must always be made to the ratio of neurons that drop at every layer. Finally, a classification task is performed by the on the last layer, the softmax activation function is used, and then a class-activation map is created, Once paired with the final convolution layer, it works as a classification interpreter. Experimental study demonstrates that PDCOVID-Net improves the state of the art versions, with 95.45 percent and 91.3 percent respectively, in accuracy and recall[12].

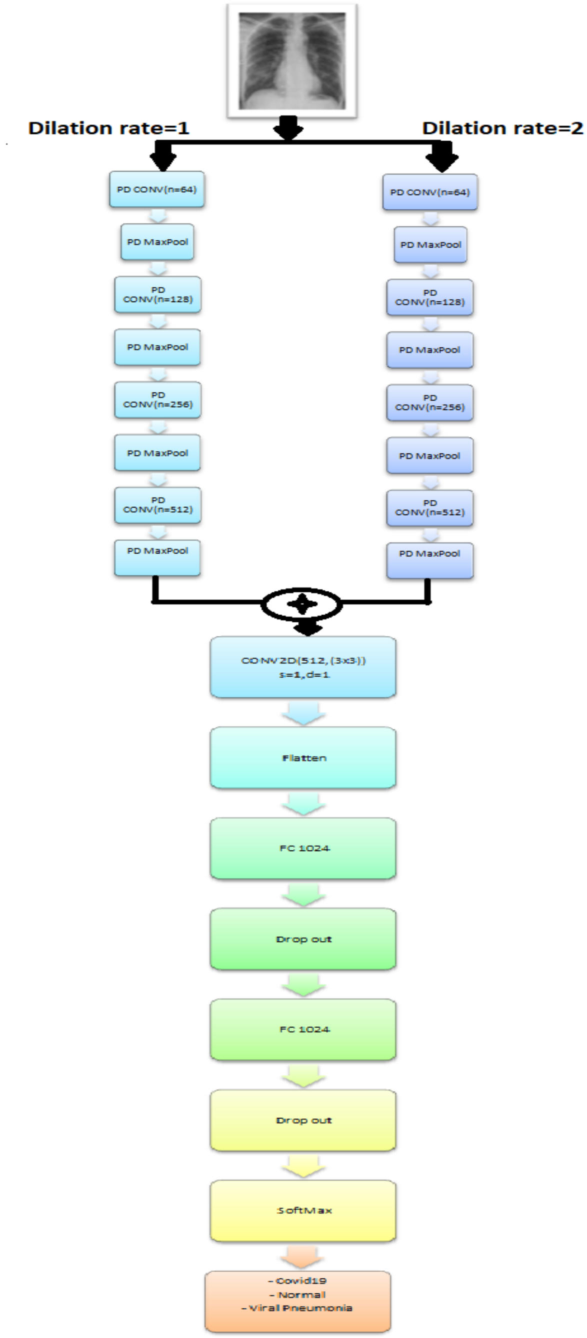


Figure 2. 3: PDCovidNet Architecture

Table 2. 1: The efficiency of various research articles in diagnosing Covid19

Literature(Authors)	**Dataset**	**Classes**	**Result**
Chowdhury, Nihad K. Rahman, Md Muhtadir Kabir, Muhammad Ashad[12]	Normal - 1341 X-rays Covid19 Positive - 219 X-rays Viral Pneumonia - 1345 X-rays	Normal, Covid19 Positive, Viral Pneumonia	Accuracy - 96.58%
Vrbancic, Grega Pecnik, Spela Podgorelec, Vili[9]	Covid19 - 182 X-rays Other - 660 X-rays	Covid19, Other	Accuracy - 94.76%
Asif, Sohaib Wenhui, Yi Jin, Hou Jinhai, Si[11]	Normal - 80 X-rays Covid19 Positive - 105 X-rays SARS - 11 X-rays	Normal, Covid19 Positive, SARS	Accuracy - 95.12%
Sekeroglu, Boran Ozsahin, Ilker[4]	Healthy - 1583 X-rays Covid19 Positive - 225 X-rays Viral Pneumonia - 4292 X-rays	Healthy, Covid19 Positive, Viral Pneumonia	Accuracy - 98.50%

2.2 OVERVIEW

This section will describe the planned approach for doing x-ray picture detection for Covid-19, which is implemented on a deep CNN model. In which we designed a deep CNN as from scratch.

2.2.1 Deep Learning

Deep learning is a subclass of machine learning that, like a human brain, analyses data and creates patterns that may be used to take decisions.

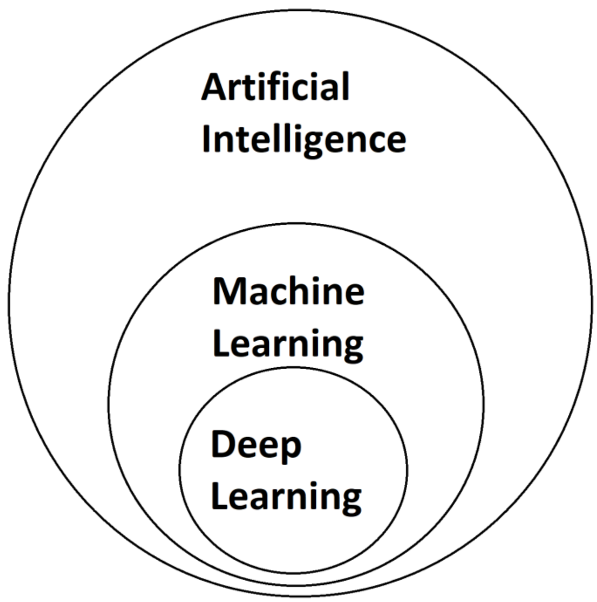


Figure 2. 4: Artificial Intelligence v. Machine Learning v. Deep Learning

Deep Neural Networks evaluate data in/ an structured manner to reach comparable results as humans. Deep learning achieves this by putting a algorithms to work with multiple layers known as neural networks.

We may use neural networks to accomplish a wide range of activities, like as, classification, regression and clustering. Based on the patterns between the samples, we may utilize neural networks to categorize / classify unlabeled data. In the classification step, we can train the DNN model on a labeled dataset for categorize the data in this dataset among various categories.

2.2.2 CNN:

A CNN is a technique that takes an image is processed and assigns weights to the features in the image so that they can be discriminated. Compared to other classification techniques, CNNs don't require that much preprocessing. The filters can be learned by the convolutions themselves. The architecture of CNN is the structure of neurons as a source of inspiration in the human brain.

In an image, it can capture many temporal and spatial connections. CNNs are capable of performing complex tasks using multi-modal data such as images, text, audio, and video. LeNet, ResNet, VGGNet, AlexNet and GoogLeNet are examples of ConvNet designs[13].

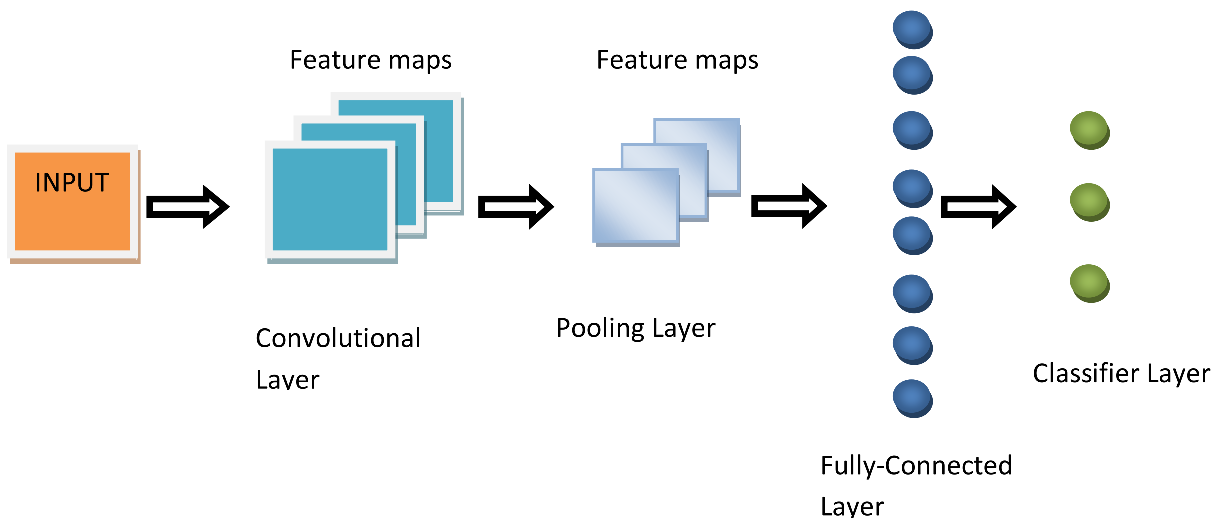


Fig 2.5: CNN Architecture

CNN uses multiplication of an image matrix with a for extracting features and pre-determined characteristics from it. We use a channel to filter the image and get only the predominant important features. The images are matrices of pixel values, and the filters are commonly 3x3 or 5x5. The filter is moved over the picture with a defined stride, and the weights are multiplied and added to provide a more understandable matrix output.

A CNN performs four different sorts of operations:

- **Convolution** :

The convolutional layer is the first layer of CNN, and it is used to extract features from the input pictures. The dot product between the filter size of (N*N) and the section of the picture has been accomplished using a sliding filter with stride = 1 on the image in this process. Because the technique was designed for 2D input, the multiplication is done using an array of data input and a 2D array of weights, known to as a filter, mask, or kernel.

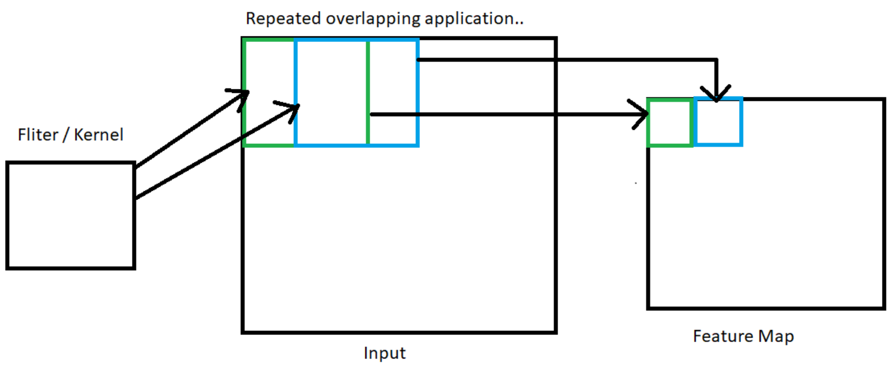


Figure 2.6: Applying filter on input layer of neural network

In the convolution process, we have input as an image or 2D matrix of pixel values and filter/kernel/mask which contains weights then the filter is applied to the input and convoluted matrix is computed. Non-Linearity

- **Pooling:**

This layer has been built to minimize the size or dimension of a picture (feature representation). Max pooling was discovered to be the most commonly employed method through studies. We utilize a window of size (m*m) in Max pooling and take the maximum pixel value among all the pixel values in the feature map window and slide it to a stride of 'k', covering the entire feature map. There are several forms of pooling, such as maximum pooling, minimum pooling, average pooling, and so on.

There are 2 common functions used in pooling

i. **Max-Pooling:**

A method of determining the highest weight of sectors by pooling them together of a feature map and uses it to construct a down sampled (pooled) map of features is called as Max-Pooling. After a convolutional layer, it's typically used. By employing pooling layers, the size of the convolutional matrix is reduced. As a result, the number of learnable parameters is reduced, as is the network's processing complexity.

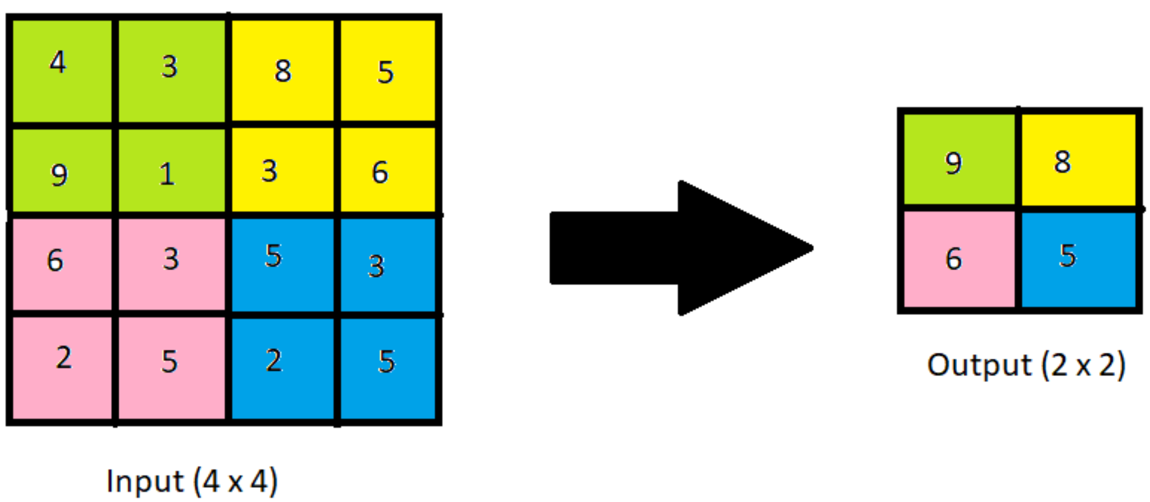


Figure 2.7: Applying 2x2 max-pooling on input

ii. **Average Pooling:**

The average of the values accessible in the region of the feature space covered by the kernel is used in average pooling. The pooling layer creates a connection between the convolutional and fully -connected layers in general.

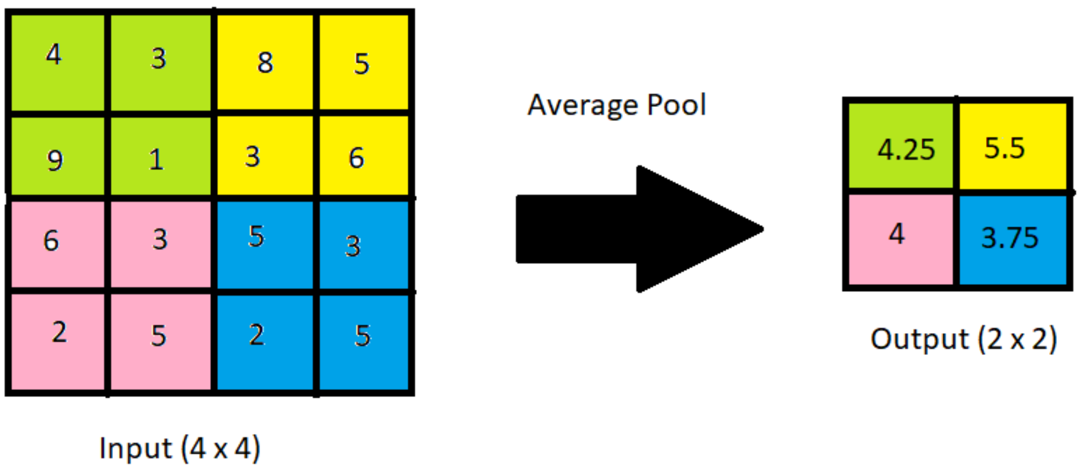


Figure 2.8: Applying 2x2 Average pooling on input

- **Non Linearity:**

In the feature space, it is used to replace only those negative weights with zero. In the feature space, it is used to replace only those negative weights with zero. The objective of incorporating nonlinearity in convolutional neural network is to simulate the nonlinearity of actual data. some common non-linear activation functions:

- Relu
- Sigmoid
- Tanh
- Softmax

- **Classification:**

CNN classification uses an image as an input for image classification and embedded text vectors for text classification, applies algorithms to the data, and categorizes it as Covid-19 positive or negative. An array of pixels is viewed by the machine. The computer calculates height, width, and dimension based on the data resolution. In required to train as well as evaluate convolutional neural networks models, input data is processed through a series of convolution layer, an activation function, fully connected layers, and SoftMax for output, which generates probabilistic results ranging from zero to one.

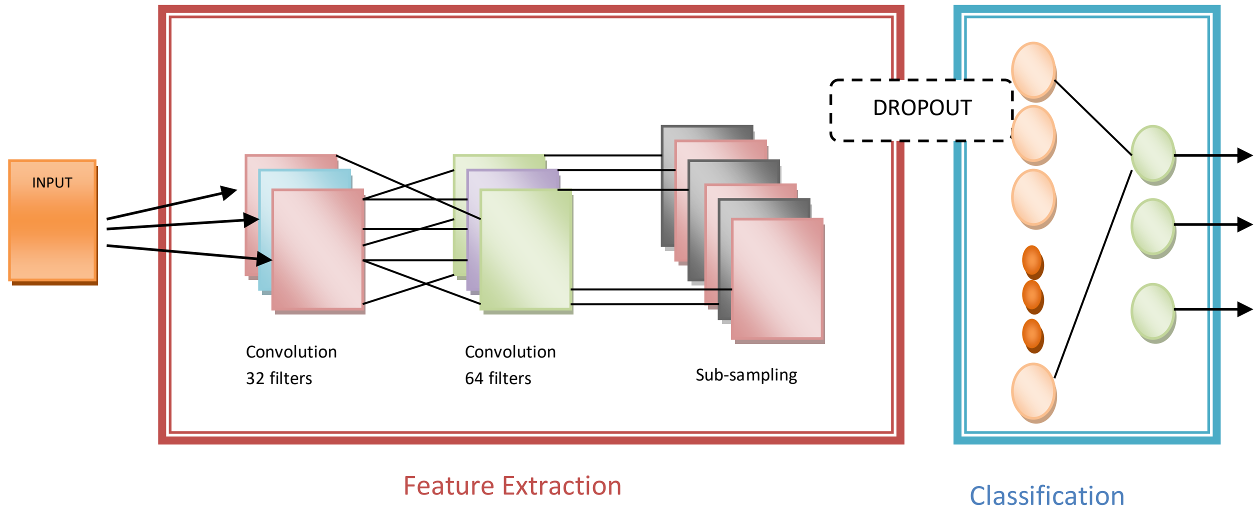
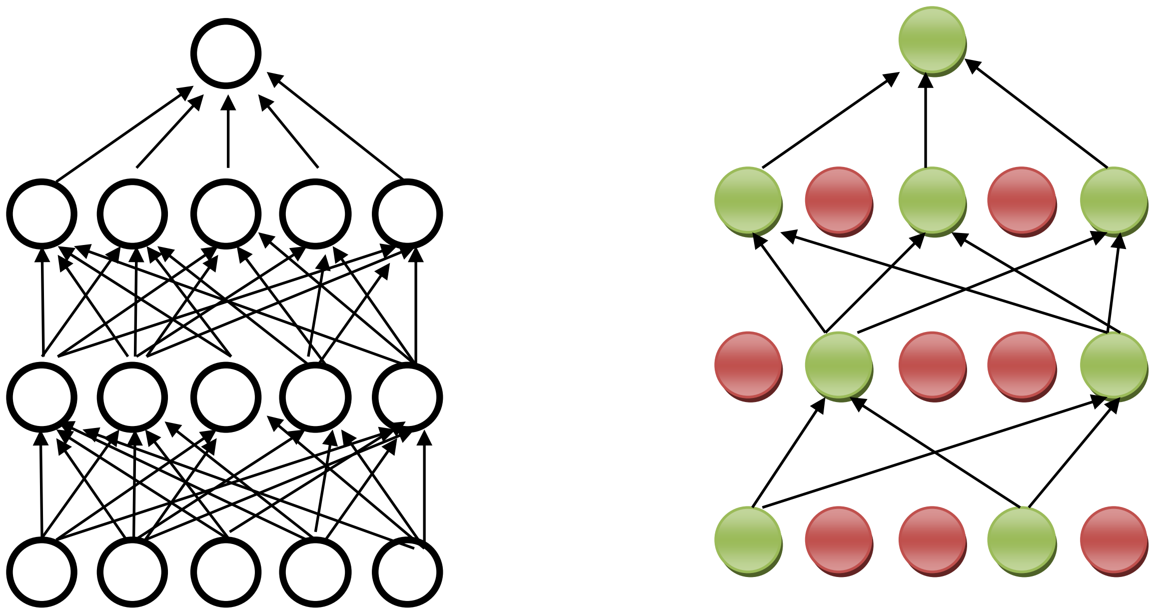


Figure 2.9: Example of Image classification

- **<u>Dropout Layer:</u>**

When a perceptrons/neurons in a neural network is turned off with a probability P during training, the term "dropout" is used. Assume a probability of P = 0.25, which means that throughout training, 25% of the neurons will be dropped. As a result, a quarter of the neurons with in neural network would not be examined, and the neural network will become easier. To avoid over fitting, we add a dropout layer in the CNN. Simple terms, throughout the training process, a certain number of neurons are discarded from the deep neural network in the dropout layer.



Standard Neural Network

After applying dropout layer

Figure 2.10: Dropout layer in the neural network

2.2.3 <u>Activation Function :</u>

To evaluate whether a neuron should be triggered or not, the activation function produces a weighted sum and then incorporates bias to it[14]. We apply any non-linear activation function in this layer to incorporate non-linearity into our model, which speeds up training and computation. It is used to learn and comprehend complicated patterns in our data, as well as to prevent the numbers from aggregating to zero. The most common activation function is RELU (rectified linear units).

- **Linear activation function**

The linear function's equation is y= m*x.

Equation : f(x)= x (2.1)

Range: -∞ to ∞

- **Sigmoid Function:**

The sigmoid or sigmoid activation function's curve resembles an 'S' shaped curve. Between zero and one is the range of the logistic activation function. Because value of the sigmoid function is limited between zero and one, the outcome is likely to be one if the value is greater than 0.5 & zero else.

Equation: $f(x) = \frac{1}{(1+e^{-x})}$ (2.2)

Range : [0 , 1]

- **Tanh activation function**

Tanh is a hyperbolic tangent function, similar to the logistic sigmoid. The curves of the Tanh and sigmoid activation functions are quite similar, as illustrated in figure 2.13, however Tanh is preferable since the whole function is zero centric.

Equation : $f(x) = \tanh(x) = \frac{2}{(1+e^{-2x})} - 1$ (2.3)

Range : [-1, 1]

- **ReLU activation function**

It's most often used activation technique in hidden layers of a deep neural networks. It's the most used activation method in DNN hidden layers. Because the ReLU function is non-linear, we may quickly back transmit errors and trigger multiple layers of neurons. ReLU is less expensive than hyperbolic tangent and sigmoid because it uses fewer complex computations.

Because just a few perceptrons are engaged at any given moment, the cnn is sparse and quick to process.

Equation : $f(x)= \max(0,x)$ (2.4)

Range : $[0 \text{ to } \infty)$

- **Softmax activation function**

The softmax function deals with classification tasks at fully connected layer. When dealing with many classes, this is commonly employed. The softmax function has range from zero to one. The softmax function is best used at the output layer of the deep neural network, where we want to use probability to characterize the classification from each input.

2.2.4 Dilated Convolution:

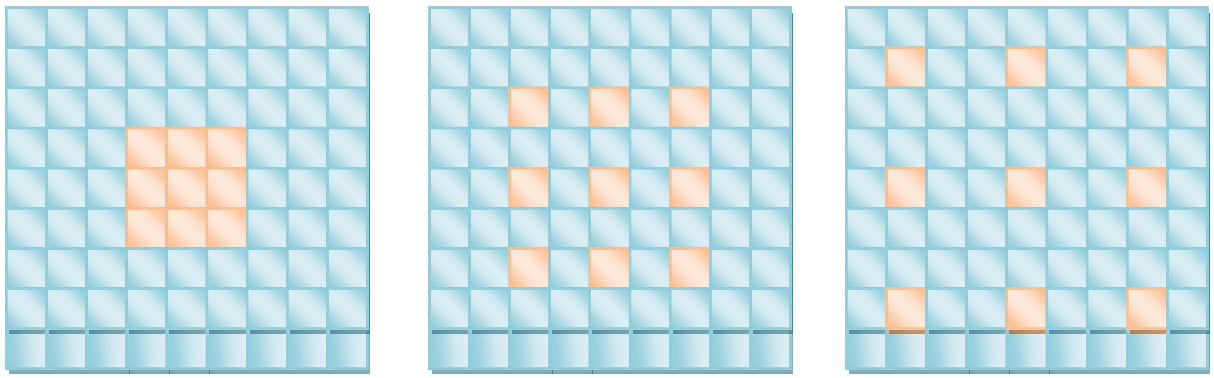
It's a mechanism for expanding a kernel or filter by making holes in between the elements. In layman's words, that's the same as convolution, but now with pixel skipping to cover a broader area of the input. The 'dilation factor' argument specifies just how far the input is stretched. In other terms, the filter skips (dilation factor-1) pixels dependent on the value of dilation rate.

We can get additional information without increasing the number of filter parameters by employing this technique. Dilated convolution allows you to cover a larger region of the input images without pooling. The goal is to extract more details from the output after each convolution layer. At the same computing cost, this approach provides a larger field of vision. We calculate the value of a 'dilation factor' by evaluating how much knowledge is collected with each convolution at different 'dilation factor' values.

Dilated Convolution's Benefits:

- A more expansive receptive field is available.
- Effective in terms of computation.

- Memory usage is lower.
- There is no degradation in the produced image's resolution.
- The convolution's structure assists in keeping the information in order.



Kernel Size: 3x3
Dilation rate=1

Kernel Size: 3x3
Dilation rate=2

Kernel Size: 3x3
Dilation rate=3

Figure 2.11 : Dilated Convolution

2.2.5 Other Training Models

- VGG19:

Vrbancic, Grega, Pecnik, Spela, Podgorelec, Vili[9] used VGG19 as base model. VGG19, a well-known deep learning model available in the TensorFlow library, is often used as a classifier. This model was utilized as a starting point for developing a newly untrained head. The VGG19 is a deep Neural Network design made up of two convolutional filter layers and 1 pooling layer that are repeated twice. Then 4 convolutional filter layers and 1 pooling layer were applied three times. Then, there are two fully connected layers and a softmax output. To accommodate the different classification task, the pretrained network's last layers are removed and replaced with new layers. The new layer is made up of a 0.2 dropout layer then a flatten, and two completely linked networks of dimensions 128 and 64, respectively, joined with another 0.2 dropout layer. The last layer consisted of three class heads with a categorical cross entropy loss function.

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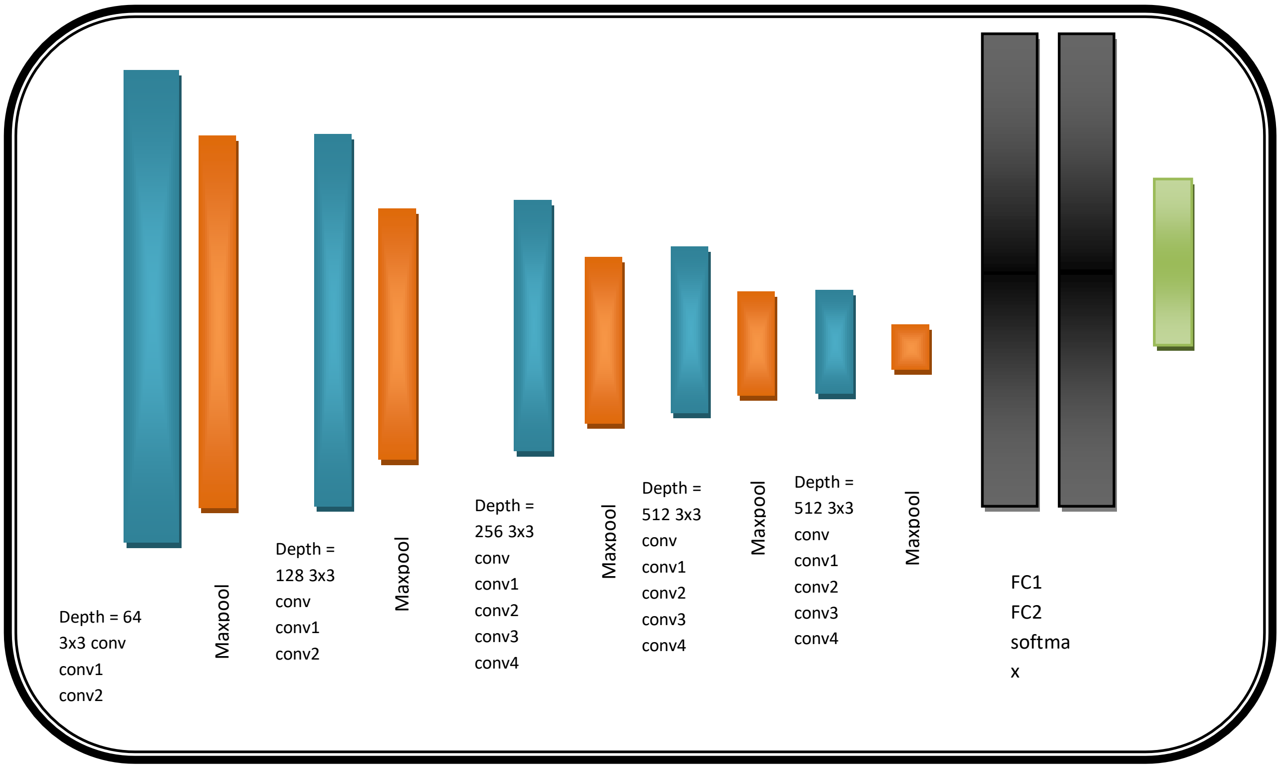


Figure 2.12: Architecture of VGG19

- **ResNet-50**

S. Ying et.al[13] used this as a base model. Deep convolutional neural networks with 50 layers, such as the widely used ResNet-50 model, are known as residual networks. ResNet is available in multiple of configurations, each with its own varying number of layers but the same proposed design. ResNet was a game-changer in cnn training in computer vision challenges. The term Resnet50 refers to a variation that can work using 50 layers of deep neural network. Figure 2.18 represents the typical Resnet50 model. Each convolutional layer's residual kernel size, units, and outputs are shown in the ResNet50 design.

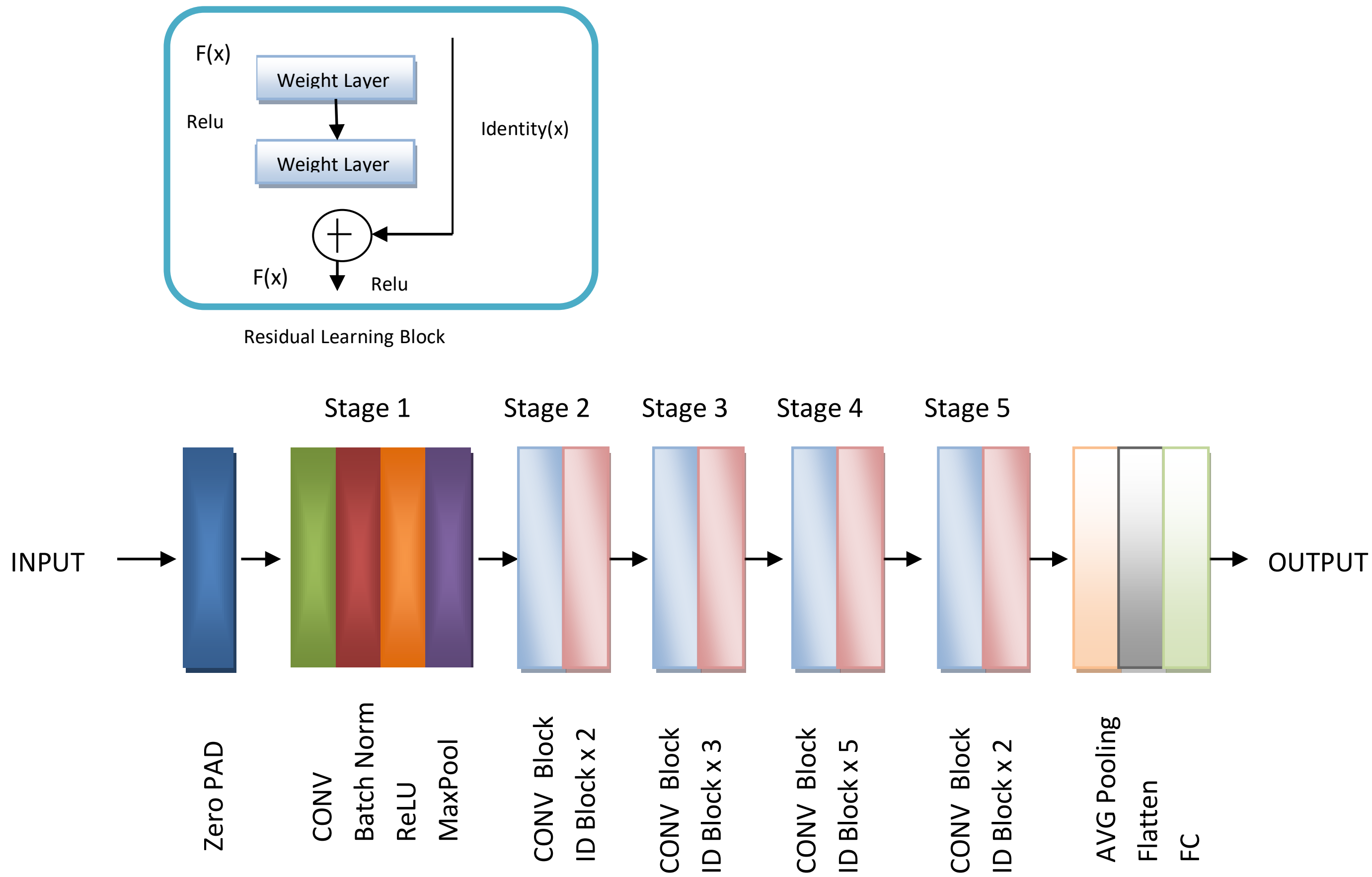


Figure 2.13 : Residual Learning Block and Architecture of ResNet-50

CHAPTER 3
PROPOSED MODEL

3.1 Approach:

We have implemented novel CNN Architecture using two convolutional neural networks. The purpose of this study is whether a chest Xray is impacted by viral pneumonia, Covid19, or is normal. Deep learning approaches have emerged as a standout artificial intelligence methodology in recent years, owing to their ability to discover complicated patterns within input data as well as develop proper classification tasks of the underlying data at various levels. We have developed and trained novel model and obtained their accuracy on a dataset. We have performed image augmentation before feeding it to the image classification model. All of the implementations have been performed on Google Colab using the Keras module of TensorFlow. First, let's look over the image datasets used in this research.

3.2 Model Architecture:

In this research, we have used 2 deep neural networks models and then merge them to built a novel model. Let's discuss both models and then the merged model.

- **Model X - CNN Model**

  This network was built in a similar fashion. It was built sequentially with three repetitions of convolutional and pooling layers, then a 0.2 dropout layer. Another convolutional and pooling layer along with flattening. A 3x3 kernel size is used in every convolutional layer. Finally, there are two fully connected layers of dimensions 128 and 64, that are ReLU activated, with a 0.2 dropout layer in between, and for the three-class classification, a softmax output layer was used.

- **Model Y - CNN Model with dilation rate=2**

  This network was built in a similar fashion. It was built sequentially with three repetitions of convolutional with dilation rate = 2 and pooling layers, then a 0.2 dropout layer. Another convolutional with dilation rate = 2 and pooling layer along with flattening. A 3x3 kernel size with dilation rate=2 is used in every convolutional layer. Finally, there are two fully connected layers of dimensions 128 and 64, that are ReLU activated, with a 0.2 dropout layer in between, and for the three-class classification, a softmax output layer was used.

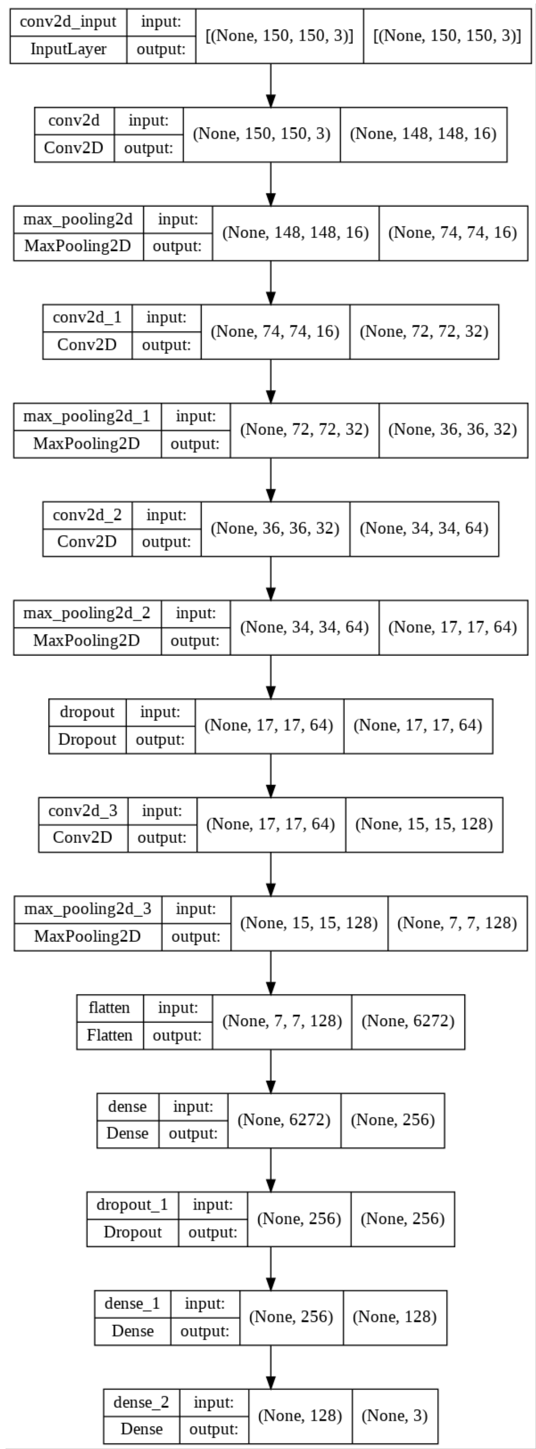


Figure 3. 1: Architecture of CNN model used in ‘Model X’ & ‘Model Y’

- **Merged Model using Model X & Model Y**

The proposed merged CNN architecture will be discussed in this chapter. Our proposed deep neural network model is a stack of parallel convolutional layer, max pooling layer dropout layer and activation layer. Then, we concatenated two parallel max-pooling layers at the feature level of the same dimensions and performed convolution with the ReLU activation function on that concatenated layer. The output of convolution layers features will then be flattened. We added a 20% dropout layer to the proposed convolutional neural network to avoid over fitting. Finally, the classification task is performed by the final layer, which uses the softmax activation function. Figure 3.2 represents the proposed convolutional neural network model's architecture.

<u>Feature Extraction:</u>

The proposed convolutional neural networks model is composed of four dilated convolutional layers in parallel stack form which are alternatively max-pooled in the first stage. The size of all kernels in our architecture is 3 x 3. In the parallel arrangement, the input picture feed simply alters the dilation rate, particularly dilation rate = 1 as well as dilation rate = 2. Consider the first block in Figure 3.2's left branch, where the dilation rate = 1, There are 16 kernels in all, and the semantically block process is carried out. Except for the dilation rate, the initial block, as well as the rest of the blocks in the left and right branches, are identical. A convolution with a dilation rate greater than one extends the receptive field(RF), leading in smaller visual perception when computing data at a higher resolution. The receptive field is just an input with a specified gap the area of the picture where a kernel gathers characteristics without affecting kernel shape is referred to as the feature extraction area. The shape of a receptive field size is represented in the following equation.

- Receptive Field = dilation rate*(kernel size -1) + 1 (3.1)

The Equ.(3.1) produces the final equation, which gives the dimension of the output, where (m * m) is the input.

- Size of the output = $\left\lfloor \frac{m + 2 * padding - Receptive\ Field}{stride} \right\rfloor + 1$ (3.2)

It gathers significant features with in observation area at various scales after using two receptive fields of varying sizes.

Figure 3. 2: The proposed convolutional neural network model's architecture

CHAPTER 4

THE EXPERIMENTAL APPROACH

In this chapter, we'll look at our proposed CNN model's experimental approach. This experiment was carried out with the following system configuration:

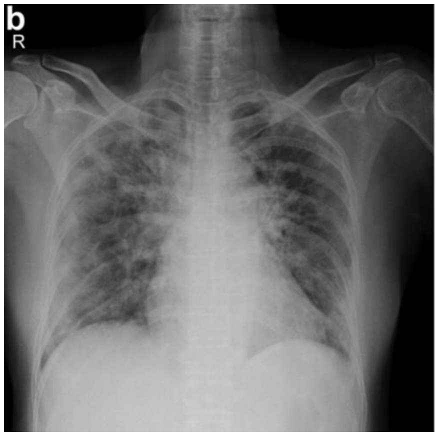
- Processor: Intel Core i5 (6th Gen)
- Main Memory: 8GB
- Secondary Memory: 1 TB
- Tools Used: Jupyter Notebook, Google Colaboratory, Anaconda.

4.1 <u>Data analysis:</u>

Data analysis is the first stage with the purpose of conserving the best out of trash since it is the sequence of the process of analyzing, cleaning, converting, and modeling data with the goal of identifying important data, reporting conclusions, and supporting decision making. One of the main factors for data analysis is to determine the data's complexity and appearance, and to ensure that the data is legitimate as well as contains the required fields.

4.2 <u>Dataset:</u>

Aerial perspective chest xray images from viral Pneumonia, Normal, Tuberculosis, Pneumothorax and COVID19 cases were used in this investigation. The data has been taken from Kaggle's chest xray dataset[15]. COVID-19 images are obtained using a second dataset because the number of Xray samples is relatively low in comparison to the other two cases. The 9034 chest xrays used in this study were divided into three categories (4273- Pneumonia, 1583 – Normal, Tuberculosis – 700, Pneumothorax – 1008 and 1470 -COVID19). The train folder has 6979 photographs, the test folder has 1320 images and the validation folder has 735 images. Before training the model, some preprocessing steps are applied to the images. The pictures have been reduced in size to 150x150 pixels. The radiographs are classified as COVID-19, Healthy/Normal, Tuberculosis, viral Pneumonia, Pneumothorax, with class indices of 0, 1, 2, 3, 4 respectively.



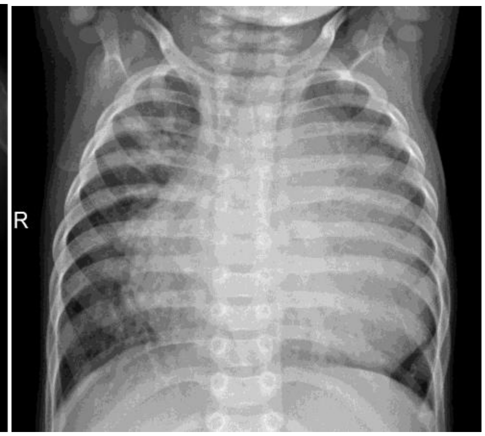
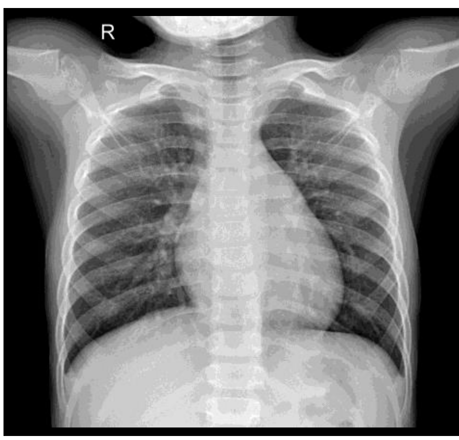


Fig 4.1 : Covid19 Positive

Fig 4.2 : Viral Pneumonia



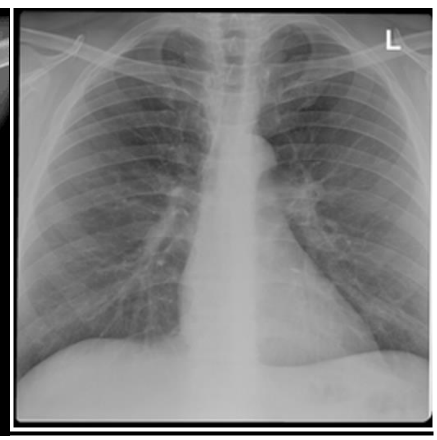


Fig 4.3 : Healthy Patient

Fig 4.4 : Tuberculosis

Fig 4.5 : Pneumothorax

4.3 Model Training , Testing and Validation;

Slicing the train dataset from our dataset is used for training. Accordingly, for testing purposes, a portion of the dataset is taken from the dataset. A normal, viral pneumonia, Tuberculosis, Pneumothorax and Covid19 affected person's train, test, and validation datasets are shown in Table 4.1. There are 6979 records in the training dataset, 1320 records in the test dataset, and 735 records in the validation dataset.

Table 4. 1: Train, Test and Validation dataset details

Column1	Normal	Viral Pneumonia	Covid-19	Tuberculosis	Pneumothorax	Total
Train	1224	3520	1088	470	677	6979
Test	234	390	275	170	251	1320
Validation	125	363	107	60	80	735

CHAPTER 5

EXPERIMENTAL RESULTS

5.1 Model Evaluation

We use the following measurements based on confusion matrices conclusions for prediction evaluation.

5.1.1 Precision

Simply expressed, precision refers to the proportion of positive findings that are clearly positive out of all positive results anticipated by the model. The following Equ. 5.1 can be used to calculate precision values:

$$\text{Precision} = \frac{Sum\ y\ in\ Y\ (TruePositives_y)}{Sum\ y\ in\ Y\ (TruePositives\_y + FalsePositives\_y)} \tag{5.1}$$

5.1.2 Recall

The rate at which the system is able to relearn information is referred to as recall. As an outcome, Recall estimates how many true positive (TP) traits our model identified and labeled as positive.

The following Equ. 5.2 can be used to calculate recall values:

$$\text{Recall} = \frac{Sum\ x\ in\ X\ TruePositives\_x}{Sum\ x\ in\ X\ (TruePositives\_x + FalseNegatives\_x)} \tag{5.2}$$

5.1.3 F1-score

A significant number of True Negatives (TN), which in most business situations do not rely on much, contribute to the accuracy, although False Negatives (FN) and False Positives (FP) frequently have business consequences. If we need to find the right balance between Recall and Precision There is an unequal class distribution, F1-Score would be an appropriate statistic to utilize.

$$\text{F1-Score} = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{5.3}$$

5.1.4 Accuracy

The data that is correctly categorized divided by the whole dataset evaluated is how accuracy is calculated. It can also be calculated as a 1-error.

The accuracy can be calculated by using the Equ. 5.4 below:

$$\text{Accuracy}=\frac{TruePositive(TP) + TrueNegative(TN)}{TruePositive(TP)+ TrueNegative(TN) + FalsePositive(FP)+FalseNegative(FN)} \tag{5.4}$$

5.2 Model Prediction

After cleaning, preprocessing, and analyzing the data, the first action we do is integrate it into a model that generates probabilistic results. The confusion matrix is a performance metric for machine learning classification. Precision, Recall, Accuracy, Specificity, and, most importantly, AUC-ROC curves may all be calculated using the confusion matrix. It is used to evaluate machine learning classification performance.

By looking at the confusion matrix, we can determine various metrics for measuring the model we've utilized for the Covid19 positive cases of the test dataset.

- $$\text{Recall} = \frac{TP}{TP + FN} \tag{5.5}$$

$$= \frac{TP}{Total\ predicted\ as\ Covid19\ positive}$$

$$= \frac{211}{211+6+7+39+12}$$

$= 76.72\%$

- Precision = $\frac{TP}{TP + FP}$ (5.6)

$$= \frac{TP}{Total\ Covid19\ positive}$$

$$= \frac{211}{211 + 3 + 7 + 50 + 39}$$

$$= 68.06\%$$

- F1-Score = $2 * \frac{Precision * Recall}{Precision + Recall}$

$$= 2 * \frac{0.6806 * 0.7672}{0.6806 + 0.7672}$$

$$= 72.13\%$$

- Accuracy = $\frac{TP + TN}{TP + TN + FP + FN}$ (5.7)

$$= \frac{211+221+354+191+113}{1320}$$

= 82.58%

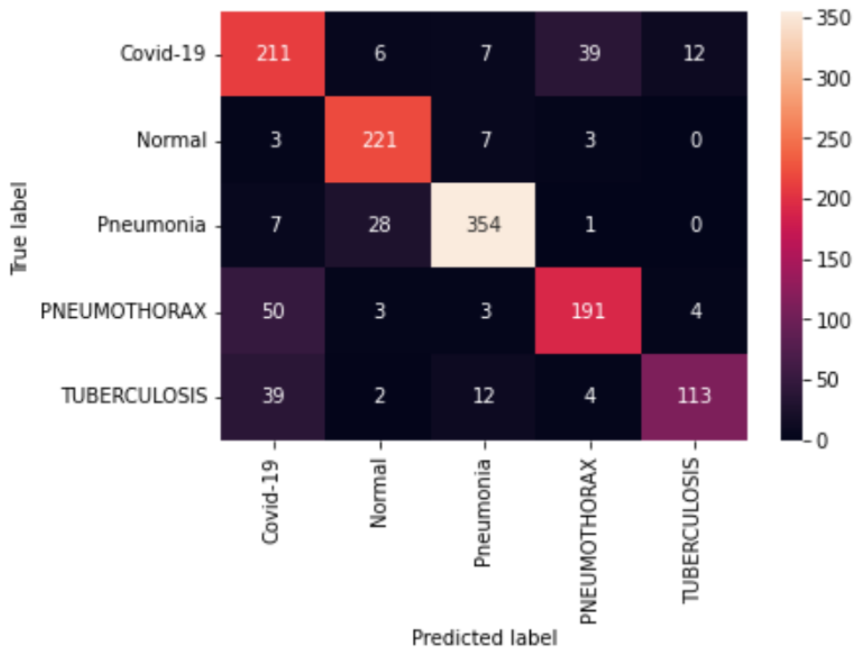


Fig 5.1: Confusion Matrix

	precision	recall	f1-score	support
COVID19	0.68	0.77	0.72	275
NORMAL	0.85	0.94	0.89	234
PNEUMONIA	0.92	0.91	0.92	390
PNEUMOTHORAX	0.80	0.76	0.78	251
TUBERCULOSIS	0.88	0.66	0.76	170
accuracy			0.83	1320
macro avg	0.83	0.81	0.81	1320
weighted avg	0.83	0.83	0.83	1320

Figure 5.2: Performance Metrics

In the classification job, the proposed convolutional neural network model scored, with a precision of 76.72 % and a recall of 68.06 %. Now moving on to the accuracy and F1-scores of the proposed model, the proposed model achieved the score with 82.58% accuracy and 72.13% F1-score.

Figure 5.3 depicts the proposed model's accuracy and loss during the training and validation stages for each epoch.

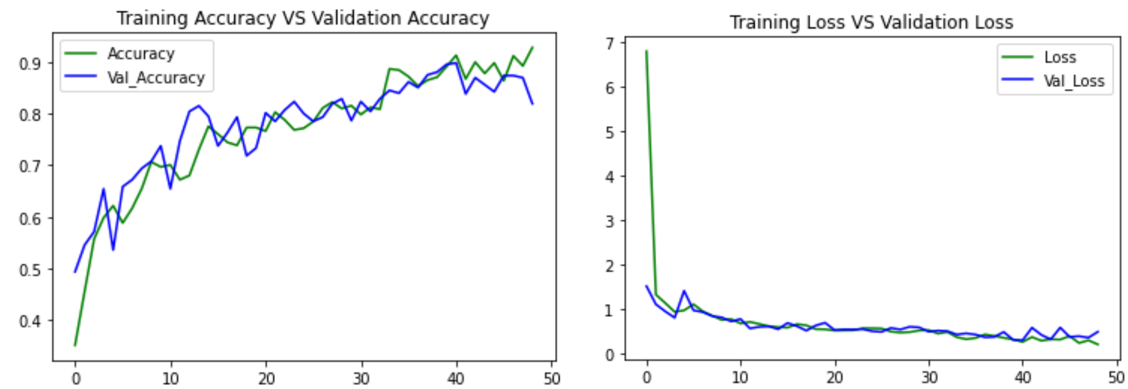


Figure 5.3: Performance of the proposed model

Table 5. 1: Comparison of classification of various convolutional neural networks architectures

Model		Precision	Recall	F1-Score	Accuracy
VGG16[7]	Covid-19	0.56	0.88	0.69	77%
	Normal	0.8	0.94	0.86	
	Pneumonia	0.92	0.86	0.89	
	Pneumothorax	0.79	0.32	0.45	
	Tuberculosis	0.93	0.84	0.88	
ResNet50[16]	Covid-19	0.57	0.78	0.66	78.63%
	Normal	0.9	0.89	0.66	
	Pneumonia	0.88	0.94	0.91	
	Pneumothorax	0.77	0.5	0.61	
	Tuberculosis	0.93	0.71	0.8	
Xception[3]	Covid-19	0.41	0.81	0.54	61.74%
	Normal	0.79	0.84	0.82	
	Pneumonia	0.74	0.8	0.77	
	Pneumothorax	0.5	0.1	0.12	
	Tuberculosis	0.79	0.49	0.61	
MobileNet[17]	Covid-19	0.61	0.87	0.71	79.62%
	Normal	0.77	0.93	0.84	
	Pneumonia	0.94	0.85	0.9	
	Pneumothorax	0.88	0.61	0.72	
	Tuberculosis	0.92	0.62	0.76	
Model X - CNN Model	Covid-19	0.54	0.81	0.65	75.15%
	Normal	0.89	0.78	0.83	
	Pneumonia	0.86	0.93	0.89	
	Pneumothorax	0.72	0.56	0.63	
	Tuberculosis	0.98	0.49	0.66	
Proposed Model	Covid-19	0.68	0.77	0.72	**82.53%**
	Normal	0.85	0.94	0.89	
	Pneumonia	0.92	0.91	0.92	
	Pneumothorax	0.8	0.76	0.78	
	Tuberculosis	0.88	0.66	0.76	

We have compared our model performance with other five architectures (VGG16, ResNet50, Xception, MobileNet and Model X - CNN Model).A comparison of different convolutional neural network models is shown in the table 5.1 on testing dataset.

It is clear that the proposed model demonstrates a better performance against other existing models.

CHAPTER 6
CONCLUSION

The convolutional neural network model was successfully deployed on the dataset and produced of accuracy of around 82.53% in Covid19 positive, viral pneumonia, Tuberculosis, Pneumothorax diagnosed by x-ray. The Kaggle was used to get the covid19 positive images, viral pneumonia images, Tuberculosis, Pneumothorax and normal xray images. As we've seen, our proposed model uses dilated convolution in a parallel stacked of convolution layers to effectively capture Covid19 feature, resulting in excellent classification. In future study, we aim to investigate more efficient results by using a larger dataset. We'll try using some more advanced deep learning models to detect covid19 traces in the infected host. Since India has never experienced a pandemic like this in the past century, the lockdown, the policies of government, and so on should all be investigated in order to gain a better knowledge of the condition, the lockdown, government policies, and so on should all be explored. The findings may aid doctors in recognizing Covid19, viral Pneumonia, Tuberculosis and Pneumothorax from a chest xray at an earlier stage, allowing them to make a more timely diagnosis. We will continue to work on scans of diverse chest xray images of Covid19 variants and other diseases which are diagnosed based on chest xrays in the future, aiming to detect various variants and other disease.

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