A FRAMEWORK OF CONVONET FOR DETECTION OF COVID-19 IN CHEST X-RAY IMAGE

A DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTSFOR THE AWARD OF THE DEGREE

OF

MASTER OF TECHNOLOGYIN INFORMATION SYSTEMS

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(2019 - 2021)

CANDIDATE'S DECLARATION

I Himanshu Raj, Roll No. 2K19/ISY/09 student of M. Tech Information Systems, hereby declare that the project Dissertation titled "**A framework of ConvoNet for detection of Covid-19 in Chest X-ray Image**" which is submitted by me to the Department of Information Technology, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any degree, Diploma Associateship, Fellowship or other similar title or recognition.

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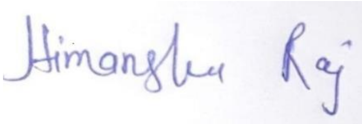

CERTIFICATE

I hereby certify that the Project Dissertation" A framework of ConvoNet for detection of Covid-19 in Chest X-ray Image" which is submitted by Himanshu Raj, Roll No 2K19/ISY/09, Information Technology, Delhi Technological University, Delhi in partial fulfilment 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 Diplomato this University or elsewhere.

Place: Delhi **Dr. Dinesh Kumar Vishwakarma**

Date: **SUPERVISOR**

ACKNOWLEDGMENT

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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

COVID-19 cases are increasing worldwide day by day leads to a huge load on health amenities. Due to the limited accessibility of reverse transcription-polymerase chain reaction **(**RT-PCR) kits, every patient with respiratory illness could not get tested by it. The tests are time-consuming, and they have limited sensitivity x-ray for the detection of covid-19 in patients. Meanwhile using an x-ray machine is a more feasible, available, and economical option. For the same reason, we consider x-ray images for our research purpose. We implemented the CNN model on the image dataset of the x-ray of the patient and successfully achieved an accuracy of 96%. Sometimes RT-PCR is a false negative in such a situation it would be helpful and avoid RT-PCR. By using modern AI techniques, the x-ray images of covid-19 patients in an automated manner can be used to diagnose at the settings where trained radiologists are not available.

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Chapter 1

INTRODUCTION

The disease emerged in December-2019 in Wuhan city of China and was declared a pandemic in March 2020 by World Health Organization (WHO). The very first people with covid-19 infections had links to an animal and seafood market. However, people with more recent diagnoses did not show such a connection confirming that humans also transmit the disease to each other. The virus is very contagious due to its great ability to fast mutation. the disease may present with cold or flu-like symptoms like fever, dry cough, malaise, body ache, etc.; but symptoms may vary from person to person and in some, it may lead to life-threatening respiratory illnesses.

This highly contagious disease needs special precaution while treating the patients and well-equipped hospitals and ICU facilities in ample number. Being a developing country, we don't have adequate availability of PPE kits, hospital beds, ventilators, and many other resources for managing this infection. It is quite difficult to manage a patient with severe acute respiratory illness (SARI) with limited resources. X-ray is a basic radiological facility, available in PHC level hospitals these days. So we are using x-ray images for our CNN model to detect covid-19.

1. X-Ray imaging has a lower cost than any testing kit present in the market for covid-19. The main reason is time and cost and with our method, both are reduced.

2.The diagnostic process is extremely quick, all processing happened in a single place, the analyser test the chest x-ray, and the radiologist can check the result at the same place or if we have a model like our model then we can quickly detect the covid-19 positive cases.

3. Contrary to CT scan, we can place X-Ray machines in the isolation ward or machine available in the covid-19 dedicated ward, which reduces exposure to others and need of additional Personal Protective Equipment (PPE), health worker need will go down and there is very less chance of infection from covid-19 patients. So, from these patients hospital acquire less infection from patients.

The main objective of this project is, using a deep neural network-based CNN model for the detection of COVID-19 infection with more accuracy with the help of chest X-Ray images of the patients. As this virus is emerging and mutating fastly, there is a lack of adequate expertise, and any specialized findings in x-ray and specialists are also not trained enough to identify the disease. Therefore, if we implement this project for deployment then this project can guide the health workers who have not much knowledge about x-rays also.

Using the CNN model, we can even help the patient with severe acute respiratory illness. This study is a way to triage the patients with SARI, is not an alternative way to diagnose and grade the infection and is not challenging.

1.1 Motivation

During the outbreak of infectious disease, triage and screening are of particular importance. Triage is prioritizing the need for care depending upon the severity of the disease and screening is to identify the disease in an asymptomatic person. These steps are very helpful and effective in preventing infection in patients and healthcare workers.

For triage in hospitals, the entry points should be limited, registration desks should be there, mask physical barriers, provision of hand hygiene and dedicated clinical staff for physical evaluation of the patients should be present. Before arriving at the hospital, patients of concerned disease should inform regarding their symptoms to the hospital authority, should wear a mask notifies the triage registration desk about their symptoms, wash hands, should cover mouth and nose while coughing and sneezing, and maintains social distance. The healthcare provider should ask for the symptoms of the patient and inform of preventive measures.

Patient education and awareness are the main pillars for screening a disease. More awareness of the community is much helpful it proves for the healthcare provider to identify and treat the condition. It is done in health care settings, in communities by the health care providers, or by telemedicine. for this outbreak, diagnosis of the patient should be done at a distance of one meter. Screening protocols should be there at all health care sites and in the community. The diagnosis criteria should be appropriately adjusted for certain settings and situations in which the presentation of the disease is atypical like old age, immunocompromised conditions, etc. Table 1.1 shows clinical severity of the Covid-19 patients with a brief on clinical presentation, clinical parameters and remarks.

There are three cases basically:-

- **Mild**: 80 % of people have mild disease presenting with fever, dry cough, fatigue, and Exira

- **Moderate:** 15 % of people have Severe illness which requires hospitalization or very least medical attention.

- **Severe:** 5 % have critical conditions in this required to transfer in intensive care units(ICU).

Table 1.1 Clinical severity of Covid-19

Clinical Severity	**Clinical presentation**	**Clinical parameters**	**Remarks**
Mild	For patients with a simple upper respiratory tract infection, it's possible to have gentle Symptoms like such as fever, cough, etc. throat irritation, nasal congestion, malaise, headache	Shortness of breath or hypoxia (normal saturation) is not present.	Hospital OR (as per the plan) Isolation at home as per guideline from the doctor.
Moderate	Pneumonia with no indications of a serious illness	Adults with dyspnea and/or hypoxia, fever, cough, and other symptoms, including On room air, SpO2 levels range from 90 to 93 percent. Higher or equal to respiratory rate to a rate of 24 per minute.	Managed by Hospital (Dedicated Covid Health Centre)
Severe	Severe Pneumonia	Adults with Pneumonia and one of the following symptoms: respiratory rate >30 respiratory distress (breaths per minute). On room air, SpO2 is 90%,	Managed by Hospital (Dedicated Covid Health Centre)

		indicating distress.	

1.2 Objective

This thesis examines and detects the Covid-19 pandemic in chest x-ray image in great detail. The major goal of this thesis is to improve the speed of the Covid-19 suspicious patient test in a realistic way. Because, in this circumstance, India has already experienced two waves of Covid-19, and the third wave is expected to arrive in a few weeks, the situation will deteriorate, according to the team monitoring the Covid-19 issue. So, the first line of defense is testing, and as soon as the testing is through, the patients will be isolated. So, our first aim is to test suspect individuals as quickly as possible, and we've observed in the past that because to the strain on testing laboratories, results on Covid-19 took 3 to 5 days to arrive, and the suspicious patient was able to move around during that time. To avoid these issues, we should look at other methods of detecting Covid-19 in patients. This research proposes a new approach for detecting covid-19 that takes far less time.

In the mild presentation of disease, patients isolated to break the chain of transmission and detailed history of any comorbidities taken and followed for temperature, spo2, and vitals. They also make aware of complications;

Patients with a respiratory rate more than 24 per minute and spo2 less than 94% comes under it and need close monitoring of signs and symptoms and progression to a severe condition should be monitored, may present to health care provider at hospital facilities or be encountered on home visits or by telemedicine.

In severe disease may need ICU care, ventilatory support, and having the highest mortality rate. might require due attention in the various health facilities.

The data of the top ten nations are shown in Table 1.2 in which confirmed cases, received cases and the number of death cases of the patients per nation have shown.

Table 1.2:- Statics of top ten nations Confirmed cases, received cases, and number of death cases as of JULY 20, 2021

S. No.	Countries	Confirmed cases	Recovered	Deaths
1	USA	33,741,532	33,137,652	603,880
2	INDIA	31,174,322	30,759,840	414,482
3	BRAZIL	19,376,574	18,834,360	542,214
4	RUSSIA	6,006,536	5,856,614	149,922
5	FRANCE	5,753,579	5,643,066	110,513
6	TURKEY	5,537,386	5,486,782	50,604
7	UK	5,473,481	5,344,754	128,727
8	ARGENTINA	4,756,378	4,654,829	101,549
9	COLOMBIA	4,639,466	4,523,159	116,307
10	ITALY	4,289,528	4,161,654	127,874

Infection prevention control (IPC) is a vital element of patient clinical treatment and should begin from the time of patient admission to the hospital (OPD or ED). Precautions should be taken regularly. In every. aspect of a healthcare facility Hand hygiene is a must, as is the use of protective equipment. To avoid direct contact. with patients' bodily fluids and secretions, use proper PPE. (This includes secretions from the lungs). Preventing the spread of infectious diseases is also part of standard measures. Injury from needles Or sharps proper waste management and washing and disinfection of needles and. sharps cleansing of the environment and equipment.

1.3 Organization of Dissertation

Chapter two give you brief about the topic and how its need is generated also highlighting how useful it could be it also includes a literature review of Covid-19 detection content. The basic definition of deep learning related content is presented and is followed by how it is affecting diversity.

Chapter three presents the processing of research methodology of proposed model.

The fourth chapter contains the results of our approaches on a benchmarks dataset and validates the results showcasing the probability of truthfulness of a statement.
The fifth chapter contains the experimental approach of the model.

Chapter sixth of thesis is directed towards a conclusion and further ideas for future work have been proposed.

Chapter 2

BACKGROUND

2.1 Literature review

Till now many deep learning models have used to tackle many diseases like pneumonia Wang et al [1] choose cheXNet to detect covid-19 via artificial intelligence detector. The model named as covid-19 AI detector to detect Covid-19 including pneumonia. Covid-19 AI detector can also detect pneumonia from chest x-ray at its high level of detecting at which radiologists are practicing, the cheXNet is trained on the largest publicly available dataset of chest x-ray named ChestX-ray14. It gives good results from other previous approaches and the architecture of the model was also simple than others.

With the rapid increase in covid-19 cases, so many approaches have been put forward to identify covid-19 positive cases. We don’t have many publicly available chest x-ray datasets. Covid-19 [2] detection is one approach to tackle covid-19. This can help to detect covid-19 as well as pneumonia. CovidNet is also a machine learning approach x-ray images can be provided as input and output prediction can be obtained. The prediction which classifies the output is normally pneumonia and covid-19. We can take this model as the reference point and we can further compare our results associated with covid-19 detection from x-ray. The ROC value is 0.99 for the positive cases and the average is 0.9738 for four-class classification.

Elene et al [3] used transfer learning for Covid-19 infection classification, for classification they consider SVM classifier in which they consider linear and RBF kernels. They took two datasets for both datasets they considered the same covid-19 image but healthy chest x-ray images are different in both datasets. They used 80% of the dataset for training and the rest for testing. Buyut et al [4] introduced a new way to detect Covid-19 using CLAHE and CNN, where they used CLAHE to improve image quality, it also used to enhance the image contrast to get better results. In the analysis part, they took two cases. In the first case, they compared the detection between the normal dataset and the second dataset which upgraded through CLAHE. In the second case, they compared the basic CNN model and VGG-16 transfer learning.

Abdul et al [5] used VGG-16 architecture connected with four custom layers for detecting Covid-19 in which they associated synthetic CXR images developed using CovidGAN. Wang et al [6] focused on the pneumonia classification task, for the classification they compared the proposed multitask prior attention residual learning strategy for the COVID-19 screening with two baselines. There are two types of residual learning: one without attention and one with the self-attention mechanism. Table 2.1 compares the performance of several computing models suggested in different research articles for Covid-19 detection.

Table 2.1 :- Performance of different research articles for Covid-19 detection

Literature	Cases	Task	Method	Result
Zheng et al. [7]	$499\ for\ training$ $132\ for\ validation$	$Classification$ 1. Covid-19 2. Others	2D-U-Net 2D-CNN	90.7% ($Sensitivity$) 91.1% (Specification
Wang et al.[8]	$Total\ 250\ images$ Not clearly mentioned training and validation set	$Classification$ 1. Covid-19 2. Viral pneumonia	2D-CNN	82.9% ($Accuracy$)
Song et al.[9]	$164\ for\ training$ $27\ for\ validation$ 83 for testing	$Classification$: 1. Covid-19 2. Bacterial 3. pneumonia	2D-ResNet-50	86.0% ($Accuracy$)
Xu et al. [10]	$528\ for\ training$ 90 for testing	$Classification$: 1. Covid-19 2. Influenza-A 3. Normal	2D-CNN	86.7 % ($Accuracy$)
Shi et al. [11]	$Total\ 2685$ $5-fold$	$Classification$: 1. Covid-19	Random Forest	87.9 % ($Accuracy$)

	cross validation	2. viral, Bact. Pne.		
Proposed		Classification: 1. Covid-19 2. Normal	2D-CNN	95.0% (Accuracy)

2.2 Overview

In this portion, we outline the designed solution which we have used to perform x-ray image classification for Covid-19, this model is based on a deep convolutional neural network. In which, we have implemented a deep neural network from the scratch. There are total of fourteen layers of CNN.

2.2.1 Deep learning

It is the subsidiary of machine learning which works like a human brain in data processing and creating pattern applied in decision making. In this, models learn to classify the image, text, sound directly. Applications of deep learning are in medical research, aerospace, automated driving, industrial automation, electronics, and fields related to other many technologies. Mainly deep learning methods uses a network of neurons-like architecture which is called an artificial neural network, before discussing artificial neuron first we have to understand biological neuron, Individual biological neurons appear to be fairly simple, yet they are linked to thousands of other neurons in a huge network of billions, Although the architecture of biological neural networks (BNN) is still under investigation, some regions of the brain have been mapped, and it appears that neurons are frequently organized in layers, particularly in the cerebral cortex. An artificial neural network is the same as biological neurons. If there is more than one hidden layer in the architecture, then we can say that the architecture of the model is deep. Deep learning may be regarded as a technique to make predictive analytics more automated. Deep learning algorithms build up in a hierarchy of ever-rising complexity and abstraction, whereas the algorithm is linear in machine learning. Deep learning computer programs go through the same process as a young child recognizing a cat. Input is in the form of rising hierarchy for each algorithm which performs a nonlinear transformation and then utilizes, what it learns to generate a statistical model as an output. The processes continue until the result is precise enough to be useful. The term was inspired by the number of levels of processing that data must go through. Deep learning has the benefit of creating a set of functions on its own, without the need for supervision. Not only is unsupervised learning faster, but it is also often more accurate.

2.2.2 Convolutional Neural Network(CNN)

Firstly, CNN was developed and used in the 1980s. At that time mostly, CNN was used to identify handwritten numbers like pin codes, zip codes, etc. Neural networks are thought to be multiplication of matrix, but it isn't true with ConvNet. CNN uses the method known as convolution. Mathematically Convolution means operation on two functions that gives results as a third function that shows how the form of one is changed by the other. If we must perform image classification, then we have to go through a convolutional neural network.

It is one of the in-demand algorithms of deep learning. A CNN generally learns features from input data using 2D images, so it uses 2D convolutional layers for refining 2D data such as images. CNN is used to extract features directly from images. In CNN no need for manual feature extraction. To observe different types of features of an image a convolutional neural network may contain many layers. whenever we get output from the convolved image that will be an input of the next layer. To increase the complexity to unequally define the object we are required filters.

A typical CNN consists of the layers as follows :

Convolutional layer, Pooling layer, Fully connected layer.

Convolutional layer

Convolutional neural networks include three layers: convolutional, pooling, and fully connected (FC). When these layers are layered a CNN architecture is made. Additional essential factors associated with this convolutional neural network architecture are the dropout layer and the activation function. They are explained below, in addition to convolutional layer, pooling layers, and fully-connected (FC) layers. The first layer of CNN is convolutional layer used for excerpting the feature from the input images. In this operation, the dot product between the filter size of N*N and the part of the image has been performed by sliding filter upon the image with stride = 1. The output is called a feature map which provides information about the image like edges and corners. After that, we take the feature map as an input and fed it to other layers to extract some other features from the input image.

Pooling layer

A convolutional neural network's convolutional layer put on learned filters to input pictures in a systematic manner to generate feature maps that summarise the presence of certain characteristics in the input. Convolutional layers are very effective and stacking them in deep models allows layers near the input to learn low-level properties (such as lines), while layers further in the model learn higher-order or more abstract features, such as shapes or specific objects.

The pooling layer's major goal is to minimise computational costs, it reduces the computational cost by decreasing the size of the convolved feature maps. In most CNN, the pooling layer comes after the convolutional layer. Generally pooling layers are of following types.

Max pooling is the most common pooling method in which a large number has been selected from the filter only affects the region of the feature map that is covered by the filter. Average pooling takes the average of the elements available in the zone of the feature map covered by the filter. Generally, the pooling layer works as a link in between the convolutional and the fully connected layers.

Fully connected layer

The main goal of the fully connected layer is to classify images into a category, previously we performed the operations like convolution and pooling where we reduced the size of input images and retain exclusive and useful information for the classification and then ‘flatten’ the output feature map because we know MLP (Multilayer perceptron) requires input vectors (1-D array) and go through some more fully connected layers. We must put MLP on the top of the last convolutional layer.

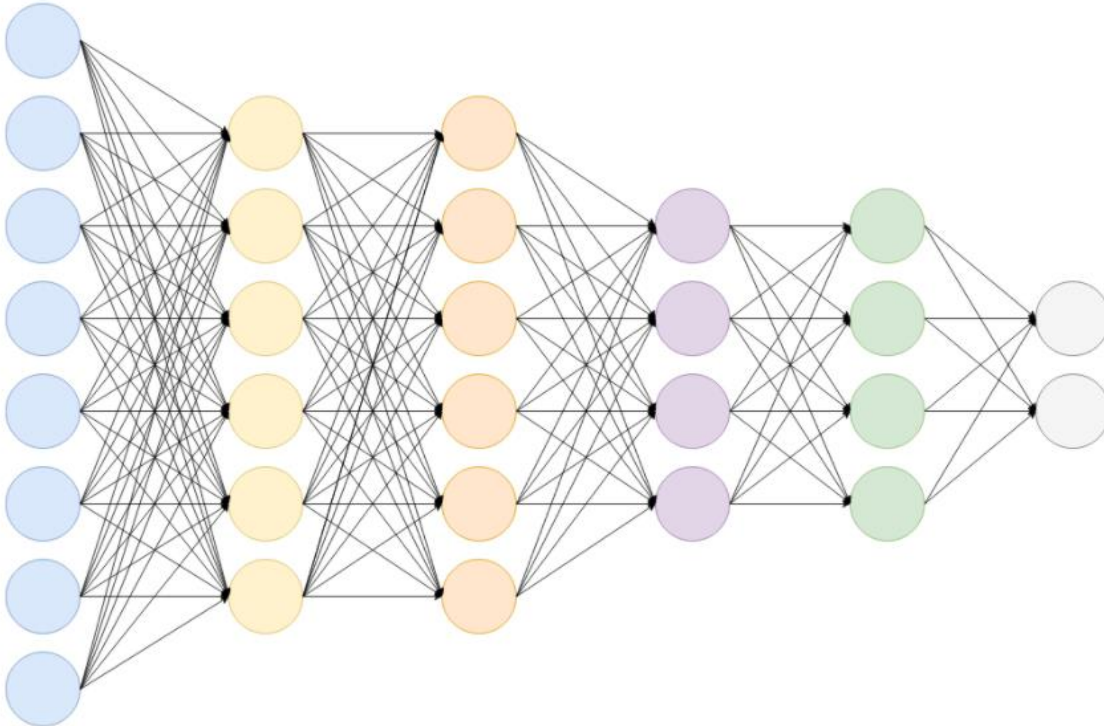


Figure: 2.1 Fully Connected layer

From the pooling or convolutional layers, the output which we got is flattened and fed into fully connected layers. Whenever we get output from the convolutional layers or pooling layer that becomes the input to the fully connected layers.

2.2.3 Regularization

Regularization is a collection of strategies for preventing overfitting in neural networks and, as a result, improving the Deep Learning model accuracy when confronted with entirely fresh data from the issue domain. In this, we'll look at the three most common techniques of regularization: L1, L2, and dropout. If you've ever created a neural network, you're aware of how difficult they are. They are more prone to overfitting as a result of this. Regularization is a strategy for improving the generalisation of a learning system by making minor changes to it. As a result, the model's performance on previously unknown data increases as well.

L2 Regularization

The L2 regularisation approach, also known as Ride Regression or weight decay, is the most frequent of all regularisation procedures. This regularization's mathematical derivation, as well as the mathematical explanation of why this approach reduces overfitting, is lengthy and difficult. Because this is a highly practical topic, I won't go into more detail on mathematics than is necessary. Instead, I'd want to explain the logic behind this method, as well as how to put it into practice, so you can avoid overfitting in your deep learning projects. Regularization is a term in which loss function is extended, which is termed as L2 regularisation here.

L2 norm which also known as the Euclidean Norm of the weight matrices, where L2 norm is the sum of weight values of a weight matrix all squared, is the regularisation term. The regularisation term is added to the regular loss function for the current job, which is multiplied by the scalar $\propto$ and divided by 2. As a result, the loss function has a new expression shown below:

$$\hat{\mathcal{L}}(W) = \frac{\alpha}{2} ||W||_2^2 + \mathscr{L}(W)\sum_i \sum_j wij + \mathscr{L}(W)$$

The regularization rate, also known as alpha, is an extra hyperparameter that we put into the neural network. Simply $\propto$ decides how regularised our model is. After this the gradient of the new function called loss function will then be computed, and then put the slope into the updated rule for the weights :

$$\nabla_w \hat{\mathcal{L}}(W) = \alpha W + \nabla_w \mathscr{L}(W)$$

$$W_{new} = W_{old} - €(\alpha W_{old} + \nabla_w \mathscr{L}(W_{old}))$$

L1 Regularization

We simply apply another regularization term known as L1 regularisation (also known as Lasso regression). In a weight matrix, this term is the total of the absolute values of the weight parameters:

Here alpha will be multiplied by the regularization term and add the entire result calculated previously to the loss function, just like in the prior instance.

$$\hat{\mathcal{L}}(W) = \alpha\|W\|_1 + \nabla_w \mathscr{L}(W)$$

The derivative of the new loss function leads to the following expression, which the sum of the gradient of the old loss function and sign of a weight value times alpha.

$$\nabla_w \hat{\mathcal{L}}(W) = \alpha \text{sign}(W) + \nabla_w \mathscr{L}(W)$$

Dropout

Apart from the L2 and L1 regularization techniques there is another regularization technique known as dropout, dropout regularization is a well-known and effective regularization approach. The term "dropout" refers to when a neuron in a neural network is turned off during training with a probability P. Assume a probability P = 0.5 means 50 % of the neurons will be dropped during training. That means half percentage of the neurons will not be considered as a part of neural network as a result neural network becomes simpler. Dropout regularization is a straight forward process. As we know, we use dropout layer in the CNN to avoid overfitting. Simply we can say that in dropout layer some percentage of neurons are dropped from the neural network during the implementation of training process.

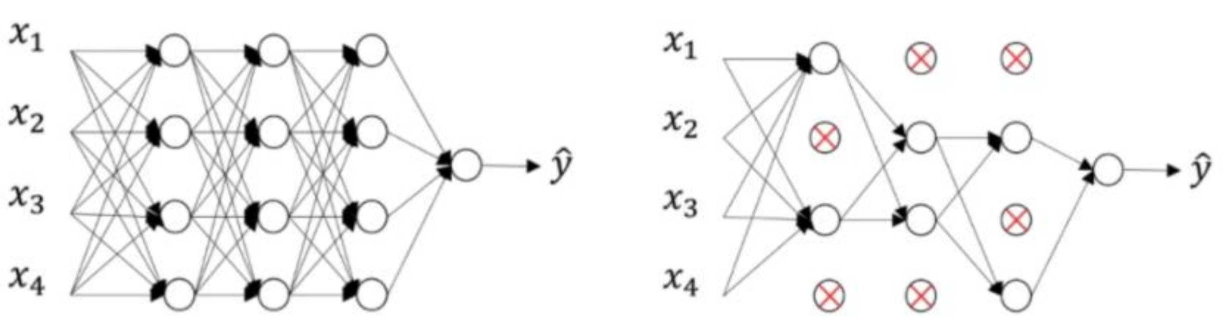


Figure: 2.2 Dropout

2.2.4 Activation function

It is the most important part of the CNN model for reading and determining any form of continuous and complicated relationship between CNN variables. It is used to determine if the output of a neural network is yes or no. The values are converted from 0 to 1, -1 to 1, and so on. Basically, it is one of the important parts of the neural network it determines whether neurons should be activated. It adds nonlinearity to the network in the CNN models like sigmoid and tan h. Activation functions are divided into two types.

1. **Linear activation function**

   As the name suggests function is linear, as a result, the function's output will be unconstrained by any range.

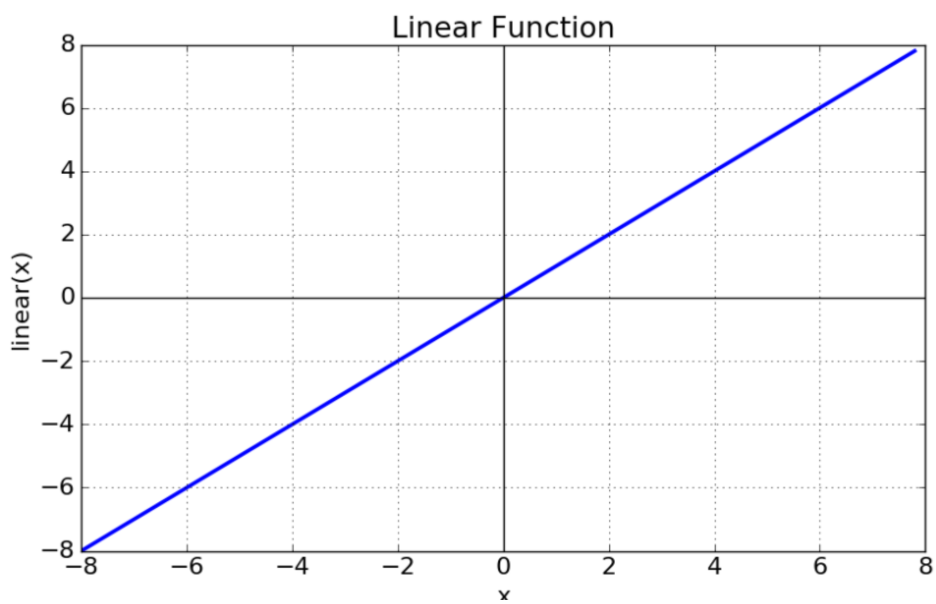


Figure: 2.3 Linear activation function

$$\boldsymbol{Equation} : -f(x) = x$$

$$\boldsymbol{Range} : -(-\infty\ to\ \infty)$$

2. Non-linear activation function

The most often utilised activation functions are nonlinear activation functions. Nonlinearity contributes to the appearance of this graph.

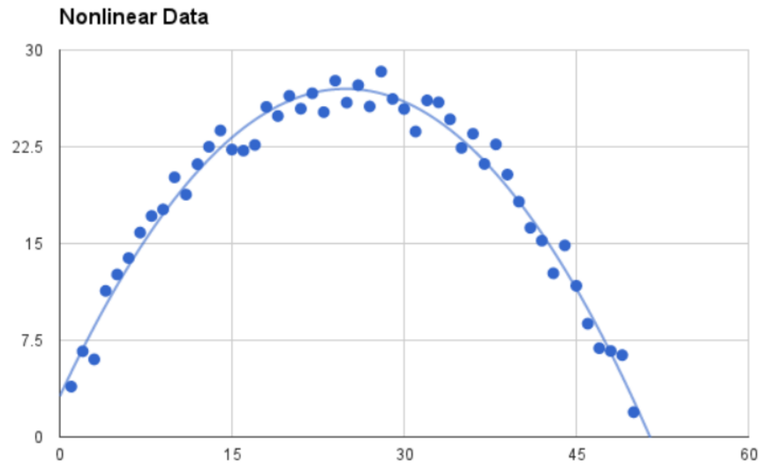


Figure: 2.4 Non – linear activation function

The non-linear activation functions are categorized based on their range.

a. Sigmoid or Logistic Activation Function

The curve of the sigmoid or logistic activation function looks similar to S-shaped curve. The range of logistic activation function occurs in between 0 to 1. As a output sigmoid function is useful where probability is to be predicted. Because everything can only happen between zero and one, then logistic activation function is one of the good options. Generally, for binary classification sigmoid function is used. On output layer sigmoid function is used, not like a Tanh Function which is used at a hidden layer. These things are not static in all the cases and which activation function to be used must be analysed according to the specific problem.

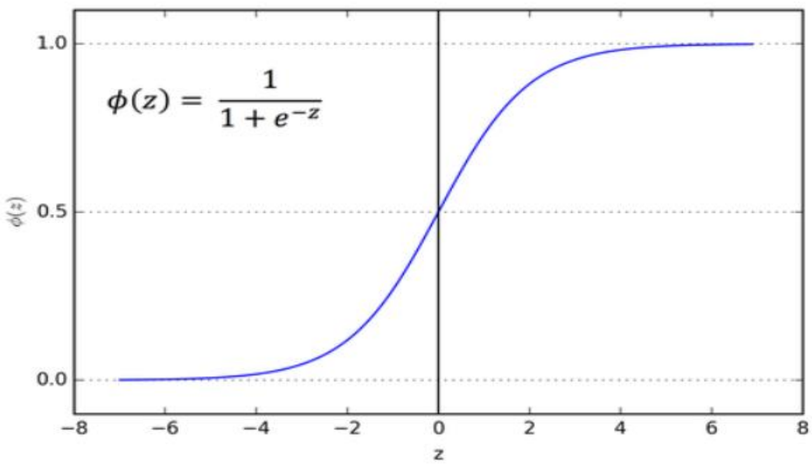


Figure: 2. 5 Sigmoid function

b. Tanh Function

Tanh is like the logistic sigmoid, it is a hyperbolic tangent function. Both Tanh and sigmoid activation function's curves are relatively similar as shown in the figure 2.6 however, Tanh is superior because whole function is zero centric. The tanh function has a range of values between -1 and 1. (-1 to 1). tanh is also S-shaped. In this graph, the benefit of Tanh graph is that it maps zero as well as negative input.

Generally, for the binary classification, both tanh and sigmoid activation functions are used. On output layer sigmoid function is used, not like a Tanh Function which is used at a hidden layer. These things are not static and which activation function to be used must be analysed according to the specific problem. But all these things are totally depending on the debugging.

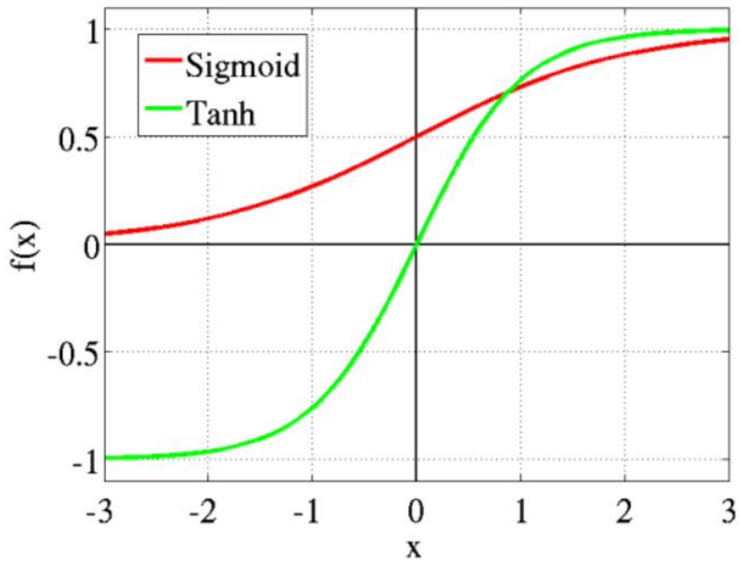


Figure: 2.6 Tanh Function

c. ReLU activation function

At present, most widely utilized activation function on the planet is the ReLU activation function. Since then, it's been utilized in nearly all convolutional neural networks and deep learning systems. Actually, ReLU activation function takes maximum value. The point which have to note here is that this is not fully interval-deliverable. But we can take sub-gradient as shown in the figure 2.7.

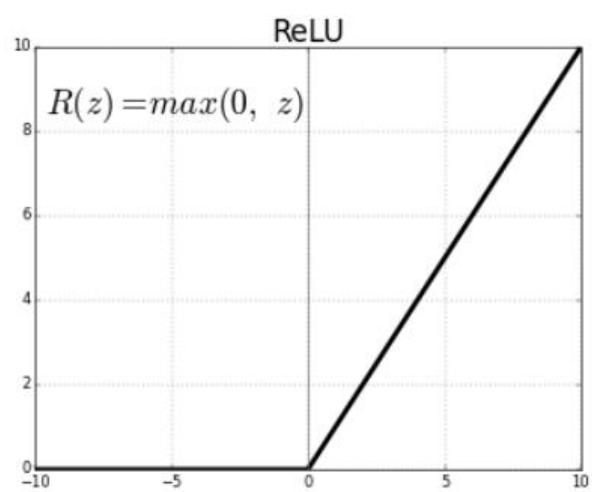


Figure: 2.7 ReLU activation Function

Range :- (0 to infinity)

2.2.5 Other training models

A. Resnet-50

Song et.al[9] used ResNet50, a 50-layer deep residual network that enables accurate diagnosis of novel coronavirus. It is based on residual learning, which is the same architecture as ResNet101 and ResNet152.

What is residual learning, exactly? When it comes to neural networks, “deeper is better” in general. With additional layers, the network learns more features and generalizes better. There is, however, a limit. As the model grows more complex, the neural network's training becomes more challenging, and the model's performance begins to saturate and even decline. This is primarily due to the well-known vanishing gradient issue. A typical Resnet-50 model illustrated in figure 2.8. The ResNet-50 architecture shows the residual units, filter size, and outputs of each convolutional layer. The DRF for this network is also shown, which was obtained from the last convolutional layer.

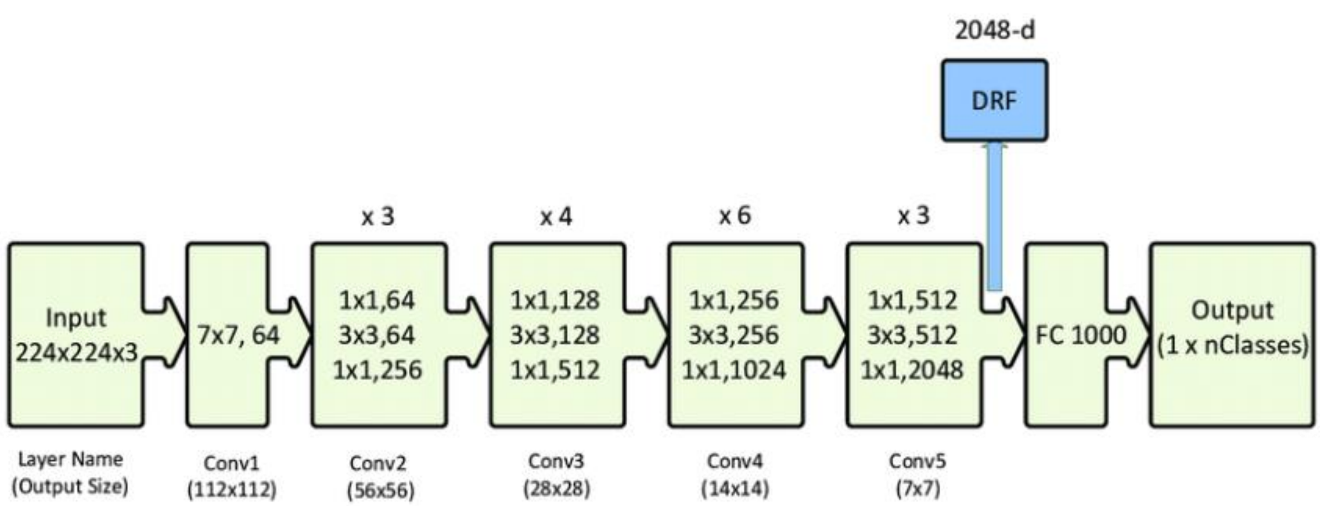


Figure: 2.8 Resnet-50 architecture

B. Unet

The architecture shows a structure like letter 'U,' therefore the name of the architecture is Unet. The contraction part, bottleneck, and the expansion are the three section of which the architecture of Unet is made up of. Many contraction blocks make up the contraction section. An input is received by each block and they applies two 3X3 convolution layers before applying a 2X2 max pooling layer. After each block, the number of kernels or feature maps doubles, allowing architecture to successfully learn complicated structures. The function of bridge is carried by bottommost layer between the contraction and expansion layers. A 2X2 convolutional layer is preceded by two 3X3 CNN layers. Zheng et al.[7] used this architecture for detection of COVID-19 from chest CT using weak label. A typical Unet architecture illustrated in figure 2.9.

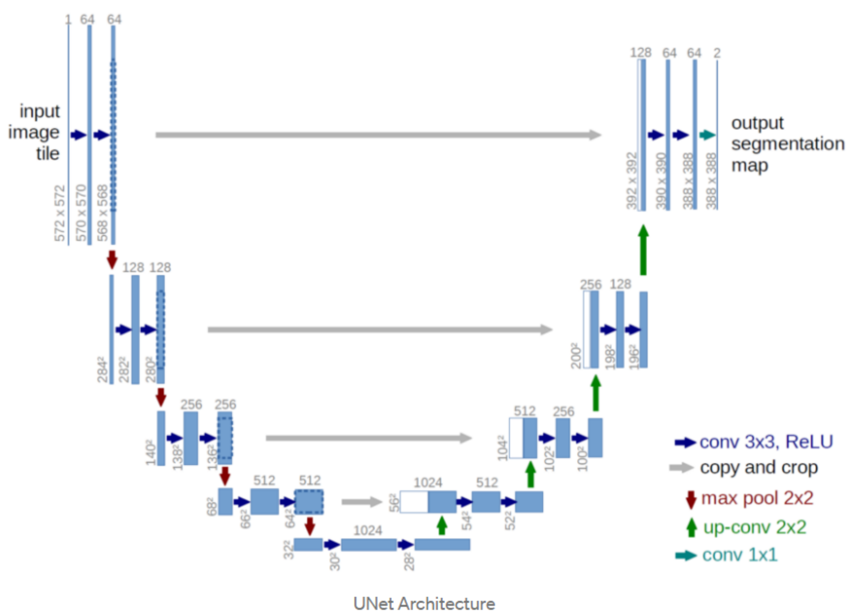


Figure: 2.9 Unet architecture

C. Random forest

Random Forest is a well-known machine learning algorithm that uses the supervised learning method. In machine learning, it may be utilized for both classification and regression issues.

The basis of random forest is ensemble learning. Ensemble learning is a method of integration of many classifiers to solve a complicated issue and enhance the performance of a model. There are different number of decision trees contained in a random forest classifier on different subsets of a given dataset and takes the average to enhance the prediction accuracy of that dataset," according to the name. Prediction from every single tree is collected in the random forest to make a decision which is based on most votes obtained from each tree. Shi et al[11] used random forest classifier for covid-19 classification.

A typical random forest machine learning algorithm illustrated in figure 2.10. Here we can see different decision trees giving their own respective votes contributing to the final classification.

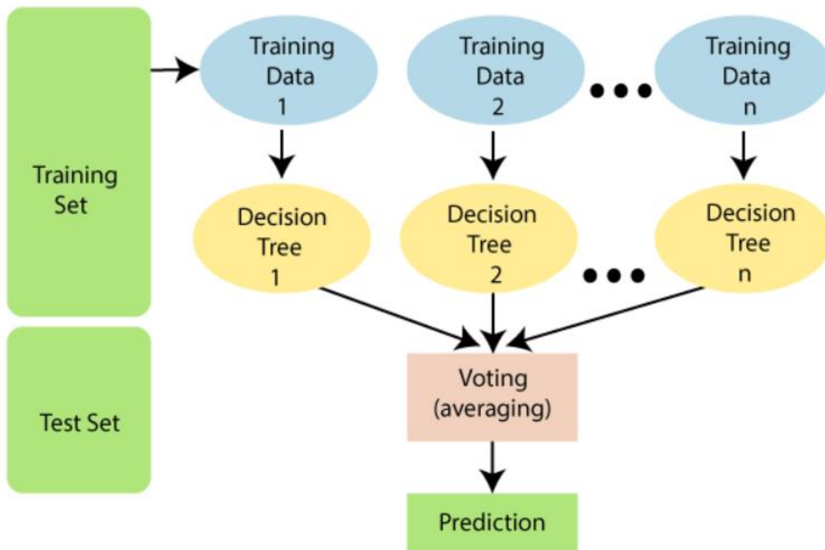


Figure : 2.10 Random forest algorithm

Chapter 3

PROPOSED MODEL

3.1 Approach

We are trying to solve the testing problem of Covid-19 with the help of one of the deep learning CNN based model. Deep learning methods have shown to be an outstanding artificial intelligence approach in recent years, owing to its potential and capacity to detect complex patterns from raw input data, learning correct hierarchical representations of the underlying information at various levels. These approaches are increasingly being utilized in a variety of disciplines related to medical imaging, such as computer-aided detection/diagnostic systems and analysis of medical images, which helps in accurate early detection, diagnosis, treatment, and monitoring of a variety of illnesses. Our proposed model will classify the patients with the help of chest X-ray images of a healthy patient or a patient affected by COVID-19 is provided in this study. First, we'll go through the picture datasets that were employed in this study.

3.2 Model Architecture

As the architecture of the model is shown below. We have used 14 layers, as a backbone there is a dense layer followed by fully connected layers. We have used the sigmoid activation function to produce the final output. Our proposed model is illustrated in the figure 3.1.

Input features are feed into the model and that passes through the two subsequent convolutional layers with ReLu activation function applied in each just after the corresponding convolution operation in each. After applying convolution, we get the convolved feature map of reduced dimension. There are so many types of pooling techniques available, among which we have chosen max pooling to be applied on our convolved feature map. This extracts relatively more useful feature map to train our model. The feature map resulted after pooling is applied a dropout to avoid overfitting of the model.

We repeat the same steps from convolution to dropout to further extract a more diminished feature map. The output so resulted is again passed through a series of three convolutional layers stacked one over the other. After that we again passed this convolved feature map to pooling layer and again a dropout is applied.

The resulted feature map is flattened to a long vector, passed through the dense layer with ReLu activation function and an appropriate dropout is applied, this feature map is found very much of reduced dimension is compared to the input feature we started with initially. We have one more dense layer just after this step but here we are considering sigmoid activation function since our problem is a classification problem. And finally, we reach the final output.

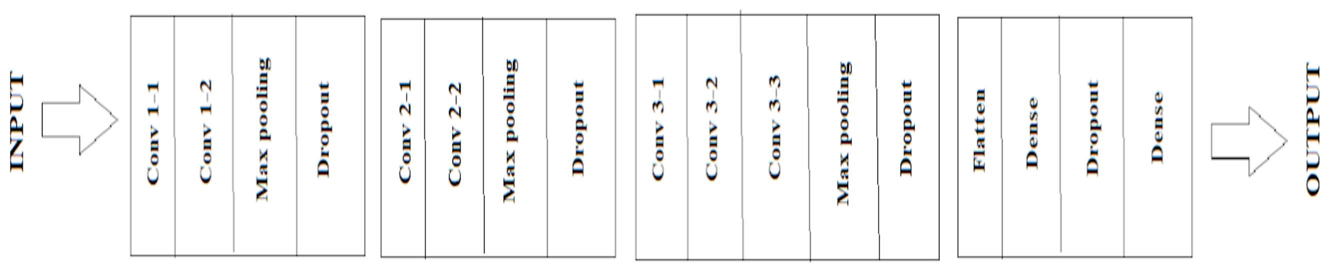


Figure:3.1. Model architecture

CHAPTER 4

THE EXPERIMENTAL APPROACH

In this chapter we will see the experimental approach of our proposed model. The following system configuration has been used while conducting this experiment:

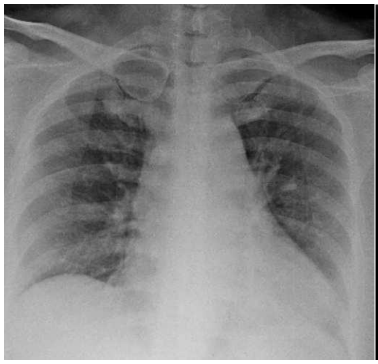
- Processor: Intel Core i5
- Main Memory: 8 GB
- Hard Disk Capacity: 1 TB
- Software Used: Notebook 6.0.1 and Anaconda.

4.1 Data analysis

Since data analysis is the sequence of the process of evaluating, cleaning, converting, and modelling data with the objective of discovering valuable data, reporting conclusions, and supporting decision making, it is the acute stage with the goal of preserving the best out of waste. One of the primary reasons for analyzing data is to identify the complexity of the data and how it appears, as well as to guarantee that the data is legitimate and has the essential fields.

4.2 Dataset

We used frontal-view chest X-ray pictures in our research. The only X-ray images obtained were posterior-anterior (PA) and anterior-posterior (AP). For this dataset, we used the collection of 194 Covid-19 positive patients chest X-ray pictures from Kaggle's "Chest X-ray Images competition. We chose 194 samples at random from the “normal” X-ray pictures, which belong to healthy patients. This source was chosen because it has been often referenced in studies that suggest COVID-19 detection techniques in X-rays[12]. All the X-ray images from this source, however, are of children. Because the COVID-19 class's X-ray pictures are primarily of adult patients. The joint photographic experts group (JPG/JPEG) format is used for all pictures in the databases. Figure shows samples of pictures from the datasets. Figure 4.1 shows one of the chest X-ray image of a patient with coronavirus illness with PA view and AP view, respectively, while Figure 4.2 shows one of the chest X-ray image of a healthy patient from Dataset.



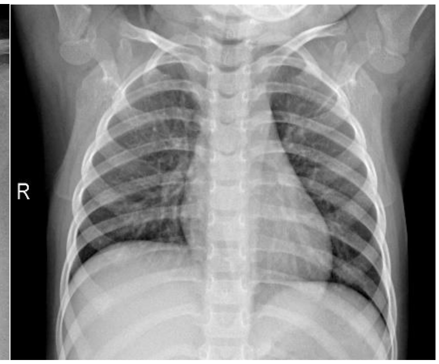


Figure: 4.1 Covid-19 positive patient **Figure: 4.2 Healthy patient**

4.3 Data augmentation

Computer vision tasks including image classification, object identification, and segmentation have been quite effective among the popular deep learning applications. In these cases, data augmentation may be utilized to successfully train DL models. Color space modifications like color casting, changing brightness, and noise injection, as well as geometric adjustments like flipping, rotation, translation, cropping, and scaling, are just a few of the easy alterations made to the image. Data augmentation is primarily used to get more data from limited data. Meanwhile it can also be used to avoid overfitting. If our model is overfitting, it will be unable to generalise and will hence be inefficient.

4.4 Model Training, Testing and Validation

After we perform the data augmentation on our dataset, this gives us sufficiently large amount of dataset to effectively perform the training and testing of our proposed model. Training is performed by slicing out the training dataset out of our augmented dataset. Similarly, a section of the dataset is selected out of the augmented dataset for the testing purpose. Table 4.1 shows train, test and validation dataset details of a normal and a Covid-19 infected person. The training dataset consist of 2728 records, test dataset consist of 1136 records and validation dataset consists of 682 records.

Table 4.1 Train, Test, Validation dataset details

	Normal	**Covid-19**	**Total**
Train	1364	1364	2728
Test	568	568	1136
Val	341	341	682

Chapter 5

EXPERIMENTAL RESULTS

5.1 Model Evaluation

For prediction evaluation we are using the following measurements based on confusion matrices conclusions.

5.1.1 Precision

Simply precision means out of the total positive predicted result by the model what is the percentage of actual positive result. Precision value is the level of measure of what information system is generating output and what user demanded from the system. Calculation of precision can be mathematically written as follows: -

$$Precision = \frac{TP}{(TP + TF)}$$

Equation of precision can also be written as follows :

$$Precision = \frac{Relevent\ data\ foud}{All\ data\ found}$$

Where: TP = True Positive means prediction of a model and actual result, both are positive. For example, 10 people are Covid-19 Positive are predicted positive by the model.

FP = False Positive means the prediction of model is positive, but result is actually negative. For example, 5 people in the confusion matrix are predicted Covid-19 positive but actually they are not Covid-19 positive patients.

Also, to estimate precision value from the confusion matrix, we need to look at positive labeled attributes and find its average value as depicted in the picture below.

		Predicted	
		Negative	Positive
Actual	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

Figure: 5.1 Representing Precision values in the Confusion matrix

5.1.2 Recall

The rate of achievement of the system to rediscover information is called a recall. Therefore, Recall really computes the number of the real positive aspects that our model captured over anddone with a positive label on it.

Calculation of recall values can be written in the form:

$$Recall = \frac{TP}{(TP + FN)}$$

Equation of Recall can also be written as follows:

$$Recall = \frac{Relevant\ data\ found}{Relevant\ data\ in\ a\ database}$$

Where: *TP* = True Positive means prediction of a model and actual result both are positive. For example, 10 people are Covid-19 Positive are predicted positive by the model.

FN = False Negative means prediction of model is negative, but result is positive. For example, 10 people in a confusion matrix are Covid-19 positive but predicted negative by the model.

We have acquired different recall values for each algorithm used, which is depicted in the table below: Also, how to estimate Recall from the confusion matrix.

		Predicted	
		Negative	**Positive**
Actual	**Negative**	True Negative	False Positive
	Positive	False Negative	True Positive

Figure: 5.2 Depicting Recall values in the Confusion matrix

5.1.3 Accuracy

Accuracy can be calculated as the data which is correctly classified divided by total dataset tested. It can also be calculated as 1- ERR.

Accuracy can becalculated and written as follow:

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

Equation of Accuracy can also be written as follows:

$$Accuracy = \frac{\text{Data that is correctly classified}}{\text{Total data tested}}$$

Where: TP = True Positive means prediction of a model and actual result, both are positive. For example, 10 people are Covid-19 Positive are predicted positive by the model.

TN = True Negative means prediction of model and actual result, both are negative. For example, 10 people who are not Covid-19 positive are predicted negative by the model.

FP = False Positive means the prediction of model is positive, but result is actually negative. For example, 5 people in the confusion matrix are predicted Covid-19 positive but they are not Covid-19 positive patients.

FN = False Negative means prediction of model is negative, but result is positive. For example, 10 people in a confusion matrix are Covid-19 positive but predicted negative by the model.

5.2 Model prediction

When we obtain the data, after cleaning, pre-processing, and analysing it, the first thing we do is put it into a model, which produces probabilistic outcomes. But hold on! How are we supposed to assess our model's efficiency ? Higher efficiency equals better performance, and that's precisely what we're looking for. And this is when the Confusion Matrix comes into focus. The confusion matrix is a machine learning classification performance metric. The Confusion Matrix is a machine learning classification performance metric. There are four different combinations of anticipated and actual values in this table. The confusion matrix may be used to calculate Recall, Precision, Specificity, Accuracy, and, most significantly, AUC-ROC curves. It is used to performance measurement for machine learning classification.

So, we can find different metrics measuring of the model which we have used by observing confusion matrix .

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

$$= \frac{(434+475)}{(434+475+31+4)}$$

$$= 96.29\ \%$$

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{(\boldsymbol{TP}+\boldsymbol{TF})}$$

$$= \frac{434}{(434+31)}$$

$$= 93.33\ \%$$

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{(\boldsymbol{TP} + \boldsymbol{FN})}$$

$$= \frac{434}{(434 + 4)}$$

= 99 %

$$\boldsymbol{F1\ Score} = \frac{\mathbf{2{\times}Recall\ {\times}Precision}}{(\boldsymbol{Recall{+}Precision})}$$

$$= 2\,\frac{99 \times 93.33}{(99{+}93.33)}$$

= 96.08 %

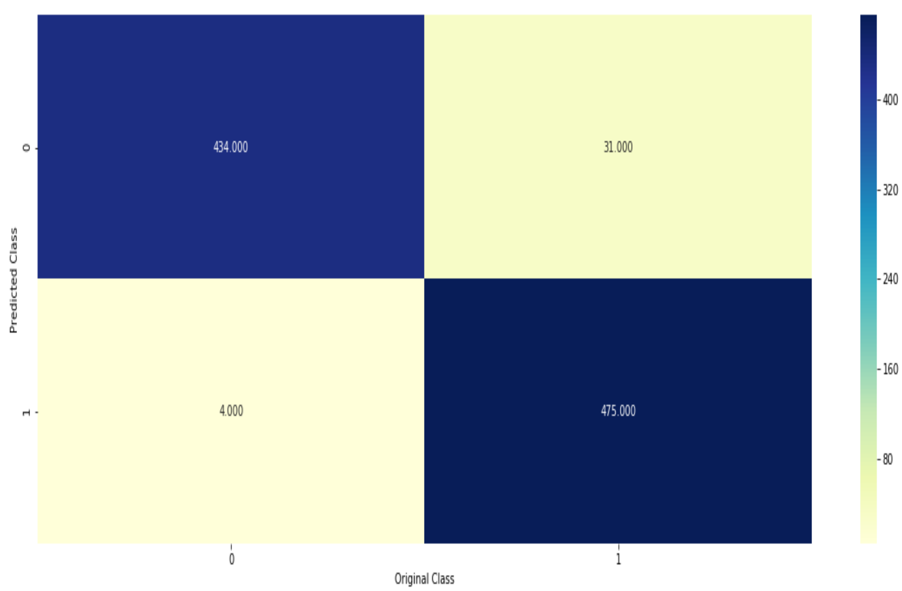


Figure: 5.3 Confusion matrix

Chapter 6

CONCLUSION

The CNN has been successfully implemented on the dataset and successfully achieved a good accuracy of approximately 96 % in SARSCOV2 identified using x-ray. The covid-19 positive images and the normal x-ray images have been taken from the Kaggle. We look forward to exploring more efficient results by incorporating a relatively larger dataset in future work. We will try to deploy some more advance deep learning models to discover the traces of covid-19 in the host body. India has never seen a pandemic like this in the previous 100 years, therefore what do people think about it, the lockdown, the government's response/policies, and so on May all be researched to gain a better insight into the epidemic. In the future, we will work on the images of different chest X-ray images of Covid-19 variants like delta variant, delta plus variants, etc. And will try to detect different variants.

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