# Chapter

**Prediction Models for Detecting COVID-19 from Chest X-ray Images using Multi-Layer Convolutional Neural Network**

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**Abstract**  
The cases of COVID around the world have been rising exponentially. In rural areas as well as in underdeveloped countries, it has become impossible to conduct RT-PCR tests on every patient suffering from respiratory illness due to limited health facilities and medical kits. The drawback of the RT-PCR test is that it takes longer to deliver results and has limited sensitivity. A variety of approaches have been developed to extract information from X-rays of chest of infected patients. X-ray equipment [14] is generally available in all countries in most health systems, and with the availability of digitized X-ray equipment, The systems reduce the transport time of samples. Digitization of modern X-ray machines has contributed to the introduction of AI and machine learning applications in medicine and healthcare. Therefore, we proposed a CNN Model which can autonomously detect COVID-19 in human bodies from X-Ray of chest samples of patients where radiologists are not readily available. Consequently, our proposed method is highly efficient and can be easily scaled. Our ‘h5’ model: A Multi-layered CNN model was utilized to provide patients with preliminary appropriate testing. In the First Dataset, our model achieved 97% of accuracy, 97% of precision, 93% of recall, and 95% of f1-score for the COVID infection classification. Furthermore, publicly available covid X-ray of chest dataset of the Second Dataset, our model achieved 92% of accuracy, 86% of recall, and 91% of f1-score for the classification of X-rays of chest samples.

**Keywords**: Multi-layered CNN · COVID-19 · Chest X-ray

1. **Introduction**

WHO was apprised by Chinese authorities of the emergence of COVID-19 in China in December 2019 [1]. As of 31st May 2022, WHO had received 6,390,401 deaths reports and 572,239,451 confirmed cases attributed to COVID WHO [2]. The most harmful contagious respiratory illnesses are Influenza (flu) and Corona but different viruses cause them. Coronavirus, which was first identified in 2019 is mainly responsible for transmitting COVID-19 disease in human beings, whereas flu disease is caused by influenza viruses. Comparing the effects of corona and influenza viruses, it was found that COVID-19 disease causes more serious illnesses [14] in some people, especially aged people. Sometimes, it takes longer to detect the functioning of coronavirus in the human body. Therefore, people remain infected with the virus for a certain period. The new variant of the virus (popularly known as Deltacron) that is responsible for causing this disease is rapidly spreading among people to date [3]. The virus is transmitted through human contact and the inhalation of aerosols, which are small particles that are released when a person coughs or sneezes [4] serving as the medium of transmission. WHO has recommended a test as a standard test called RT-PCR for diagnosing the disease. [5]. SARS-CoV-2 is responsible for COVID-19 and through Polymerase Chain Reaction (PCR) we can detect SARS-CoV-2. A molecular diagnostic technique that detects the presence of genetic material (RNA) in upper respiratory specimens from human subjects. By using PCR technology, Scientists produce multiple copies of small amounts of RNA from the collected specimens to make an exact copy of DNA (Deoxyribose Nucleic Acid) until the SARS-CoV-2 virus is detectable. Therefore, the PCR test has been considered the standard gold test for diagnosing COVID-19 which has been authorized since February 2020. The RT-PCR test is performed using nasal swabs, and throat swabs and the molecular test is sometimes conducted at hospitals and clinics. But the RT-PCR test performed using deep nasal swabs has been found to provide fewer false negatives compared to the tests conducted using throat swabs or saliva tests. In certain cases, RT-PCR tests are reported to yield results within 1 to 2 days. Furthermore, the molecular test results indicated a false negative for the patient's virus status, Consequently, the false positive rate varied from 2% to 37%. Moreover, it was ascertained that the deep nasal swabbing procedure was uncomfortable for children [6]. Researchers effectively examine lung samples for indications of this serious disease with the help of CT scans and X-rays. Three different methods of study CT scans, X-rays and Lung Ultrasounds have been done by physicians and radiologists to detect the Novel CoronaVirus. The studies varied their approaches and employed divergent techniques to explain their findings. Few studies have conducted an analysis of chest X-rays and chest ultrasounds, and a limited number of studies have directly compared the efficacy of one type of imaging test against another. As a result, reliable conclusions cannot be drawn from the results of the studies presented in this report [7]. COVID-19 is exponentially transmitted, resulting in a higher rate of a spread than other respiratory illnesses. Consequently, we need faster, more reliable and less costly technology to detect the virus. Over the past few years, the CNN deep learning technique has demonstrated excellent performance in various applications such as sample processing, computer vision, and video processing. In some cases, CNNs even outperform humans on these tasks.

1. **Literatures**

On 11th September 2020, Kaushik Roy and his group [7] proposed a Deep Neural Network in their paper. The dataset comprises 168 sample samples of X-rays of chest from various sources referenced in online articles, which are associated with positive cases of COVID-19, and 65 sample samples of X-rays that are not related to COVID-19. They used two different sources to gather different CT Scan X-ray samples and this dataset included 146 positive and 167 negative cases. Their proposed model as mentioned in the paper [7] consists of 3 alternating convolution layers with dimensions 32, 16 and 8 with filter sizes of 5x5, 4x4 and 3x3 respectively. Activation functions like ReLU and Softmax are deployed by them in Convolution and output layers respectively. They set the size of the pooling window matrix to 2x2, and the stride value is set to 1. The Densely Connected layer in their model consists of 2 layers with dimensions 256 and 50 respectively. The proposed model obtained 96.28% of accuracy, 94.81% of precision and 97.92% of recall on the entire test dataset (consisting of CXRs and CT scans).

Mohammed Elgendi and his team proposed [8]. They used 17 pre-trained neural networks and a comparative study on X-rays of chest samples of disease, Other Bacteria and Viral Pneumonia infected patients in their paper. They used two datasets in their work, the first dataset is taken from the publicly available Kaggle website The dataset includes 85 COVID-19 samples, 2772 of bacterial pneumonia and 1493 of viral pneumonia. Additionally, hospitals like Vancouver General Hospital (VGH) contributed 85 X-rays to the data set. The data set was split into 80% and 20% for training and validation. They have kept the architecture [8] of all the pre-trained CNN models the same, but they only changed the last layer of the densely connected networks for every model to classify two classes (a) Corona and (b) Bacterial Pneumonia. The parameters were set to a fixed value by them in all 17 pre-trained neural networks having a validation frequency of 5 and learning rate of 0.0001, a maximum epoch set to 8 for a minimum batch size of 64. They used the Second Dataset as mentioned above as a test dataset for assessing the performance of all 17 models. After training and assessing all the models on the first dataset, It was observed that DarkNet-19 and ResNet-50 achieved an accuracy of 100% in training, whereas ShuffleNet attained 90.91% of training accuracy and 85% of Validation accuracy. A comparison study was conducted by them in evaluating the DarkNet-19 and ResNet-50, the former achieving 96.55% of accuracy and latter achieving 86.21% of accuracy in different samples from X-rays of chest.

The implementation of a transfer learning pipeline [9] was proposed by Tahmina Zebin and Sahadate Rezvy to classify COVID-19 X-ray samples from two publicly available X-ray datasets in their article. The researchers individually employed configurations of convolutional layers originating from multiple pre-trained CNN such as “VGG16'', “ResNet50'' and “EfficientNetB0'' as the foundation of their model to bring out features from the X-ray samples. The researchers incorporated a gradient class activation approach to emphasize regions of the input samples that are pertinent to prognoses. Their dataset is composed of 673 samples of thoracic X-ray and CT scans from 349 patients with Corona Virus. They used the publicly available Kaggle data source to collect normal and pneumonic chest X-ray samples, of which they selected only 300 random samples. They developed a comprehensive dataset wherein 80% of the data was allocated to the training set, while the rest 20% was used for the test set. To minimize time complexity while training and testing, they resized the samples to 224x224 pixels, and the samples were collected from various sources (have different contrast and brightness), therefore sample normalization technique [9] has been applied to their datasets. CycleGAN (Cycle Generative Adversarial Network) has been used in this work to increase the number of samples from the normal X-ray samples in the training and test datasets. Different models are implemented corresponding to pre-trained CNN, and all three models were subjected to 50 training epochs and tuned using Adam Optimizer and achieved 0.0001 as the learning factor, a stack size set to 8, and a categorical class entropy loss function, which is used here anyway for the multiclass classification. It was found that the model with the Resnet50 architecture as the basis achieved an accuracy of 0.943 in classifying Corona affected chest x-ray samples. In this paper [10] they showed transfer learning CNN for the identification of the corona virus affacted using x-ray chest samples. Tensor Flow was utilized to implement the model, which employs a pre-trained DenseNet-201 model to categorize radiographs as showing normal, bacterial, viral, tubercular, or COVID-19 pneumonia. The dataset of each of the above mentioned lung diseases contains 50 to approximately 1000 samples. The distribution of X-rays of lungs in the dataset is as follows: - (a) 34% healthy (b) 28% viral pneumonia (c) 27% bacterial pneumonia (d) 5% corona (e) 4% tuberculosis. The Tensor Flow Keras simple Data Generator function was utilized to randomly augment each sample in the dataset prior to being trained by the model. The training dataset contained 6324 samples, while the validation dataset and test dataset contained 1574 and 1970 samples respectively. The proposed model utilized DenseNet-201, which had been pre-trained on the imageNet database, as its convolution layer. In their work, they employed default Adam Optimizer and Categorical cross-entropy loss functions as metrics to assess the predictions generated by the proposed model. A batch size of 5 was used to train the model over the course of 50 epochs [10]. The Training Accuracy of the model was 88.71%, while the Validation Accuracy was 82.97%. Upon evaluation, the accuracy of the model on the test set was found to be 83.4%. According to the results obtained from the Test Dataset, the precision, recall, and f1 score of the model were determined to be 0.95, 0.98, and 0.96, respectively. These findings suggest that the model performed well in terms of accurately classifying COVID-19 chest X-rays. Because this automated diagnosis tool will offer a straight forward detection solution, The proposed model of this research can have a beneficial impact on developing nations and areas where access to molecular testing and experienced radiologists is limited.In this paper [11], researchers hypothetically created a model called as COVIDPEN. The input of the model is X-rays of chest sample, and the output is a binary classification (positive, negative) of COVID, where positive = +1 corresponds to a positive diagnosis and negative = -1 corresponds to a negative diagnosis. They used Residual Convolution Neural Network to recognize the frontal view of X-Ray samples and the model outputs a binary label that helps to predict whether the bacterial disease is positive or negative. To address the challenge of training the model on a limited dataset, the authors utilized Transfer Learning [11] as a means of mitigating overfitting, minimizing errors, and reducing the time spent on pseudo-labelling. The proposed COVIDPEN model comprises 18 convolution layers, with each layer featuring filters measuring 1x1, 3x3, and 5x5 in size. The model takes an RGB Chest X-Ray sample with a resolution of 224x224 pixels as input. In order to improve the accuracy and accelerate the convergence of their model, the researchers employed a "One Cycle Policy" to optimize the global learning rate. The dataset includes over 746 samples that are labeled as either COVID-19 or non-COVID-19. 75% of the samples have been allocated to the training set, while the other 25% are reserved for the test set. To assess the effectiveness of the model, they utilized an additional dataset comprising chest radiograph samples categorized into five classes: Normal, bacterial, tuberculosis, viral and corona. To divide the second dataset, 80% of the data was assigned to the training set, while the remaining 20% was kept aside for the test set. The Adam Optimizer is utilized to train the model, while Test Time Augmentation (TTA) is employed to create multiple versions of samples within the testing dataset. They employed a range of evaluation metrics, including accuracy, precision, recall, F1 score and Sub-Receiver Area Operating Characteristics (AU-ROC) to assess model performance. On the test dataset of Chest X-Ray samples in the identification of corona, COVIDPEN model achieved an accuracy of 0.96 in the first dataset of chest radiography, and the second dataset yielded an accuracy of 0.85. They developed a Neural Network Classifier. It is capable of accurately classifying corona affected from both Chest radiographs and X-rays of chest datasets. In a recent experiment [12], two CNNs models VGG16 and Resnet50 were trained on coloured camera samples sourced from the imageNet dataset. The VGG16 CNN model has 16 layers, comprising 13 convolution layers, each employing a 3x3 filter with stride =1 and padding =1 to identify features. In this model, five max-pooling layers with a 2x2 window and a span of two are applied after each block of the convolution layers, [12] The final layers of the VGG16 model were replaced with a trainable component consisting of global average pooling, a fully connected layer of 64 units with dropout and a sigmoid-activated classification layer. The same architecture is applied to the Resnet50 model. They established a basic 0.0001 learning rate and a maximum 0.001 learning rate. The loss Function used in the experiment is Binary Cross-Entropy. The researchers conducted 10 cross-validations to evaluate the applicability of chest radiographs for diagnosing corona affectec people. The overall accuracy rate was 89.2%, with 80.39% of COVID-19 cases accurately identified. The analysis yielded approximately 6% false positives, but this rate could be decreased by balancing the training data to include a greater number of non-COVID-19 cases.

1. **Methods Datasets Used**

Two datasets are used, the first dataset used in my work is taken from github.com. In this First dataset, The training dataset comprised 1266 Normal samples of X-rays and 545 samples of Covid-19 X-rays, while the test dataset contained 167 Covid and 317 Normal X-ray samples, respectively. Consequently, the dataset contains a total of 1,811 training samples and 484 test samples. The second dataset is publicly available and downloaded from CoronaHack Kaggle. Within the training dataset, there are 2643 normal X-rays of chest and 1402 of COVID-19. 316 and 317 COVID-19 samples [16, 21]respectively in the test dataset. Thus, the training set had 4045 samples, while the test set had 633 samples. The training dataset of both datasets is split into one Set for training the model that consists of 80% of samples and the other set for validating the performance of the model, consisting of 20% of samples of the training set. Fig. 1 and2 display the relevant X-ray sample from the first dataset**.**



Fig. 1: Samples of theFirst Datasets of Normal X-rays of chest.



Fig. 2: Samples of the First Datasets of Covid X-rays of chest.Fig. 3: Samples of the Second Datasets of Normal X-rays of chest.



Fig. 4: Samples of the Second Datasets of Covid X-rays of chest.

1. **Image Augmentation and Normalization**

Training a CNN Model on a large dataset is crucial for the effective learning of intricate patterns and edges from samples, which ultimately leads to better performance on unknown datasets [19]. Sometimes, enough samples are not available to train a CNN Model, therefore the method of Image Augmentation [15,16] is applied in our work. Image Augmentation is a process of creating new training examples from the samples present already in the dataset. A new image sample is created from the existing samples by making the new one brighter or cropping the original image or designing a mirror image. Therefore, We applied normalization on the samples of the dataset so that pixels of the samples lie between 0 and 1 which will help the neural network in processing the image. We also applied augmentation techniques like horizontal flipping and Random Zoom Augmentation on the samples of the dataset. Therefore, We used the Image Data Generator class which combines the functions of image data preparation and image augmentation techniques. Thus, in the First dataset, after applying the Image Augmentation technique, the samples in the training test and validation datasets increased to 1449, 362 and 484 respectively. Whereas, in the Second dataset, the application of the augmentation method on the samples of this set led to rising in figures of 3237, 808 and 633 samples for training, validation and test sets respectively.

1. **Proposed CNN**

A type of artificial neural network called CNN is utilized in tasks such as image processing and recognition, and it was created by humans. Multi-layered CNN is designed because the piling of convolution layers allows each layer to understand the various patterns in an image and communication between the layers will help our proposed model get a general overview of the input sample. The filters in the input layer of our CNN model[14,15, 18, 23]operate on the original pixel values of an input sample and therefore extracts low-level features from the sample such as lines. The filters in this layer take as input a matrix of low-level features, which are the basic characteristics output by the previous layer. The filters present in this layer undergo the convolution process with the low-level input functionality matrix to generate a matrix of multiple lines to express the forms. This process continues until the convolution operation in the last layer results in the form of a sample of Chest X-rays. This is Our idea behind the implementation of 23 layered Convolution Neural Network model in Google Collab Notebook to predict COVID with the help of an X-Ray sample. Our experiment is carried out on a workstation having GPU NVIDIA GeForce GTX 1050Ti, RAM 8GB, UHD Graphics 630 of Intel and Core i7-8750H CPU @2.20 GHz of Intel. The CNN model is made up of three fundamental layers which are the convolution layer, pooling layer, and dense layer. According to the complexity of the problem, the arrangement of the first two fundamental layers may vary. The Output Layer, which is the Dense Layer[17, 18] of our proposed model, dimension is set to 1 because our model will predict two classes (i) Covid-19 and (ii) Normal. Our Proposed Model consists of an input layer made of 32 filters [18, 23] each of dimensions 3x3 and the input to this convolution layer are samples of size 150x150 and we use the RELU activation [18] function in this layer. The Filters mentioned in these input layers move across the image matrix and undergo the process of matrix multiplication with each pixel value of the image, thereby resulting in the generation of feature maps that may be the smaller or sometimes larger format. Therefore, to help the filter with processing the image, I have padded the input image with zeros (known as Same padding) to make the dimensions of the filter matrix equal to the newly padded image matrix for smooth convolution operation. Thus, adding extra pixel values to an image matrix by the method of padding helps the layers of the CNN model to derive a more accurate analysis from the samples. Equation (1) expresses the mathematical operation performed by the Convolution layer. In equation (1) mentioned below, an input sample is given as 𝑓 and the filter is given as 𝑗. The indexes of the row and column of the resultant matrix are denoted by 𝑜 and 𝑝 respectively. After placing the filter over a selected pixel, the multiplication of each value of the filter with corresponding values in the image is done in pairs, thereby summing up the values and putting up the values in the right place to generate an activation map **[16]** (output feature map). As our CNN model goes deeper and larger, the size of the parameter value at each layer increases and the training process of the model becomes slower. To overcome this problem, we positioned a pooling layer in between two Convolution layers, and it operates on a matrix of features by applying a pooling operation to each sub-matrix. We added a Max\_Pooling\_2D layer[25, 26, 27, 28, 29], and the pooled matrix [14, 18, 22, 23]dimension is taken as 2×2 sizes. The operation of the Pooling\_ Layer starts, and the input dimensions of the feature maps get reduced which results in a smaller number of parameters to learn. Therefore, the training of the model becomes faster and efficient computation is done. The Max\_Pooling operation is utilized in this step, which involves selecting the maximum value from a set of input feature maps. These feature maps are generated by applying convolution operations to the previous layer in the model.

Therefore, the results of the max-pooling layer generate a feature map of less dimension compared to an input one that contains the most important features from the previous feature map. We added a Dropout Layer [17, 22, 23, 25, 26, 27, 28] between two convolution layers and before dense layers, which drops 50% of the neurons which are selected in random order and are discarded during the training process of the model.

Therefore, the proposed CNN model considers the predictions of the other remaining neurons whose feature values are necessary for the successive convolution layers to detect complex features in the input feature map matrices. Moreover, the Dropout Layer also makes the model less complex and prevents the model from getting overfitting during the training process. Thus, Dropout Layers in the Convolution Model are accountable for the efficient performance of the CNN model on the validation as well as on the test dataset. The input samples that are provided into the CNN are in RGB format i.e., three 2D input features, therefore each layer of our proposed CNN model will generate activation maps that are of three 2D.

**(1)**

From the 3D activation maps, it is impossible to conclude that the input image belongs to which class. Therefore, I applied the method of Flattening [28, 29] that converts the 2D Activation Maps into a 1-dimensional vector of input features to each of the 64 neurons present in the Dense Layer of the model. The generation of the output of the CNN model is the same as the number of classes our model The generation of the output of the CNN model is the same as the number of classes our model feed into an Artificial Neural Network (ANN). After, then this input 1-Dimensional feature vector is passed to the Densely Connected Layer consisting of 64 neurons. RELU activation function **[25, 26, 27]** is applied to the output values of will need to classify, therefore our output layer consists of only 1 neuron. The last layer of the artificial neural network (ANN) receives input from the densely connected layer's neurons, and it uses the Sigmoid activation function (in place of ReLU) to obtain a probability value. The probability value at the last layer decides what are the greater chances of our input image to the class of Interest (in our problem it is Covid-19). In our problem, the interest class is a positive class (class-0) and the least relevant class is the negative class (class-1). Therefore, if p is the likelihood that the sample belongs to class-0, then (1-p) is the likelihood that the image belongs to class-1. In this experiment, we have proposed designing a CNN model comprising 22 convolution layers and 3 pooling layers. The convolution layers are of 32, 64, 66, 68, 70, 72, and 74 dimensions with each of filter sizes of 3x3; 82, 84, 86, 88, 90, 92, 94, 96, 98, 100, 120, 122, 124, 126, 128 dimensions with each of filter size 4x4. The layers of convolution used the ReLU (Rectified Linear Unit ) activation function 𝑓(𝑘) = 𝑚𝑎𝑥(0, 𝑘), where 𝑘 is the going into to a neuron. The ReLU function is used in each convolution layer for faster calculation and efficient model training. From the formula of the ReLU function, negative values of x will describe the function’s output value as 0; for positive values, the function will output the same positive value. The multi-layered architecture of the CNN model is described in Table 1 below.

The result is finally passed on to a Sigmoid Activation Function present at the output layer of our dense layer part of the neural network. The Model’s goal is to classify whether a sample belongs to Class-0 (COVID-19 X-ray) or Class-1 (Normal X-ray) [15,19,20,25, 27, 28], therefore Sigmoid function is used at the output layer. It is also used in these models where the output determines how much more likely a subject is to be of the positive class or the negative class, as mentioned earlier. Thus, Sigmoid Function is the best probable use case for binary classification problems [28]. Since the chances of an entity belonging to a certain group are measured by Probability, therefore Sigmoid is the right choice to determine the output of our model of 32, 64, 66, 68, 70, 72, and 74 dimensions with each of filter sizes of 3x3; 82, 84, 86, 88, 90, 92, 94, 96, 98, 100, 120, 122, 124, 126, 128 dimensions with each of filter size 4x4. The layers of convolution used the ReLU (Rectified Linear Unit ) activation function 𝑓(𝑘) = 𝑚𝑎𝑥(0, 𝑘), where 𝑘 is the going into to a neuron. The ReLU function is used in each convolution layer for faster calculation and efficient model training. From the formula of the ReLU function, negative values of x will describe the function’s output value as 0; for positive values, the function will output the same positive value. The multi-layered architecture of the CNN model is described in Table 1 below.

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1. **Training of the Model on Two Datasets**

We ran our model 70 times on both the training and validation data-sets of the First Data-set, with a batch size of 32 samples, where each epoch was trained on 46 samples of the training set. The efficiency of the CNN model is measured on the validation dataset (by setting batch size = 32 samples) and the evaluation of accuracy [22, 25, 28, 29, 30] and loss of the model is determined on 11 samples of the validation dataset in each epoch. The model was trained on both the training and validation datasets of the Second Data-set 75 times, with a batch size of 70 samples, resulting in 47 samples being trained on each epoch. The model’s performance is measured on the validation data set (by setting batch size = 40 samples) and the evaluation of accuracy and loss of the model is determined on 20 samples of the validation dataset in each epoch. After training the model using the training set, with each epoch being trained on 46 samples, the next step in evaluating the performance of the multi-layer CNN model for COVID-19 prediction is to test it on the validation set. The validation data set was used to assess the performance of our proposed model (each epoch model evaluated based on 11 samples from the data set) over 70 epochs, yielding an accuracy of 99.72% in training and an accuracy of approximately 97.73% in validation. The training and validation loss of the model were 0.0200 and 0.0581, respectively. Fig. 5andFig.6 present graphical illustrations of the training and validation accuracy and loss metrics of our proposed model on the First Dataset, after 70 epochs.

**Table 1**: **Our Proposed 23-layered Convolution Architecture**

| **Layers (type)** | **Output Shapes** | **Parameters** | **Layers (type)** | **Output Shapes** | **Parameters** |
| --- | --- | --- | --- | --- | --- |
| conv\_2d (Conv\_2D) | (None, 150, 150, 32) | 896 | conv\_2d\_14 (Conv\_2D) | (None, 75, 75, 96) | 144480 |
| conv\_2d\_1 (Conv\_2D) | (None, 150, 150, 64) | 18496 | conv\_2d\_15 (Conv\_2D) | (None, 75, 75, 98) | 150626 |
| Conv\_2d\_2 (Conv\_2D) | (None, 150, 150, 66) | 38082 | conv\_2d\_16 (Conv\_2D) | (None, 75, 75, 100) | 156900 |
| conv\_2d\_3 (Conv\_2D) | (None, 150, 150, 68) | 40460 | max\_pooling\_2d\_1 (Max\_Pooling\_2D) | (None, 37, 37, 100) | 0 |
| conv\_2d\_4 (Conv\_2D) | (None, 150, 150, 70) | 42910 | drop\_out\_1 (Drop\_out) | (None, 37, 37, 100) | 0 |
| conv\_2d\_5 (Conv\_2D) | (None, 150, 150, 72) | 45432 | conv\_2d\_17 (Conv\_2D) | (None, 37, 37, 120) | 192120 |
| conv\_2d\_6 (Conv\_2D) | (None, 150, 150, 74) | 48026 | conv\_2d\_18 (Conv\_2D) | (None, 37, 37, 122) | 234362 |
| max\_pooling\_2d (Max\_Pooling\_2D) | (None, 75, 75, 74) | 0 | conv\_2d\_19 (Conv\_2D) | (None, 37, 37, 124) | 242172 |
| drop\_out  (Drop\_out) | (None, 75, 75, 74) | 0 | conv\_2d\_20 (Conv\_2D) | (None, 37, 37, 126) | 250110 |
| conv\_2d\_7 (Conv\_2D) | (None, 75, 75, 82) | 97170 | conv\_2d\_21 (Conv\_2D) | (None, 37, 37, 128) | 258176 |
| conv\_2d\_8 (Conv\_2D) | (None, 75, 75, 84) | 110929 | max\_pooling\_2d\_2 (Max\_Pooling\_2D) | (None, 18, 18, 128) | 0 |
| conv\_2d\_9 (Conv\_2D) | (None, 75, 75, 86) | 115670 | drop\_out\_2 (Drop\_out) | (None, 18, 18, 128) | 0 |
| conv\_2d\_10 (Conv\_2D) | (None, 75, 75, 88) | 121176 | flatten  (Flatten) | (None, 41472) | 0 |
| conv\_2d\_11 (Conv\_2D) | (None, 75, 75, 90) | 126810 | dense  (Dense) | (None, 64) | 2654272 |
| conv\_2d\_12 (Conv\_2D) | (None, 75, 75, 92) | 132572 | dropout\_3 (Dropout) | (None, 64) | 0 |
| conv\_2d\_13 (Conv\_2D) | (None, 75, 75, 94) | 138462 | dense\_1  (Dense) | (None, 1) | 65 |

1. **Results**
   1. **Modeling the First Dataset for Training Purposes**

After training the model using the training set, with each epoch being trained on 46 samples, the next step in evaluating the performance of the multi-layer CNN model for COVID-19 prediction is to test it on the validation set. The validation data set was used to assess the performance of our proposed model (each epoch model evaluated based on 11 samples from the data set) over 70 epochs, yielding an accuracy of 99.72% in training and an accuracy of approximately 97.73% in validation. The training and validation loss of the model were 0.0200 and 0.0581, respectively. Fig. 5andFig. 6 present graphical illustrations of the training and validation accuracy and loss metrics of our proposed model on the First Dataset, after 70 epochs.



Fig. 5 Loss of training and validation in the First Dataset.

Fig. 6 Accuracy of training and validation in First Dataset.

**Table 2: Loss values of training and validation for the First Dataset, which is also depicted in Fig. 5.**

|  |  |  |  |
| --- | --- | --- | --- |
| **Training** | **Epoch** | **Validation** | **Epoch** |
| 0 | 0.641892 | 0 | 1.59459 |
| 10 | 76.2932 | 10 | 69.1365 |
| 20 | 93.2905 | 20 | 88.8176 |
| 30 | 93.7378 | 30 | 93.2905 |
| 40 | 95.0797 | 40 | 92.8432 |
| 50 | 97.3162 | 50 | 93.7378 |
| 60 | 96.4216 | 60 | 94.6324 |

**Table 3: Accuracy of training and validation for the First Dataset, which is also depicted in Fig.6.**

|  |  |  |  |
| --- | --- | --- | --- |
| **Training** | **Epoch** | **Validation** | **Epoch** |
| 0 | 0.63578 | 0 | 0.6 |
| 10 | 0.22844 | 10 | 0.20367 |
| 20 | 0.0715596 | 20 | 0.101835 |
| 30 | 0.0633028 | 30 | 0.071559 |
| 40 | 0.0495413 | 40 | 0.077064 |
| 50 | 0.0357798 | 50 | 0.063302 |
| 60 | 0.0275229 | 60 | 0.090825 |

After testing the model with the first dataset, it was found that the accuracy reached 97%, with a corresponding loss of 3.3%

* 1. **Modeling the Second Dataset for Training Purposes**

After training the model on the training set with 47 samples per epoch, its performance

was evaluated on the validation dataset consisting of 20 samples per epoch. The model underwent 75 epochs of training, and the resulting accuracy was determined to be 97.13% for the training set and approximately 93.10% for the validation set. Additionally, the model's loss on the training and validation datasets was 8.11% and 22.30% respectively, as depicted in figures 7 and 8 in reference[27].



Fig. 7 Loss of training and validation in Second Dataset.



Fig. 8 Accuracy of training and validation in Second Dataset.

**Table 4: Loss values of training and validation for the First Dataset, which are also depicted in Fig. 7.**

|  |  |  |  |
| --- | --- | --- | --- |
| **Training** | **Epoch** | **Validation** | **Epoch** |
| 0 | 0.655851 | 0 | 0.655851 |
| 10 | 0.267553 | 10 | 0.323404 |
| 20 | 0.195745 | 20 | 0.307447 |
| 30 | 0.16117 | 30 | 0.35266 |
| 40 | 0.131915 | 40 | 0.262234 |
| 50 | 0.113298 | 50 | 0.182447 |
| 60 | 0.10266 | 60 | 0.254255 |
| 70 | 0.070744 | 70 | 0.203723 |

**Table 5: Accuracy of training and validation for the First Dataset, which is also depicted in Fig. 8.**

|  |  |  |  |
| --- | --- | --- | --- |
| **Training** | **Epoch** | **Validation** | **Epoch** |
| 0 | 0.651471 | 0 | 0.654412 |
| 10 | 0.885294 | 10 | 0.863235 |
| 20 | 0.926471 | 20 | 0.867647 |
| 30 | 0.942647 | 30 | 0.851471 |
| 40 | 0.952941 | 40 | 0.882353 |
| 50 | 0.960294 | 50 | 0.938235 |
| 60 | 0.966176 | 60 | 0.905882 |
| 70 | 0.976471 | 70 | 0.922059 |

After testing the model with the Second dataset, it was found that the accuracy reached 92%, with a corresponding loss of 8.2%.

1. **Confusion Matrix**

The Confusion Matrix (CM) is an essential tool for assessing the performance of a classification model on a test dataset. It offers a brief summary of the model's accuracy in classifying instances and highlights the possible errors that the model may commit. By analyzing the CM, researchers can obtain valuable insights [14, 15, 18, 19, 21, 22, 23, 25, 26, 27, 28], such as false positives and false negatives. Fig. 9 provides a visual representation of the structure of a Confusion Matrix.



Fig. 9: Structure of the Confusion Matrix.

1. T.N (True negative): The model classified a certain number of outputs as belonging to the negative class and predicted events that were also categorized as negative.
2. F.P (False positive):The model's misclassification of negative-class outcomes as positive-class outcomes.
3. F.N (False negative): The model misclassified positive class outcomes as negative class outcomes.
4. T.P (True positive): The model accurately predicted a significant number of events belonging to the positive class.
5. **Confusion Matrix on First Test Dataset**

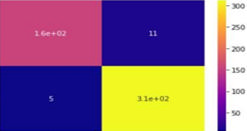


Fig. 10:Confusion Matrix Diagram on My First Test Dataset.

Based on the Confusion Matrix presented in figure.10, it is possible to draw the following conclusions.

(a) 1.6e+02 The model accurately classified the number of samples as COVID-positive.

(b) 5 samples of X-Ray are Normal but are classified by the model as COVID-positive.

(c) 11 samples of X-Ray are COVID-positive but are classified by the model as Normal.

(d) 3.1e+02 number of samples are correctly classified by the model as Normal.

1. **Confusion Matrix on Second Test Dataset**



Fig. 11: Confusion Matrix Diagram on My Second Test Dataset.

Based on the Confusion Matrix presented in figure.11, it is possible to draw the following conclusions.

(a) 2.7e+02 number of samples are correctly classified by the model as COVID-positive.

(b) 44 samples of X-Ray are COVID-positive but are classified by the model as Normal.

(c) 8 samples of X-Ray are Normal but are classified by the model as COVID-positive.

(d) 3.1e+02 number of samples are correctly classified by the model as Normal.

## Precision (p):

To evaluate the proposed model's classification accuracy for the Positive Class, a metric was used that calculated the ratio of true positive results to the total number of positive events (true positives and false positives), where the measurement served as a measure of the model's effectiveness. This metric provides an indication of how accurate positive predictions are (2)

* 1. **F1 score (f.s)**:

The calculation of the metric involves taking the weighted harmonic mean of both Precision and Recall metrics, where a score between 0.0 and 1.0 can be attained. Both Precision and Recall metrics are equally weighted in the calculation of the metric.

f.s = 2 × (r × p) ÷ (r + p) (4)

* 1. **Support:**

The support in the dataset for a certain event of a class is the number of occurrences of that event. Inadequate support in the training data could be indicative of deficiencies in the reported performance of the classifier and could suggest the implementation of stratified sampling or re-calibration. Support is not affected by different models, but instead indicates problems with evaluation.

* 1. **Recall (r)**:

It is the metric which shows how well our classifier model can correctly predict samples belonging to our Positive Class of Interest. Therefore, The Recall metric is defined as the proportion of the model's correctly identified positive outcomes (true positives) to the total number of positive outcomes, including those that were misclassified as negatives (false negatives).

(3)

* 1. **Model’s Performance on the First Dataset: Classification Report.**

When used to predict COVID-19 Chest X-rays in the First Dataset, "h5" model demonstrated a Precision of 97%, Recall of 93%, and F1-score of 95%.Table 6 presents the corresponding precision, recall, F1-score, and support scores for the model's differentiation of Normal and COVID-19 X-rays in the first dataset.

**Table 6**: **Assessing the precision, f1 score, recall, and support of the Model.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | precision  (%) | f1\_score  (%) | Recall  (%) | Support |
| 0 | 97 | 95 | 93 | 167 |
| 1 | 97 | 97 | 98 | 317 |
| accuracy |  | 97 |  | 484 |
| Avg Macro | 97 | 96 | 96 | 484 |
| Avg Weighted | 97 | 97 | 97 | 484 |

1. **Model’s Performance on the Second Dataset: Classification Report.**

When used to predict COVID-19 Chest X-rays in the Second Dataset, "h5" model demonstrated a Precision of 97%, Recall of 86%, and F1-score of 91%.Table 7 presents the corresponding precision, recall, F1-score, and support scores for the model's differentiation of Normal and COVID X-rays in the second dataset.

**Table 7**: **Assessing the precision, f1 score, recall, and support of the Model.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | precision(%) | f1\_score(%) | recall(%) | Support |
| 0 | 97 | 91 | 86 | 316 |
| 1 | 88 | 92 | 97 | 317 |
| accuracy |  | 92 |  | 633 |
| Avg Macro | 92 | 92 | 92 | 633 |
| Avg Weighted | 92 | 92 | 92 | 633 |

1. **Comparison of Our Model’s Performance with Other proposed Models**

**Table 8: Comparison Table**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Metrics  Model Name | Accuracy (%) | Precision  (%) | f1\_score  (%) | Recall |
| h5[1] | 97 | 97 | 95 | 0.93 |
| h5[2] | 92 | 97 | 91 | 0.86 |
| CXR | 96.13 | 93.30 | 96.25 | 0.9940 |
| XceptionNet | 96 | 96 | 96 | 0.95 |
| ResNeXt | 93 | 97 | 86 | 0.78 |
| CoroNet  [31] | 89.6 | 84.1 | 83.1 | 0.82 |

The above Comparison Table 8 presents the performance of our model "h5" on two test datasets for predicting COVID-19 through Chest X-rays, which are indicated by h5[1] and h5[2] respectively. The comparison with the CXR Model proposed by K.C. Santosh[7], evaluation of pretrained models like Xception Net, ResNeXt by Rachna Jain [30] and performance of Coronet Model [31] is also included.

1. **Conclusion**

The time to get the “COVID-19” test report ranges from 3 hours to more than 2 days and many hospitals in economically developing countries still have no access to the medical kits that give results rapidly. According to a multinational consensus statement published in the Fleischer Society, chest radiography for patients affected by "COVID-19" in a resource-limited setting has been deemed an acceptable alternative practice. The expense of medical infrastructure and laboratory supplies utilized for diagnosing patients, particularly in developing and underdeveloped nations, presents a substantial impediment to combating the deleterious virus. Thus, X-ray imaging could be a useful tool for the automated detection of "COVID" in heavily populated countries like India and China, as well as for hospitals in rural areas that do not have access to laboratory kits for COVID-19 testing. Therefore, our proposed CNN Model may be incorporated into the online website or mobile app so that a patient can upload his/her chest X-ray image and the app will give the result as COVID-19 positive or Normal. We have mentioned here the outcomes after detecting COVID-19-positive cases from chest X-rays using a CNN Model.

Our “h5” model achieved an accuracy of 97% when applied to the test dataset of the First dataset and an accuracy of 92% when applied to the test set of the Second dataset. The Model significantly outperformed the COVIDPEN Model in terms of test-data accuracy (when “h5” was applied to First Test Dataset), Precision, Recall and F1 metrics. The results are promising, despite the limited amount of publicly available data. Further validation should be conducted by applying this model to a larger X-ray image dataset and a broader range of COVID-19 clinical trials.

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