Section A-Research paper
ISSN 2063-5346

Deep Learning based Classification of Lung Diseases using Chest X-Ray Images

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ABSTRACT

Over 7 million illnesses and more than 60 lakh deaths have been due to the coronavirus, which was classified as a pandemic by the World Health Organization (WHO). Real-time polymerase chain reaction (RT-PCR) test is the most popular COVID-19 detection method. RT-PCR kits are expensive and require 6 to 9 hours to confirm infection in a patient. A lot of false-negative results are produced by RT-PCR due to its low sensitivity. To identify and diagnose coronavirus, radiological imaging methods such as computed tomography (CT) and chest X-rays are used. Through these radiological images, it is simple to identify some radiological signatures that are shown by COVID-19. Radiologists must study these signs to do this. However, it's a time consuming job and is prone to error. Therefore, analysis of these radiological images needs to be automated. In this paper, a deep learning model is trained using Convolutional Neural Networks to automate the analysis of chest X-ray images to detect COVID-19. Chest X-rays are chosen over CT scans in this paper. The availability of X-ray machines in most hospitals is the main reason for this. CT scanners are more costly than X-ray devices. In addition, compared to CT scan images, X-rays generate much less ionizing radiation. The dataset used for training the model includes 3616 X-ray images of patients with coronavirus, 1345 X-rays of individuals with viral-pneumonia, and 3616 X-ray scans of healthy individuals. The model has been trained and tested on the images from this dataset and it's performance is evaluated.

Keywords: Convolutional Neural Networks (CNNs), CT Scan, X-ray

1. INTRODUCTION

Since December 2019, the novel coronaviruse (COVID-19), which was classified as a pandemic by the World Health Organization, has been the subject of numerous health issues and media attention. In less than 30 days, this new virus moved from Wuhan to the other parts of China. The COVID-19 outbreak was first deemed as a Public Medical Crisis of International Significance by the World Health on Jan 30, 2020 and subsequently as a disease outbreak on March 11, 2020. According to the World Health Organization, more than 6.9 millions of people have contracted the disease worldwide to date, and there have been almost 61 lakh confirmed cases of death. The primary signs of a potential infection include chest pain, fever, coughing, and colds. In cases of more virulent infections, the virus may result in pneumonia. Multiorgan dysfunction, acute respiratory syndrome, septicemia, pneumonia, and ultimately death can all result from the illness.

Coronavirus 2, which causes severe acute respiratory syndrome, is the cause of COVID-19 (SARS-CoV-2). It is therefore classified as a respiratory disorder. It could take the infected person up to 14 days to develop every symptom. The RT-PCR method is the most frequently used method for diagnosing COVID-19.

COVID-19 has suddenly become more common, placing an unprecedented strain on healthcare systems around the world. The healthcare systems in many nations are already overburdened. There are a limited number of diagnostic tools, beds in hospitals for infected patients, personal protective equipment (PPE) for medical staff, and the ventilators. To effectively use the limited resources, it’s crucial to identify whether individuals having Severe Acute Respiratory Illness (SARI) maybe having COVID-19 infection. In this study, we suggest using chest X-rays to identify COVID-19 infection in the individuals displaying SARI symptoms.

Using an X-ray image has several benefits over using traditional diagnosing techniques, including:

1. X-ray images are significantly more accessible and affordable than traditional diagnosing procedures.

2. Because digital X-ray pictures may be transferred directly from acquisition point to the analysis point, the diagnosing procedure can be completed very quickly.

3. Unlike CT scans, the portable X-ray devices allow testing inside an isolation room, eliminating the need for extra Personal Protective Equipment (PPE), an incredibly precious and priceless resource in this situation. Additionally, it lowers patients' risk of contracting an infection while hospitalized.

Chest radiography and other medical imaging modalities, such as computed tomography (CT), may be crucial in the early identification and detection of COVID-19 patients. It is essential to identify and categorise the instances in order to stop the virus's further spread. Artificial intelligence can be crucial in the detection of COVID-19 and lessens the burden onto the crumbling healthcare system. The detection of COVID-19 utilizing chest radiographs is discussed in this paper using an architecture based on deep convolutional neural network. The dataset used for training and testing the prototype is housed in a number of openly accessible directories. Deep learning, a branch of machine learning (ML) in artificial intelligence (AI), has recently been demonstrated to be superior to conventional AI methodology for several medical imaging tasks (handcrafted methods). Numerous problems, including segmentation, identification, and classification, have been addressed with it. Without the use of manual feature extraction techniques, we suggest a deep learning model built on the architecture of a convolutional neural network. Deep learning is therefore clearly the best option for CXR diagnosis. This paper's main goal is to offer a useful framework for the COVID-19 automatic diagnosis.

This deep learning technique requests for initial CNN training on a sizable dataset for a specific purpose. The essential need for the method's success is the availability of a large dataset since the CNN can be trained to extract a sample's most key aspects. If the CNN is determined to be capable of extracting the most crucial picture characteristics, it is judged appropriate for transfer learning [1]. Formerly, in the transfer learning phase, a new dataset of a different kind is analyzed using the CNN to extract its features using the information from the initial training. Feature extraction using transfer learning is one popular method for utilizing the pre-trained CNN's features [2]. Having said as much, feature extraction using transfer learning makes it possible to extract many features by making generalizations the issue and avoids making too many alterations [3]. Having said as much, feature extraction using transfer learning makes it possible to extract many features by making generalizations the issue and avoids making too many alterations [4]. Apostolopoulos et al. [5] based biometric illness detection while analyzing three forms: COVID19, common pneumonia, and normal conditions. Recently, automatic medical diagnostics using machine learning techniques have grown in importance as a tool for physicians [6]. Khan et al implementations of the CoroNet, an Xception-based convolutional neural network with 71 layers that was pretrained on the ImagNet dataset, is found in [7]. The proposed model achieved a COVID19 detection accuracy of 87%. In their work, Sethy and Behra [8] shown that the ResNet50 model works better when paired with an SVM classifier to identify COVID19. 13,800 samples from a big dataset were used to validate the model. It had a 92.4% total accuracy rate. A deep model (COVID-Net) for COVID19 detection was proposed by the author Wang and Wong [9], and it was successful in detecting normal, pneumonia, and COVID-19 classes with 92.4% accuracy. 224 COVID-19 pictures with labels were used by Ioannis et al. [10] to create a model based on deep learning. For three and two classes, respectively, their model had accuracy rates of 93.48% and 98.75%. Seven different well known deep learning networks were compared in [11]. They conducted their studies on a tiny dataset of 50 photos, and it is found that VGG19 and DensNet201 had the best performance.

Research Gaps:

- The previous research results are not up to the mark due to unvailability of high quality covid-positive x-ray images.
- Since only less number of covid x-ray images are available at the time of earlier research works, transfer learning approaches are used to train the deep learning model.
- The training time taken to train the deep learning models are very long.
- Some of the proposed deep learning models had the problems of underfitting or overfitting.
- The proposed models can be further improved in terms of accuracy and other performance metrics.

Novelty of the paper:

- The experimental work mentioned in this paper is done on high quality dataset which contained large number of covid-positive x-ray images.

- The proposed deep learning model took very less training time because of availability if enough number of covid-positive x-rays.
- A new CNN architecture is proposed and it's results are better than the experimental results of transfer learning based models.
- No underfitting or overfitting problems encountered in the experimental outcomes.
- The proposed CNN architecture achieved good training & test accuracies, precision, recall and F1 scores.

2. METHODOLOGY

In this proposed methodology, two approaches were used to build and train the CNN model:

1. Simple CNN Model

2. CNN Model with Transfer Learning

Data Preprocessing:

The network architecture and input data format need to be carefully considered while developing a neural network model. The number of images, image height, image width, number of channels, and number of levels per pixel are the most typical image data input parameters. The obtained data set includes

number of images = 8577

Image Shape = (299, 299, 3)

To ensure that all of the photographs are the same size and aspect ratio, uniform aspect ratio is used. Most neural network models require input images with square shapes, so it is necessary to determine whether each image meets this requirement and then crop it correctly. In the collected data-set, each image is having 299 by 299 pixels, which does simplify things. We rescaled the images from 299 * 299 to 70 * 70 for training the CNN Model. And we rescaled images from 299 * 299 to 244 * 244 for the VGG – 16 Model. And then the dataset is being split into 3 categories: training dataset (80%), testing dataset (10%), and validation dataset (10%).

CNN Model

CNN stands for Convolutional Neural Network. CNNs analyse data using a grid-like layout, making them typically employed to evaluate visual images. The workflow of CNN model includes training of neural network by taking the data from the dataset. The features are extracted from these images and then by building the CNN model, the model being trained on the train data and tested to get the desired output.

The CNN's first layer, which is in charge of separating the various features from the input images, is the one. In this layer, the input image is mathematically convoluted with a filter of a particular size MxM. This convolution procedure aims to extract all the image's high-level information. The edges of the image might also be considered high-level features. This layer operates on low-level features as well, such as color and gradient orientation, so it is not solely confined to high-level features.

A Pooling Layer is typically applied after a Convolutional Layer. In order to reduce computational costs, the primary goal of this layer is to shrink the size of the map of the convolved feature, or to shrink the size of the feature itself. This is accomplished by minimising the connections between layers and working independently on each feature map.
The Fully Connected (FC) layer, which joins the neurons with the weights and biases, is used to connect neurons between the different layers. The outcome of the flattening process, or the transformation of all the generated 2-D arrays from the pooled feature map into a single long continuous linear vector, is the flattened matrix, which is the input of the fully connected layer.

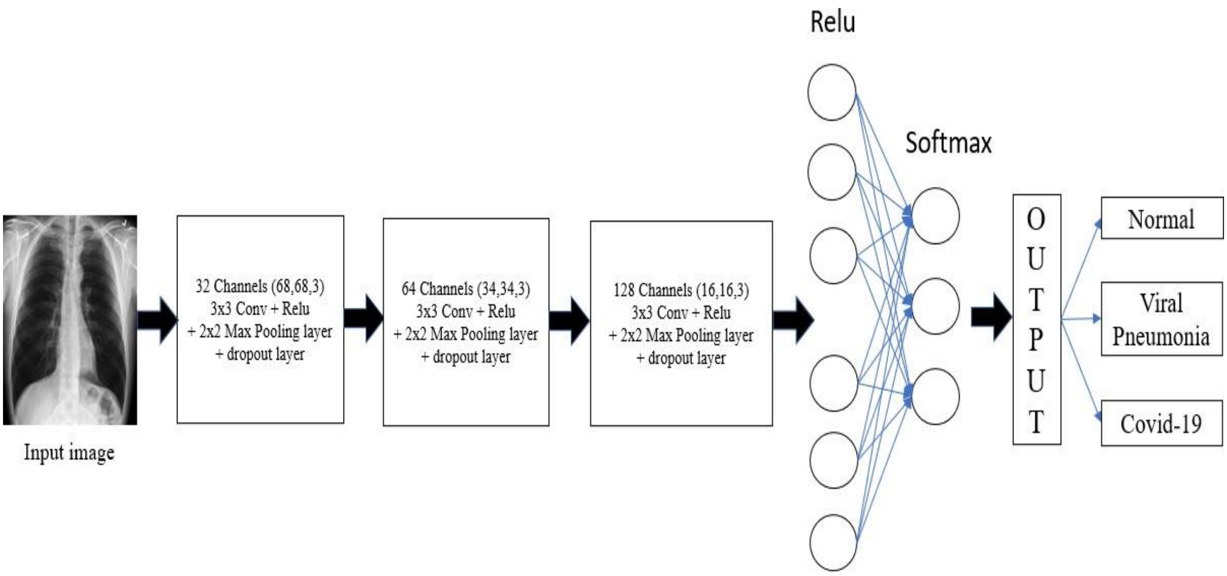


Figure 1. Proposed CNN Architecture

The first lap is almost never very large. As a result, the photos' small size can be detected much more clearly. The kernel's standard size is (3,3). The given image's size is determined as (70,70,3). Convolution and Max-Pooling layers with a 2x2 kernel size and drop-out layers make up the remaining layers. The image will be classified as one of the following 3 classes: Normal, Viral Pneumonia, and Covid.

The input layer, deep learning layers, and output layer are all parts of the deep learning architecture. The three CNN layers used to illustrate the deep learning layers in the following figure are convolutional, max-pooling, and fully connected. The convolutional layer is placed immediately after the input layer. The convolution layer's 3x3 kernels will output 32, 64, and 128 channels in subsequent rounds, as depicted in the image below.

Model: "sequential"		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 68, 68, 32)	896
max_pooling2d (MaxPoling2D)	(None, 34, 34, 32)	0
dropout (Dropout)	(None, 34, 34, 32)	0
conv2d_1 (Conv2D)	(None, 32, 32, 64)	18496
Max_pooling2d_1 (MaxPoling2D)	(None, 16, 16, 64)	0
dropout_1 (Dropout)	(None, 16, 16, 64)	0
conv2d_2 (Conv2D)	(None, 14, 14, 128)	73856
max_pooling2d_2 (MaxPoling2D)	(None, 7, 7, 128)	0
dropout_2 (Dropout)	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 64)	401472
dropout_3 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 3)	195
Total params: 494,915 Trainable params: 494,915 Non-trainable params: 0		

Figure 2. Summary of proposed CNN Model

We described a COVID-19 deep learning architecture using a deep learning algorithms to determine whether the photos of the patient's suspected lung conditions include COVID-19, viral pneumonia, or normal. In this attempt, we trained deep learning separately on X-ray and CT-scan images. Using improved VGG16 deep transfer learning models, COVID-19 X-ray binary and multi-class classification is performed, and the model performance shows promising results. The suggested model's summary is shown in the accompanying figure, where the first convolutional layer's output form with 32 filters and a 3 X 3 kernel size is (68,68,32).

VGG 16:

Despite being created in 2014, the CNN architecture VGG16 is still regarded as one of the finest models for image classification. According to figure 3 below, the VGG16 network comprises 16 layers total, including 13 convolutional layers with 3 x 3 filters and 2 x 2 max-pooling layers. between these layers, using the relu activation function. The majority of the network's parameters are then stored in three entirely interconnected layers. The probability is then computed for each category of pulmonary symptoms using a softmax function. The VGG16 model successfully employs convolutional neural networks as the core network in image recognition algorithms. It has an adaptable, specialised network design.

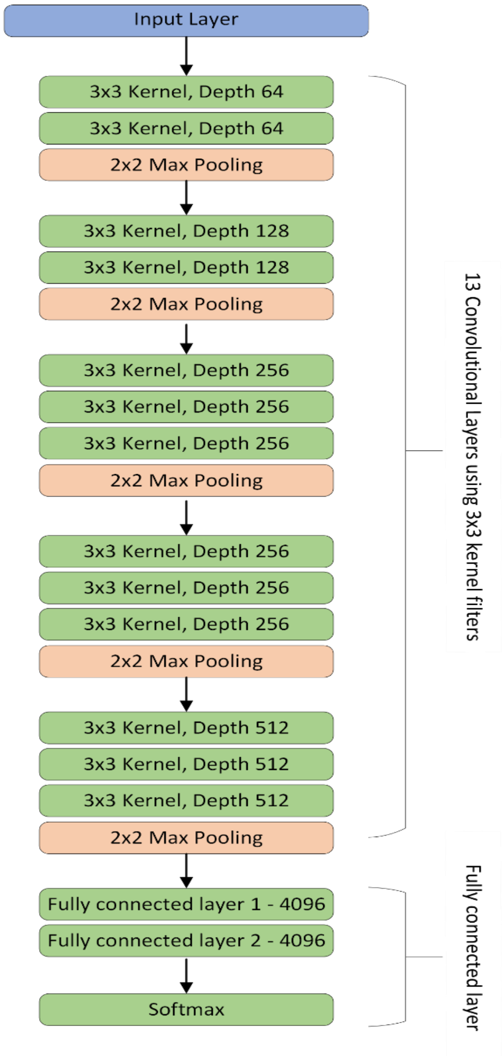


Figure 3. VGG-16 Architecture

The conv1 layer's input is an RGB image with a predetermined size of 224 by 224. With a small receptive field, the filters are applied as the image passes through a stack of convolutional layers. One of the configurations additionally employs 11 convolutional filters, which may be thought of as a linear input transformation followed by nonlinearity. A fixed 1-pixel stride is used.

Performance evaluation:

With the aid of a confusion matrix, the proposed classifier's performance on test data is assessed. Confusion Matrix is a tabular form with instances of the represented classes from test data that are real and those that were predicted. Four performance metrics were used in this study, including accuracy, precision, recall and F1 score.

$$Accuracy = \frac{number\ of\ correct\ predictions}{total\ number\ of\ predictions}$$

$$Precision = \frac{TP}{TP + FP}$$

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

$$F1 - Score = \frac{2 \times Precison * Sensitivity}{Precision + Sensitivity}$$

where True negative, true positive, false negative, and false positive are referred to as TN, TP, FN, and FP, respectively.

True-positive (TP): is considered to COVID19 cases that have been correctly categorized.

False-positive (FP): is considered to healthy cases that were misclassified as novel corona virus

True-negative (TN): is considered to healthy ones that were rightly categorized.

False-negative (FN): is considered as COVID-19 cases that were incorrectly categorised as normal.

3. RESULTS AND DISCUSSIONS

The experimental findings and a discussion of the effectiveness of the methodology proposed are presented in this section. In this project, the model is trained using two methods, one is using CNN and the other using VGG 16 architecure. The results obtained during the training and testing of the model are presented here.

Results of CNN model:

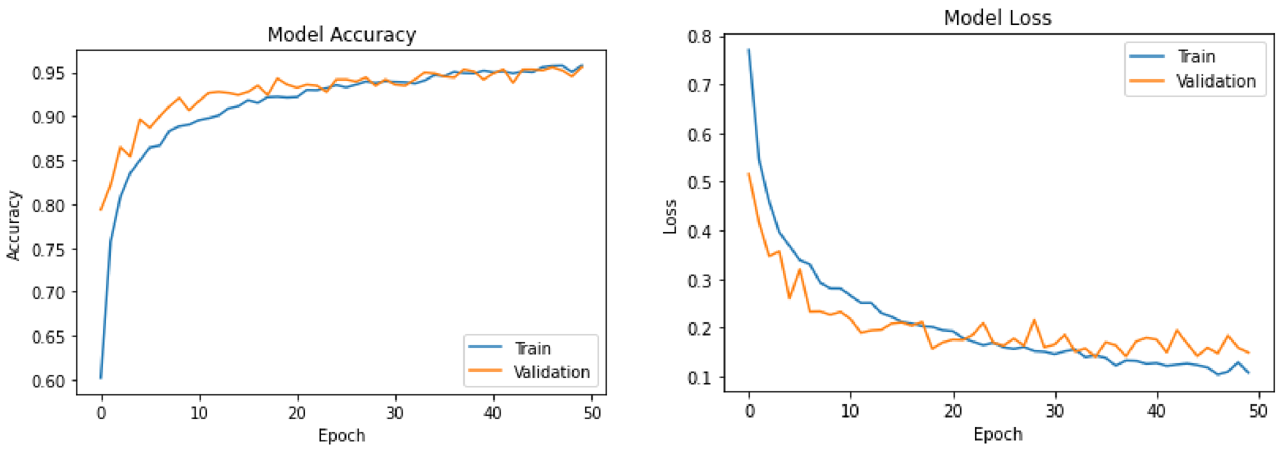


Figure 4. Training and Validation Accuracy plot & Loss plot of CNN Model

Figures 4 display the accuracy and loss graphs for the model. These figures demonstrate a little amount of overlap between the loss curve and the training and validation accuracy curves.Because of dropout regularisation, the model fits well and overfitting is therefore prevented.

Training accuracy of 99.99% is obtained using the CNN model proposed and an accuracy of 96.62% is obtained on test data.

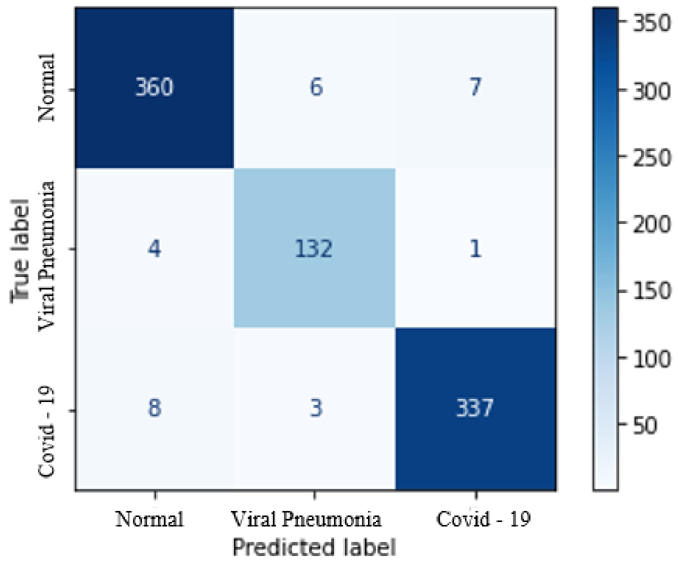


Figure 5. Confusion Matrix on Test Data using CNN Model

The three-class confusion matrix obtained on test data using the CNN model is shown in figure 5. The performance metrics shown in table 1 are calculated from this confusion matrix.

	Normal	**Viral Pneumonia**	**Covid - 19**
True Positive (TP)	360	132	337
True Negative (TN)	473	712	502
False Positive (FP)	12	9	8
False Negative (FN)	13	5	11

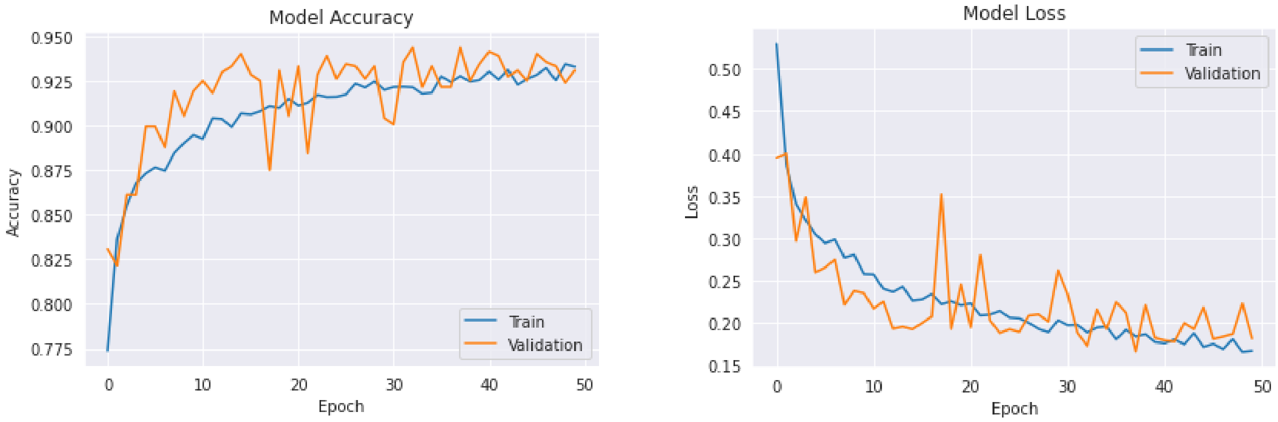
Table 1 : Class wise TP, TN, FP and FN values for CNN Model

The TP, TN, FP, and FN values are calculated for each class based on the One-Vs-Rest technique since the suggested model divides an input image into one of the three classes (multiclass classification). Table 1 displays the calculated values in detail.

Classification	**Accuracy (in %)**	**Precision (in %)**	**Recall (in %)**	**F1 – Score (in %)**
Normal	96.51	96.77	96.51	96.64
Viral pneumonia	96.35	93.62	96.35	94.96
Covid - 19	96.83	97.68	96.84	97.26
Overall	96.62	96.64	96.62	96.63

Table 2 : Classification Report on Test Data using CNN Model

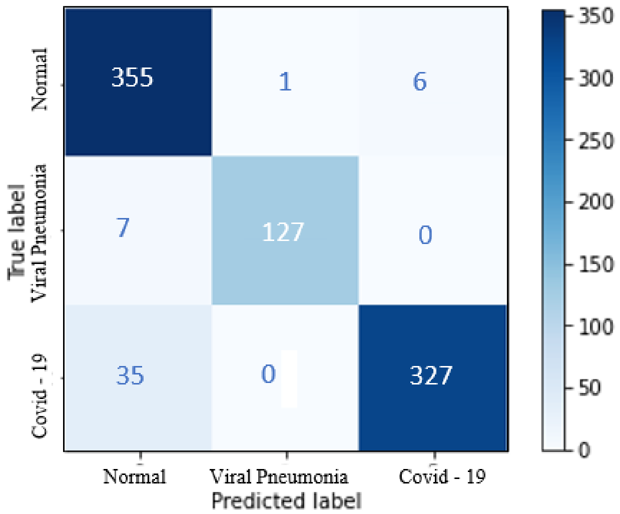
Table 2 presents three class classification reports for the classes Normal, Viral Pneummonia, and COVID - 19. The formulas presented in the performance evaluation part of this work and the information from table 1 are used to determine certain performance metrics, such as precision, recall, and f1-score.



Results of VGG 16 model:

Figure 6. Training and Validation Accuracy plot & Loss plot of VGG - 16 Model

Figure 6 shows the training accuracy, validation accuracy, and loss for the VGG-16 model, respectively. The losses for training and validation are found to be essentially equal. The model fits the data well and does not overfit. The overall training accuracy of 95.01% is obtained using



the VGG-16 model and an accuracy of 94.28% is obtained on test data.

Figure 7. Confusion Matrix on Test Data using VGG - 16 Model

Figure 7 displays the 3-class confusion matrix that the VGG-16 model generated from the test data.

	Normal	**Viral Pneumonia**	**Covid - 19**
True Positive (TP)	355	127	327
True Negative (TN)	454	723	490
False Positive (FP)	42	1	6
False Negative (FN)	7	7	35

Table 3 : Class wise TP, TN, FP and FN values for VGG - 16 Model

Table 3 displays the TP, TN, FP, and FN values calculated for each class using the One-Vs-Rest technique.

Classification	**Accuracy (in %)**	**Precision (in %)**	**Recall (in %)**	**F1 – Score (in %)**
Normal	98.06	89.42	98.07	93.54
Viral pneumonia	94.77	99.22	94.78	96.95
Covid – 19	90.33	98.20	90.33	94.10
Overall	94.28	94.65	94.29	94.31

Table 4 : Classification Report on Test Data using VGG - 16 Model

Table 4 displays three class classification reports for the classes Normal, Viral Pneummonia, and COVID-19. The formulas presented in the performance evaluation part of this work and the information from table 4 are used to determine certain performance metrics, such as precision, recall, and f1-score.

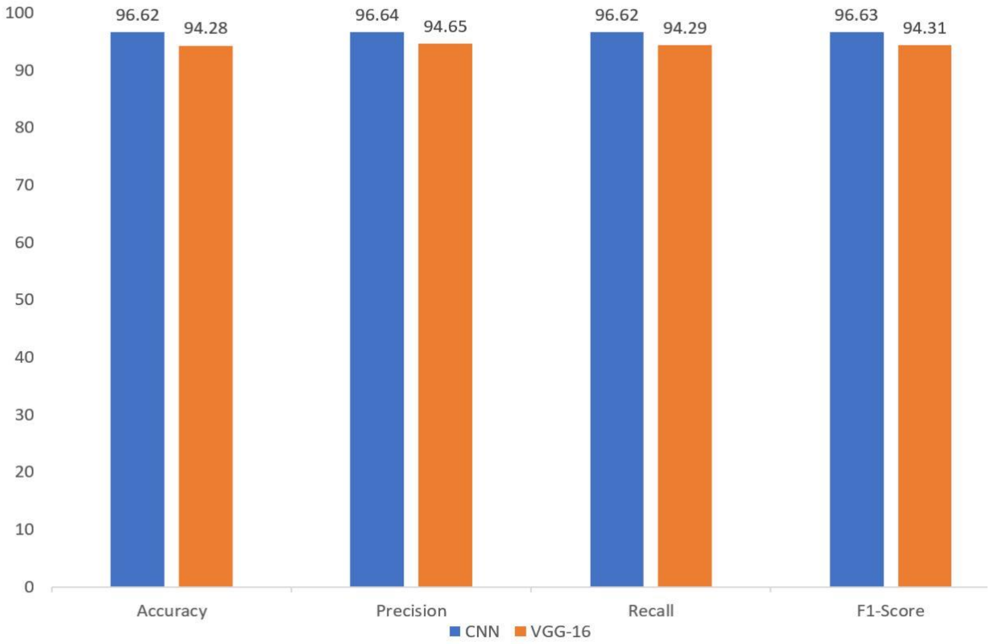


Figure 8. Comparison between CNN and VGG - 16 Model

The comparision between the performance of CNN model and VGG-16 model is shown in figure8.

4. CONCLUSIONS

The planned study used X-Ray pictures to determine lung disease types: normal, COVID19-infected, and pneumonia-infected. The CNN model is employed to distinguish between healthy and infectious individuals, including those with COVID-19 or those infected with pneumonia. The suggested model's accuracy is 96.62%. We can conclude from this outcome that our suggested strategy is highly suitable for COVID-19 CXR image categorization. One of the important conclusions of this article is that data fusion models may additionally improve performance in prediction and diagnosis by utilizing more public sources with Multi classification which our model used. The other is that by employing our models, virologists might more accurately diagnose COVID-19, and radiologists might use them to combat the COVID-19 pandemic by diagnosing critically ill patients in a short amount of time, which could be crucial for their treatment. We think that by using this study as an initial screening, healthcare providers will be able to better diagnose and treat COVID patients. It offers a non-contact automatic testing technology that is both affordable and helpful in lowering the risk of COVID infection among medical professionals.

Section A-Research paper
ISSN 2063-5346

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