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A Novel Approach to detect COVID-19 from chest X-ray images using CNN

Kurmala Marthanda Pradeep [a, *], Raghusai Vemuri [a], N. Veeranjaneyulu [a]

[a] Department of IT, Vignan's Foundation for Science, Technology and Research (Deemed to be University), Vadlamudi, Guntur, Andhra Pradesh, India.

* Corresponding Author: kurmalam@gmail.com

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Abstract: In light of the present COVID-19 pandemic, it is important to consider the worth of human life, prosperity, and quality of life while also realizing that it is difficult to restrict case spread and mortality. One of the most difficult challenges for practitioners is identifying individuals who are COVID19-infected and isolating patients to stop COVID transmission. Therefore, identifying the covid19 infection is important. For the detection of COVID-19, a 4-6-hour reverse transcriptase chain reaction is used. Chest X-rays provide us with a different method for detecting Coronavirus early in the disease phase. We detected properties from chest X-ray scans and divided them into three categories with VGG16 as well as ResNet50 deep learning algorithms: COVID-19, normal, and viral pneumonia. To test the model's accuracy in specialized cases, we injected them with 15153 scans. The average COVID-19 case detection accuracy for the ResNet50 model is 91.39%, compared to 89.34% for the VGG16 model. However, a larger dataset is required when using deep learning to identify COVID-19. It accurately detects situations, which is the desired outcome.

Keywords: COVID-19, VGG-16, Chest X-rays, pneumonia, ResNet 50.

1. Introduction

Coronavirus 2 which causes severe acute respiratory syndrome is the cause of Covid19 disease. [1] Zoonoses are coinfected diseases that severely contaminate the breathing organs, first affecting animals before spreading to people [2]. In the Chinese city of Wuhan, the first COVID case was discovered in 2019 [3]. The World Health Organization (WHO) announced a worldwide epidemic because of this dangerous virus. This virus has now spread to every country in the world. As of February 28, 2022, COVID-19 has killed 6,004,421 people and affected 446,511,318 people. To find out more about people's illnesses COVID-19 is tested using the reverse transcriptase chain reaction (RT-PCR), although this method is time-consuming and likely to false-positive results [1, 2, 4]. Currently, understanding important medical imaging procedures is a perfect way to deal with medical diagnosis systems. Case studies of diagnostic tools that can be integrated with RT-PCR include computed tomography and computer-aided chest X-rays. [5]. CT scans and chest X-ray scans are frequently used to diagnose lung infections. The expense and radiation exposure are major concerns for the COVID-19 diagnostic even if CT scans are often used. Since CXR scans are more accessible and expose users to less radiation than CT images, they should be preferred [5]. As a result, we applied deep learning algorithms to detect COVID19-infected individuals in the current study utilizing chest x-ray pictures. Our collection consists of 15153 photographs in total, containing 3616 COVID-19 scans, 1345 viral Pneumonia scans, and 10192 regular scans.

Due to the coronavirus, the human body's lungs are the most negatively impacted organs. This has an impact on the liver and kidneys in addition to the respiratory system. Compared to the lungs of healthy individuals, patients with COVID-19 infection show hazy lungs on CXR pictures. These characteristics might make COVID-19 easier to identify. Deep learning has recently been used to identify numerous diseases. Examples include finding specific sorts of swelling in the parts of the head, brain as well as lungs [7]. Numerous researchers have used deep learning methodologies with significant improvements. As the COVID-19 pandemic has spread, machine learning and transfer learning have been applied to identify patients. To identify the disease, structural analyses of coronaviruses are performed.

Convolutional neural networks have become a popular technique for identifying and analyzing COVID-19 [8]. In general, CNN is quite good at classifying patients who are at risk of contracting diseases. Applications for classification using CNN systems range from binary to multiclass and include both binary and multiclass classification. With multilayer functionalities and high-dimensional datasets, CNN has already produced amazing findings for locating complex structures. CNN implements 2D convolutional layers for 2D image processing. A CNN is made up of hidden layers, an output layer, and an input layer. Convolution, pooling, fully linked, and regression layers are some of the hidden layers.

In this work, VGG16 and ResNet50, two deep-learning algorithms that help identify photos, are examined. The defined model has several defined layers, and each layer obtains the data it requires from all earlier layers. Our model is assessed using data from the COVID19 Radiography dataset. We carefully divide the dataset into three groups using our well-considered methodology, and our results are trustworthy.

2. Linked Works

In this research, chest X-ray scans were utilized to detect pneumonia and COVID-19 using a variety of deep-learning models. Below is a list of a few such models.

Li et all. [9] divided the data into three classes using deep-learning architectures like SqueezeNet, MobileNet, InceptionV3, DenseNet, CheXNet, and VGG19. A model with a

97.94% accuracy was built using 424 COVID-19 images, 1,486 viral pneumonia photos, and then 1,576 images of normal chest X-rays. Li et all.[10] CovXNet was introduced as a network model for detecting COVID-19, viral pneumonia, and respiratory disease. The dataset includes 1,583 scans of healthy individuals, 1,493 scans of viral pneumonia, 2980 scans of pneumonia, and 305 scans of COVID-19 photographs taken from diverse victims. Their model achieved an 89.1% accuracy rate. Gunraj [11] et all. created COVID-19 Net to aid medical professionals in differentiating between pneumonia associated with COVID-19 and pneumonia unrelated to COVID-19. Researchers found that their approach was 93.3 percent accurate after providing a unique dataset of 13,976 chest X-ray scans from 13,871 patients.

As opposed to that, the article's accuracy alone was used to evaluate the 3-class categorization. Han et all. [12] Experts employed AD3D-MIL, a deeper 3D support vector learning technology based on attention, to distinguish COVID-19 infection from other viral pneumonia. Information from 79 patients, 100 pneumonia patients, and 130 healthy individuals was included in a study of 230 CT scans. They determined that their approach had an overall accuracy of 97.9%. COVID-19 was found in chest X-ray pictures by Rajaraman al. [13] a deep learning outfit that has been iteratively shortened. In their investigation, they looked at two models. The transfer methodology was used to train the first model to distinguish between normal and anomalous chest X-rays, while the learning weights from the first model were used to train the second model to distinguish between COVID-19 and pneumonia patients. Their model's average prediction performance was improved by using an ensemble technique, resulting in them being able to accomplish a 99.01 accuracy rate.

Personalized models were created by Hamoudi et al. [14] COVID-19 pneumonic side effects should be identified early in drug development. They used images from a typical chest X-ray and data from two forms of pneumonia, both bacterial and viral, to train their algorithms. Ko et al. [15] the leading track a two-dimensional deep-learning system was proposed by COVID-19 characterization organizations to examine a chest computed tomography evaluation image for COVID-19 pneumonia. The Foundation of such exchange learning technique they used to prepare the FCONet model was the best in class learning models. With scores of 99.82%, 100%, and 99.87% for prediction accuracy, true negative rate, and accuracy on the validation dataset, the ResNet50 model had the best demonstration outcomes.

[16] They provided details of an algorithm that might recognize COVID-19 pneumonia from CXR images. [17] Deep learning and laboratory data were utilized to show a method for predicting COVID-19 anomalies. For the model's testing, laboratory results from a total of 600 patients were provided. An optimization technique was applied to identify COVID-19 using a hybrid CNN suggested in [18]. CorNet, a deep convolutional neural network based on images, was created by researchers to identify COVID-19 infections [19]. This method was used to diagnose COVID-19 [20], which used deep learning. A variety of CNN models were used. COVID-19 was found using deep learning on CXR. [21] Three phases were present. The illness

was first identified as pneumonia, then COVID-19 and pneumonia, and ultimately a diagnosis was made. They used 6523 CXR scans, and their accuracy rate was 97 percent. The authors [22] used a cluster CNN to accurately describe COVID-19 in CXR pictures. [23] describes a method for identifying diseases using COVID-19 images that includes a Convolution neural network, feed-forward neural network, and COVID-19 CXR image descriptors. This study used CXR and CT images to find illnesses connected to COVID-19 [24].

3. Proposed Method

In this work, the identification framework's approach was finished, and it would accurately scan radiographic pictures for COVID-19 as well as viral pneumonia. Constructing a trustworthy method for characterization of COVID-19 utilizing chest x-rays. Sort chest x-ray scans into categories using suggested CNN pre-trained models. Compare the model shown to performance indicators.

Kaggle received a batch of chest X-ray images from the COVID19 Radiography database (dataset). The collection has 15154 scans total, including 10192 normal scans, 1345 viral pneumonia scans, and 3616 COVID-19 scans. Data imbalance can be identified as a result, which could result in incorrect classification findings. Finally, 1345 images from each category were selected for our studies.

The following are the study's main contributions:

- ➔ Patients with pneumonia and covid19 were studied and segregated using the VGG16 and ResNet50 structures.
- ➔ A simple random sample with image augmentation is used to demonstrate the training of Convolutional networks using unbalanced data.
- ➔ COVID-19 was identified using a model called the model.
- ➔ The imbalance problem was fixed by using performance measurements. COVID-19 with pneumonia detection structures is shown in Figure 1.

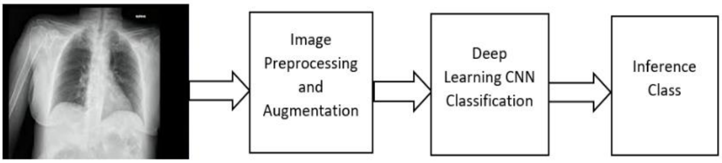

Figure 1. COVID-19 and Pneumonia Screening Process Structure

Models like ResNet50 and VGG16 are being considered. CNN was running in the foreground. CNN performs convolution, max-pooling, dense, and soft-max processes in several layers. Dataset's quantity and quality have no bearing on the model's accuracy. Accuracy in training and validation can occasionally be increased by using large datasets with more epochs. Large datasets with fewer epochs can occasionally yield better training results but worse validation outcomes.

3.1 System Architecture

The following actions need to be completed to design the suggested system:

1. For research purposes, an X-ray dataset containing scans for pneumonia, COVID-19, and routine X-rays was generated. The dataset's training and validation components were developed.
2. Before picture resampling, scaling, and enhancement, pre-processing is required.
3. We calculate the outputs of our developed framework utilizing lung (Chest) X-ray images of pneumonia, Covid-19, and healthy individuals using a created CNN structure.
4. output classification
5. By contrasting the current output with the desired output, the loss function is found.
6. Set CNN settings using the loss function and training procedure.
7. Repeat step 3 as well as step 6 until all datasets and epochs have been used

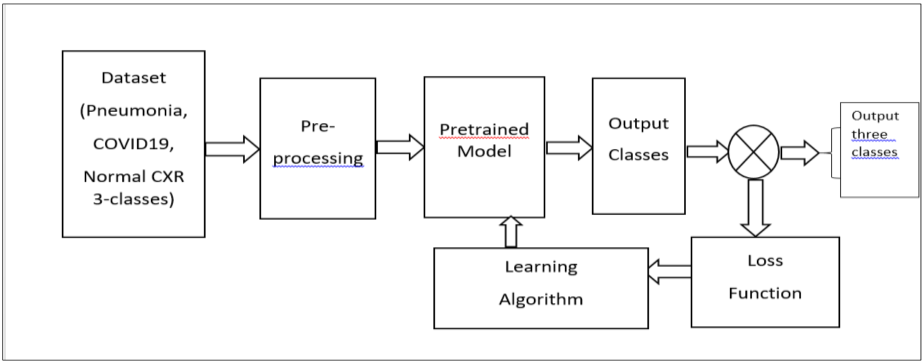

Figure2. The overall design of the proposed methodology.

3.2 Models Used

Multiple deep learning networks were successful in detecting COVID-19. The COVID-19 methods for classification, segmentation, and prediction are the main applications of CNN technologies. We present the deep learning-based COVID-19 screening test in this research. The computer uses these algorithms to determine whether the scan of the subject's suspected lungs is normal, whether bacterial pneumonia has occurred, or whether COVID-19 has manifested.

To do multi-class classification for X-Ray images, we used VGG16 and ResNet50 models, and we trained them using deep learning techniques.

3.3 VGG 16

VGG16 was developed in the year 2014. One of CNN's best picture classification models is this one. VGG16 includes 13 convolutional and three fully connected layers in total. The general setup of the VGG16 is shown in Figure 3. 13 2 x 2 max-pooling layers contain 13 3 x 3 convolutional layers.Between these levels, the ReLu activation algorithm is utilised. Finally, a softmax activation function is used to calculate the frequency of each category. Table 1 contains the VGG16 model's structure.

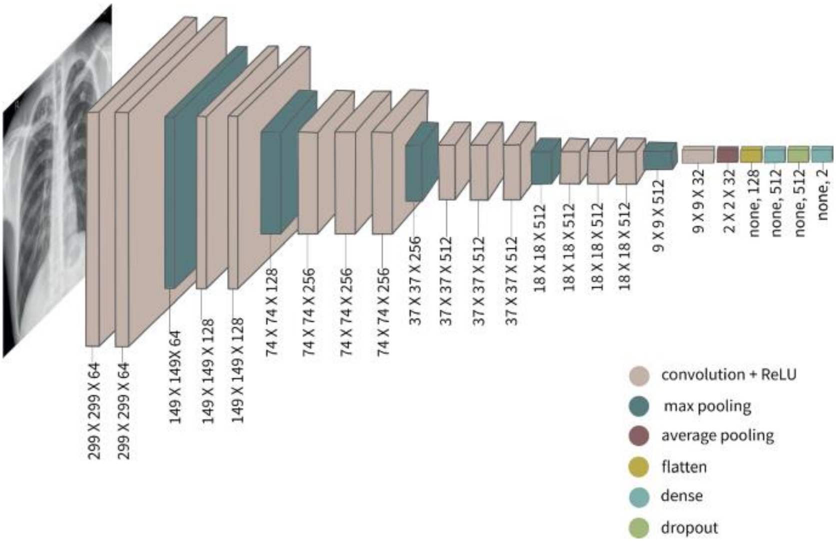

Figure3. VGG16's architectural design

Table1. Model architecture VGG16

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	224 x 224 x 3	-	-	-
1	2 X Convolution	64	224 x 224 x 64	3x3	1	relu
	Max Pooling	64	112 x 112 x 64	3x3	2	relu
3	2 X Convolution	128	112 x 112 x 128	3x3	1	relu
	Max Pooling	128	56 x 56 x 128	3x3	2	relu
5	2 X Convolution	256	56 x 56 x 256	3x3	1	relu
	Max Pooling	256	28 x 28 x 256	3x3	2	relu
7	3 X Convolution	512	28 x 28 x 512	3x3	1	relu
	Max Pooling	512	14 x 14 x 512	3x3	2	relu
10	3 X Convolution	512	14 x 14 x 512	3x3	1	relu
	Max Pooling	512	7 x 7 x 512	3x3	2	relu
13	FC	-	25088	-	-	relu
14	FC	-	4096	-	-	relu
15	FC	-	4096	-	-	relu
Output	FC	-	1000	-	-	Softmax

ResNet 50

A ResNet Architecture consists of an input image, four successive layers, and output units. In the sequential approach we are using, each support function corresponds to a phase. Using the inputs from earlier steps, a CNN step is performed, and a result is returned. Five steps make up the ResNet technique, with Stage 0 acting as an input pre-processing stage and Stages 2-4 acting as bottleneck stages. 64 output channels with such a stride of 2 are included in input stems that perform 7-7 convolutions. In the following, we possess three max-pooling stages with a step of two. The height and width are reduced by four times, whereas the channel height and width are raised by 64 times. In stage 2 and all succeeding steps, we possess residual connections as well as a down-sampling chunk. Except where the duration of the convolution layers is 1 and the general behavior of residual connections is identical to that of down-sampling chunks. We'll just provide the count of convolutional in ResNet-50 & ResNet152 even though modifying the number of pooling layers results in various models. In Figure 4, the ResNet-50 design is shown.

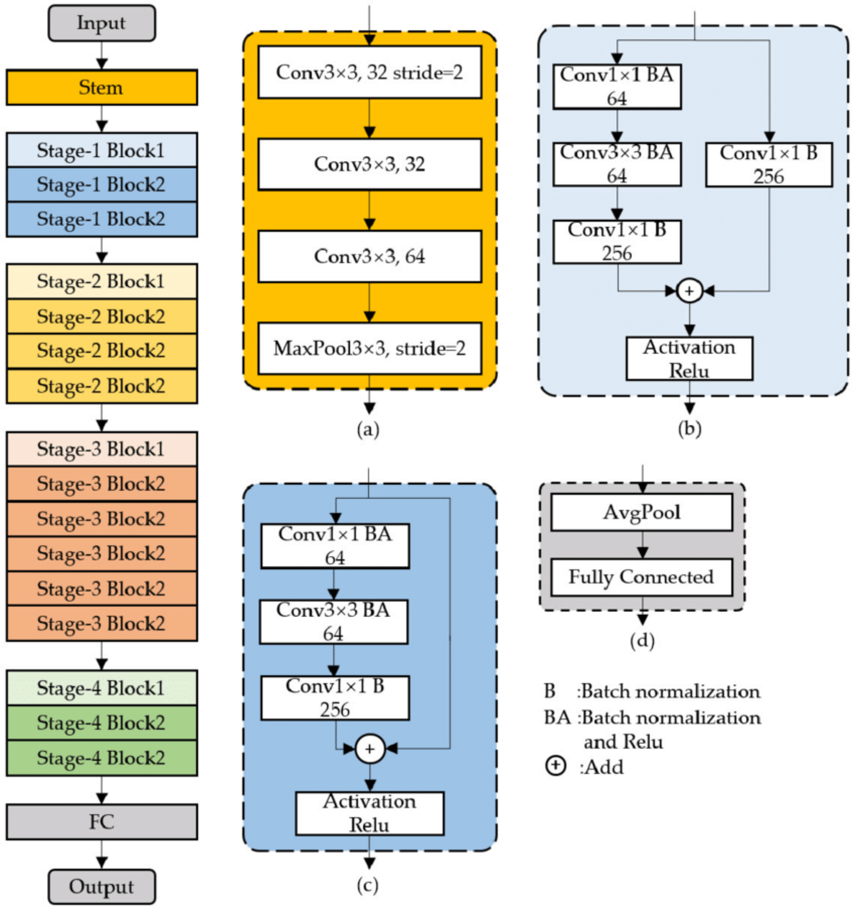

Figure 4. Architecture of the ResNet50

Dataset

The dataset was created using the COVID-19 Radiography Database. The set includes lung X-ray scans of COVID-19, pneumonia scans, followed by healthy patient scans. Researchers from Qatar University, The University of Dhaka in Bangladesh, along with collaborators from Pakistan and Malaysia, produced this dataset of clinical specialists. The collection has 15153 photos in total, including 10192 normal images, 1346 viral pneumonia scans, and 3616 COVID-19 scans.

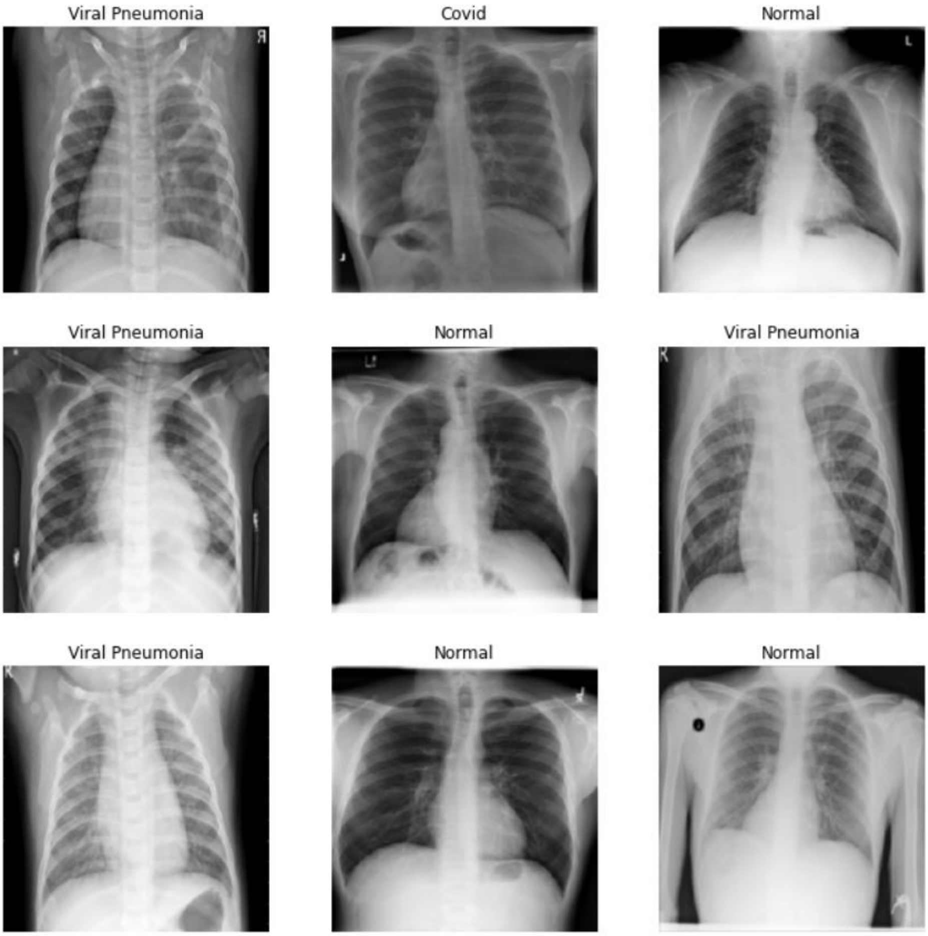

Figure5. An illustration of a chest X-ray image

4. Performance Evaluation

Various assessment criteria are employed to gauge how well different models perform regarding the issue. Others are more suited to assessing the effectiveness of classification models.

Some evaluation criteria are probably more suited to assessing the results of regression models. Although several number of assessment measures are available, the accuracy, recollect, precision, and F1 measure were utilized in this study to assess the model's performance.

For each model, three typical CNN results are shown :

1. Curve for model accuracy
2. Curve for model Loss
3. Confusion Matrix

4.1 About Confusion Matrix

Confusion matrices are tables that assess a model's performance on test data and estimate real values. In place of rates, the following definitions of the important terms are provided:

True positives: Cases in which we predicted that the person has the condition and it has been confirmed.

True negatives: They aren't infected, which is what we anticipated.

False positives: They do indeed have the virus, but that was to be expected.

False Negatives: Despite our expectations, they do have the sickness.

Accuracy: The efficiency of both classification and regression techniques is measured using a parameter called accuracy.

Accuracy = Correct Predictions / Total number of Predictions

Recall: Recall is the process of discovering positives and appropriately labeling them as such. This rate is referred to as a true positive rate. The formula is used to calculate it.

Recall= True Positives / (True Positives+False Negatives)

Precision: The proportion of positive instances explained by a model's true positives to all of its positive predictions is known as precision and serves as a gauge of a model's effectiveness.

Precision =True Positives / (True Positives+False Positives)

F1 Score: A statistic for evaluating a model's accuracy on a specific dataset is the F1 score. It is used to evaluate binary classification schemes that categorise everything into excellent and poor.

F1 score = (2 * precision * recall)/(precision + recall)

The dataset has indeed been divided into two halves, each containing 20% of the total data. In both methods, training takes up 80% of the time while validation or testing takes up the remaining 20%. In the VGG 16 model, the accuracy was 89.35%, the recall was 89%, the precision was 89%, and the F1-Score was 89%. The confusion matrix for VGG16 is shown in Table 2.

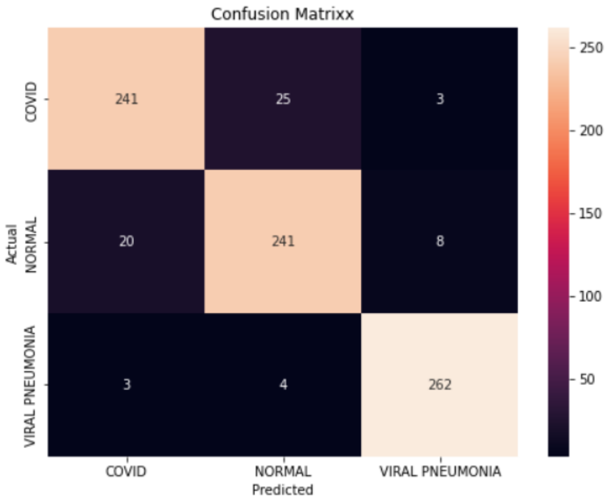

Table2. Confusion Matrix for the VGG16 X-Ray Dataset

The accuracy and loss of the VGG16 model were 89.34% and 24.42%, respectively. Figure 6 shows the VGG16 model's accuracy and loss curves throughout training and validation.

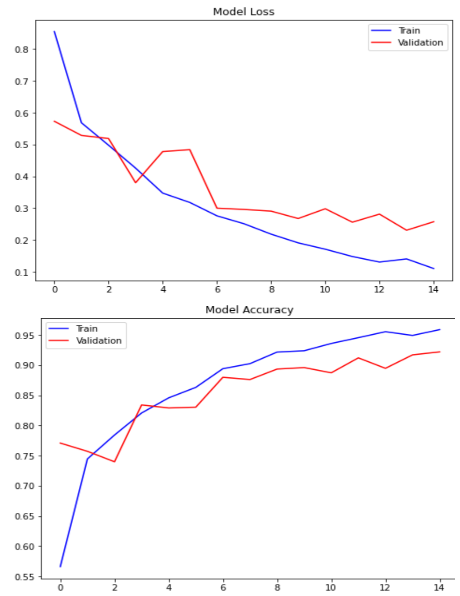

Figure 6. Model VGG16 Loss & Accuracy Curves

It achieved an F1-Score of 91%, a correctness of 91.39%, a recall of 90%, and a precision of 91.3% in ResNet50.ResNet50 lost 33.36% of its value. The correctness and loss rates for the model's development and testing are displayed in Fig. 7.

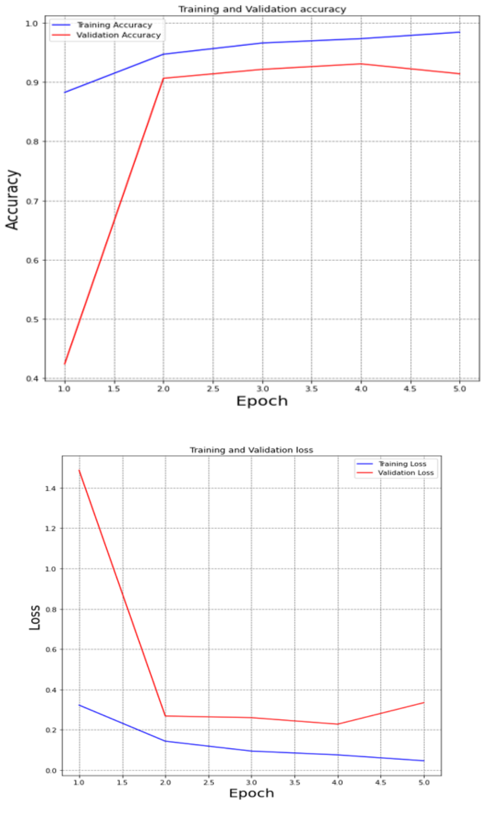

Figure 7. ResNet50 model accuracy and loss curves

5. Conclusion

The primary goal of this study is to use several deep-learning techniques to diagnose COVID-19. For multi-class categorization, the Chest X-Ray dataset was utilized. Validated COVID-19 classification models include VGG16 and ReNet50. For the diagnosis of COVID-19 and pneumonia after development to produce, VGG16's correctness, recall precision, and F1-score were 89.35%, 89.0%, 89.0%, and 89%.0, whereas ResNet50's were 91.39%, 90%, 91.3%, and 91%. In the two suggested models, ResNet50 has demonstrated efficacy in the diagnosis of COVID-19 and Pneumonia patients.

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Conflict of interest

The Authors have no conflicts of interest to declare that they are relevant to the content of this article.

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