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Detection of Pneumonia in COVID-19 Patients Using X-ray Images

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Abstract

This study explores the use of chest X-ray image analysis and deep learning methods to identify pneumonia in COVID-19 patients. Due to the pandemic, Proper as well as immediate examination of COVID-19 is now essential for patient care and disease control. This study proposes a novel approach that uses convolutional neural networks (CNNs) to automatically predict pneumonia in COVID-19 patients using chest X-ray images. In this study, an X-ray of the chest that have been categorized are one-hot encoded using machine learning techniques like LabelBinarizer and then converted into emphatic form applying the categorical functionality of Python. Following that, a method for identification is created utilizing a range of the deep learning features, including convolutional neural network (CNN), VGG16, average pooling 2D (AP2D), dropout, flatten, dense, and input. The proposed approach was evaluated on a 5000 chest X-ray images in the dataset, obtaining excellent classification accuracy of 94%, sensitivity of 60%, and specificity of 100% for healthy and infections with pneumonia. The results demonstrate The possibility of using deep learning methods with accurately and quickly identify pneumonia in COVID-19 patients, which can enhance the health of patients and contribute to preventing the disease's spread. The method carefully reduces training loss while also improving accuracy.

Keywords: COVID-19, SARS-CoV-2, Pneumonia, CNN, One hot encoding, Deep Learning, X-Ray, Bacteria, Viruses, Medical imaging**.**

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INTRODUCTION

The World Health Organization (WHO) has classified the global epidemic of COVID-19 to be a pandemic, It has significantly changed how people live their everyday lives, their immediate health, and economy around the globe [1]. Both humans and animals are impacted by COVID-19, a virus with a rapid transmission. According to World population prospects, 2,869,886 individuals have already passed away as a result of coronavirus infection [2]. Most frequently, pneumonia is what makes this illness extremely risky and life threatening. Therefore, it's crucial to identify and treat pneumonia disease in COVID-19 individuals. Deep learning techniques can assist us in achieving this objective. Using only X-ray images, deep learning systems can detect and diagnose pneumonia, saving both time and money. The use of this strategy can also be advantageous to physicians, who can more effectively separate individuals with severe symptoms from those who have milder symptoms. This will enable the COVID-19 patients to receive the proper medical care, potentially saving many lives. There are numerous vaccines that have already been authorized and are in use thanks to the efforts of numerous organizations and professional agencies. Also, on COVID-19 patients [3] have shown that the virus is especially harmful to people who already have suffered from with lung illnesses. X-rays of the chest and CT scans are well-known radiological methods for identifying lung-related diseases. Additionally, given that a throat infection and breathing difficulties are frequently the first significant COVID-19 symptoms [2], these imaging techniques can also be used to identify lung issues brought on by COVID-19. A low-cost technique for identifying COVID-19 problems is required because, in addition, In some countries, the value of figuring out COVID-19 can be expensive [4]. In this study, we took X-ray scans into consideration for identifying COVID-19 patients [5]. The picture dataset included both COVID-19 sufferers and healthy individuals. The main emphasis of this work is centred on the initial training of the VGG16 method.. It is used to figuring out the pneumonia disease. utilizing patients with coronavirus infection's chest X-ray pictures.

In recent times, there has been a growing utilisation of deep learning techniques in the field of medical diagnosis. It offers tremendous promise for kernel sampling to retrieve minuscule details. Different deep learning models have been applied in numerous domains to date [6–12]. Deep learning algorithms were employed by Bar et al. [9] to identify respiratory infections. The use of deep learning algorithms in medical imagery processing has a few issues, as Razzak et al. [10] highlighted. The study looked at people suffering from pneumonia and COVID-19 who had X-ray images of their chests from the PA aspect. We looked at a model that has been trained, VGG16, after preprocessing and using data extraction techniques on the lung X-ray pictures. From Kaggle, we downloaded 6432 chest X-ray pictures. For training, we used 5144 pictures and for validation, 1288 images. 94.12% average accuracy rate in identifying pneumonia.

The diagnosis of COVID-19-induced pneumonia can be made using genetic and imaging studies. The spread of COVID-19 can also be stopped by using a quick detection system. Some of the most significant research that have been done to analyze chest X-ray pictures in order to identify various diseases are listed here.

The VGG16 model loads a set of weights that have been trained on the network ImageNet [13], was deployed in the current study. In order to forecast pneumonia, Additionally, the algorithm employed AveragePooling2D with pool size (4,4), flattening, dense layering, and dropout of 0.5. The model had a 94.12% accuracy rate, a 60% sensitivity rate, and a 100% specificity rate, setting it apart from the models discussed in [14–17]. In addition to the previously mentioned study, several publications have presented models employing machine learning and deep learning to distinguish between COVID-19 and people without COVID-19 by examining chest X-ray images [18–25]. Due to the utilisation of diverse datasets, it is not possible to designate any particular model as a universally accepted standard.

In order to utilise chest radiography pictures for the purpose of predicting pneumonia in patients afflicted with COVID-19, This research presents a novel methodology that is grounded in deep learning techniques. This study aims to categorise chest X-ray pictures of patients diagnosed with COVID-19 and pneumonia. Furthermore, it seeks to predict the presence of pneumonia in COVID-19 patients by employing a Convolutional Neural Network (CNN) model based on the VGG16 architecture. Various deep learning approaches are employed in data preparation, encompassing AveragePooling2D, flatten, dense, Image-Data Generator, and dropout.

The procedures and resources utilized to construct the CNN-based model are described in Section 2. Section 3 of the paper provides a comprehensive presentation of the study's findings, along by a thorough analysis of these data. The evaluations are presented in Part 4's conclusion.

METHOD AND METHODOLOGY

This process begins with a chest X-ray image of a SARS COVID-19 patient The image is pre-processed and enhanced to increase data quality as presented in Figure 1. Next, convolutional layers extract significant information from the pre-processed image.

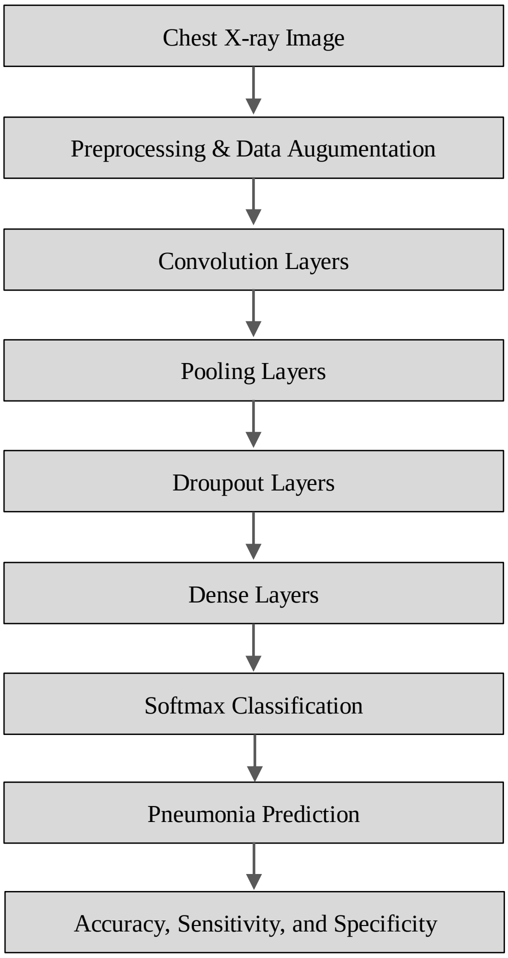

Figure 1. Block diagram showing the process of predicting pneumonia in COVID-19 patients.

These features [26] are then passed through pooling layers, which reduce the spatial size of the features, making it easier to process. Dropout layers are then employed in order to mitigate overfitting and enhance the model's generalisation capabilities. The features are then passed through dense layers, which further extract meaningful representations of the image. So, the SoftMax classification layer is used to determine the probability of the image being pneumonia or not. The prediction of pneumonia is then made based on the output of the SoftMax classification layer

Working Pneumonia Prediction Steps

In order to improve the model's ability to detect pneumonia, characteristics from X-ray pictures of patients are learned using a deep learning algorithm. Together with the flowchart, the working stages that follow provide comprehensive information of this study project.

The research employed a deep learning methodology that relied on Convolutional Neural Networks (CNNs) to identify instances of pneumonia in individuals diagnosed with COVID-19 through the analysis of their chest X-ray pictures. The proposed method involved the following steps:

1. *Data collection:* A dataset of 5000 chest X-ray images was collected from various sources, which included normal and pneumonia cases.

2. *Data pre-processing and augmentation:* The collected data was pre-processed to improve the quality of the images and reduce noise. The images were also augmented to increase the size of the dataset and improve the generalization of the model.
3. *Model training:* A CNN model was developed and trained on the pre-processed and augmented dataset using the Keras deep learning framework.
4. *Model evaluation:* The trained model was evaluated on a test dataset to determine its performance in detecting pneumonia in COVID-19 patients.
5. *Analysis of findings:* The obtained findings were subjected to analysis in order to assess the accuracy, precision, recall, and F1 score of the suggested method in the detection of pneumonia among COVID-19 patients.

The Proposed CNN Model

This study aims to propose a Convolutional Neural Network (CNN) model for the detection of pneumonia in patients with COVID-19 through the analysis of chest X-ray images. Here are some general steps we are taking to develop a proposed CNN model:

1. *Collect and pre-process your data:* Collect a dataset of chest X-ray images of COVID-19 patients with and without pneumonia. Pre-process the images by resizing them to a uniform size, normalizing the pixel values, and augmenting the dataset with techniques such as rotation, flipping, and zooming.
2. The dataset should be divided into separate sets for training, validation, and testing purposes. The dataset should be partitioned into distinct sets for the purposes of training, validation, and testing. The training set is utilised for model development, the validation set is employed for hyperparameter tuning and to mitigate overfitting, and the testing set is utilised for evaluating the performance of the model.
3. The CNN architecture is constructed by incorporating convolutional layers, pooling layers, and fully connected layers. The pooling layers down sample the features, the fully connected layers categorize the characteristics into the various categories, and the convolutional layers extract features from the input images.
4. The model should be trained by utilising the training set, while the validation set should be employed to monitor the training process and prevent overfitting. To enhance the model's performance, one might employ strategies such as early halting and learning rate scheduling.
5. *Assessing the Model:* The performance of the model will be evaluated by utilising the testing set. To evaluate the model's performance, many metrics such as accuracy, precision, recall, and F1-score can be computed. These metrics provide quantitative measures that assess different aspects of the model's effectiveness. Additionally, one can generate a confusion matrix to visually represent the performance of the model.
6. To enhance the model's performance, one may consider optimising it by modifications to the architecture or hyperparameters, in cases where the current performance is deemed unsatisfactory. You can also try using transfer learning, where you use a pre-trained model on a large dataset to extract features and fine-tune the model on your dataset.

DISCUSSION AND RESULTS

The outcomes for predicting pneumonia in COVID-19 patients using the suggested ap2roach are discussed in this section. Initially, we used the Keras image data generator technique to apply data augmentation to the photos. Figures 2,3&4 represents normal and pneumonia x-ray images respectively.

The data were then divided, into training data (80%) and testing data (20%). Table 1 displays the number of images in a data set are divided into diseases like normal and pneumonia. Two models were developed in this study: a base model and a head model. The head model underwent modifications by using the AveragePooling2D technique [27], followed by flattening, dense, and dropout layers. Subsequently, the complete model was constructed. Subsequently, the complete model was assembled employing an Adam optimizer, and the testing phase was forecast. However, after creating chest X-ray images, the accuracy for predicting pneumonia in COVID-19 patients was 94.69%.

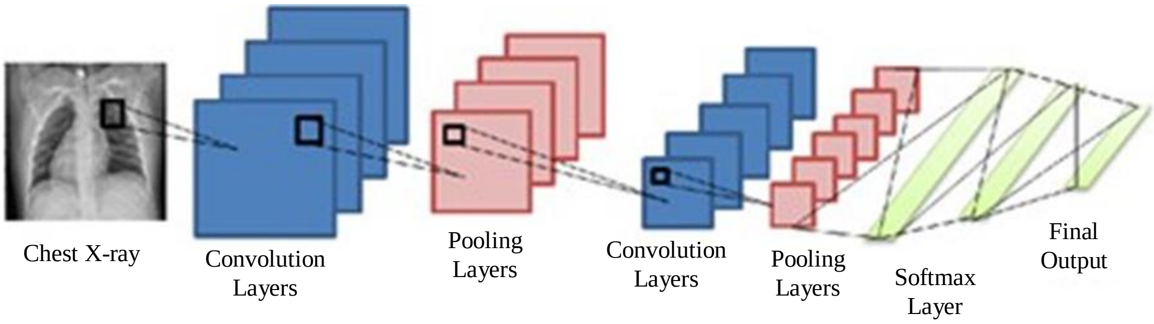

Figure 2. CNN model architure for classification of an image.

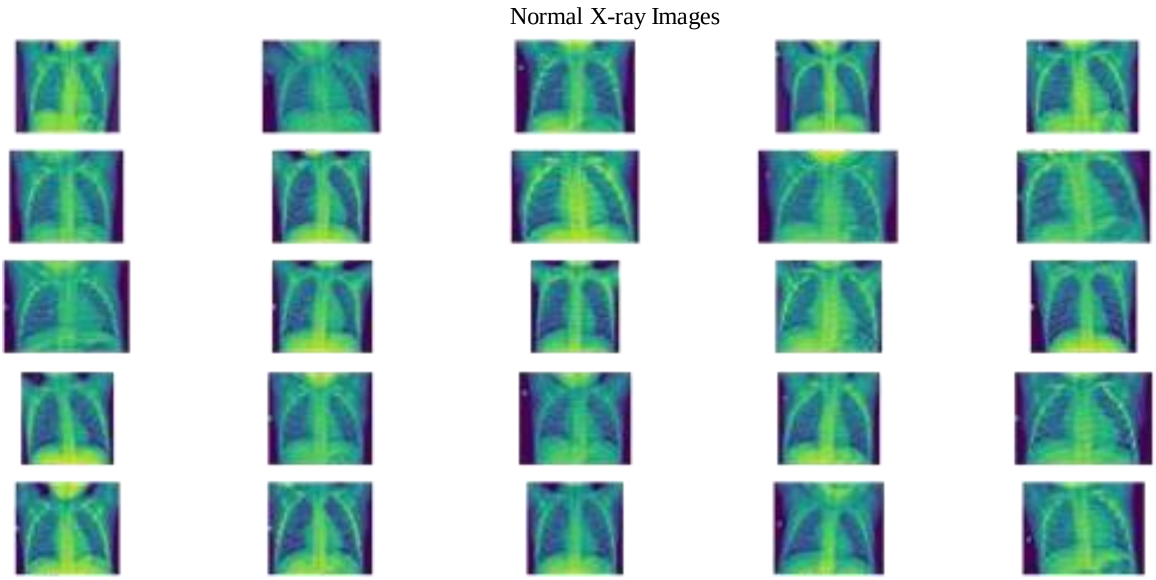

Figure 3. Normal X-Ray images.

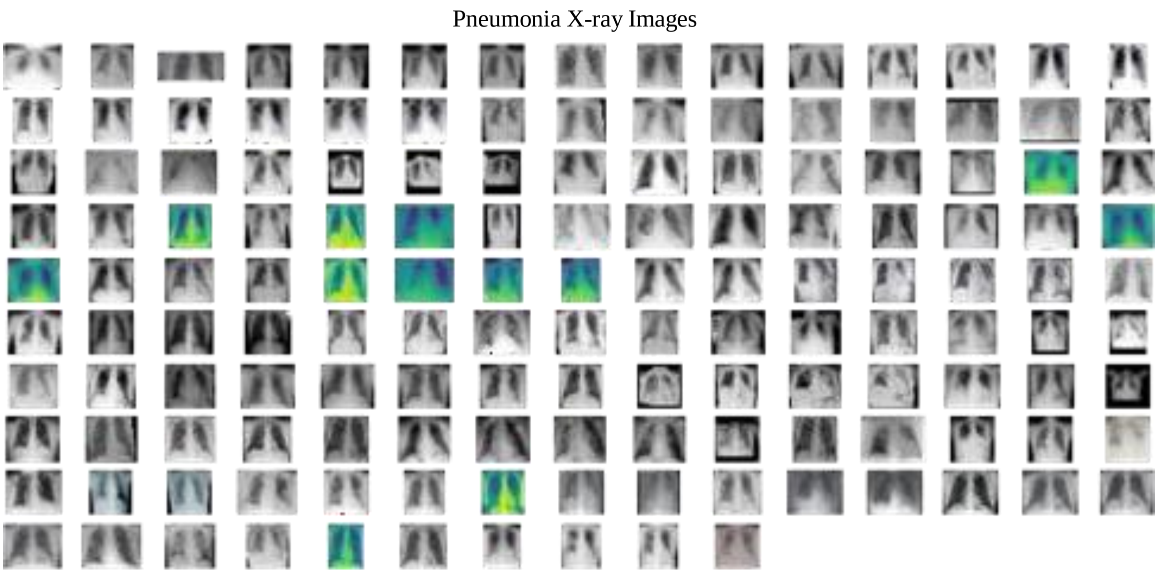

Figure 4. Pneumonia X-Ray images.

Table 1. Dataset split for the model's training.

S.N.	Dataset	Number of images

1.	Pneumonia	3875
2.	Normal	1356
3.	Pneumonia – Normal	2519

Table 2. Training loss, training accuracy, validation loss, and validation accuracy on different epochs

S.N.	Loss	Accuracy	Val_loss	Val_Acuuracy
1.	0.4535	0.8529	0.3900	0.8529
2.	0.3866	0.8529	0.3546	0.8529
3.	0.3599	0.8529	0.3129	0.8529
4.	0.3089	0.8529	0.2785	0.8529
5.	0.2916	0.8529	0.2490	0.8529
6.	0.2376	0.8603	0.2183	0.8529
7.	0.1972	0.9118	0.1883	0.9412

Table 2 presents the quantity of epochs utilised in the training phase, wherein the deep learning model progresses and enhances training and validation accuracy after each epoch. After around seven epochs, during which the training loss and validation loss rapidly decreased and the training and validation accuracy grew, the system had reached its maximum accuracy. In every epoch, the model undertakes the process of accumulating a substantial volume of data with the purpose of acquiring knowledge. As a result, the VGG16 model demonstrates enhanced accuracy and reduced training and validation loss following each epoch.

Despite the initial inclusion of 20 epochs, it is shown that maximum accuracy is achieved after only 7 epochs. During period 1, the training accuracy was recorded as 85.29% with a corresponding loss value of 45.35%. validation accuracy 85.29%, and validation loss 39.00%. After seven epochs, training accuracy was 91.18%, loss 19.72%, validation accuracy 94.12%, and validation loss 18.83%. And, finally after all epochs the training accuracy was 99.26%, loss 4.64%, validation accuracy 94.12%, and validation loss 10.81%.

Figure 5 illustrates how the proposed model, after being fitted for the testing phase, predicts that X-ray pictures will be impacted by pneumonia. The testing process has been constructed differently to be clear.

Figure 5. Proposed Model Prediction on a Test Image.

Figure 5 illustrates how the proposed model, after being fitted for the testing phase, predicts that X-ray pictures will be impacted by pneumonia. The testing process has been constructed differently to be

clear.

Presenting the classification report are Tables 3 and 4. As seen, the precision for predicting pneumonia is 94%, recall is 100%, and F1-score is 97%, whereas the precision for predicting normal case detection is 100%, recall is 60%, and F1-score is 75%, So, it can be said that utilising the suggested method, there are fewer odds of making a mistake in the diagnosis of pneumonia prediction compared to normal and COVID-19 instances.

Table 3. Evalution network on testing set

S.N.		Precision	recall	F1-score	support
1.	Normal	1.00	0.60	0.75	5
2.	pneumonia	0.94	1.00	0.97	29
3.	Accuracy	0.00	0.00	0.94	34
4.	Macro avg	0.97	0.80	0.86	34
5.	Weighted avg	0.94	0.94	0.93	34

Table 4. Performance score on test data

S.N.	Disease	Precision (%)	Recall (%)	F1-score (%)
1.	Normal	100	60	75
2.	pneumonia	94	100	97

Figures 6 and 7 present the accuracy and loss values obtained during the training and validation stages of the model. The graphs demonstrate how training accuracy and validation accuracy change as training and validation errors change. The y-axis shows loss/accuracy while the x-axis shows the amount of epochs. The training and validation accuracies exhibited suboptimal performance, whereas the loss function demonstrated a significantly high value, at epoch 0. The training accuracy and validation accuracy did, however, both rise with the number of epochs, while the training and validation loss fell. After the completion of seven epochs, it is observed that both the training loss and validation loss exhibit a proximity of approximately 2%. Similarly, the training accuracy and validation accuracy demonstrate a closer alignment with a value of around 94%.

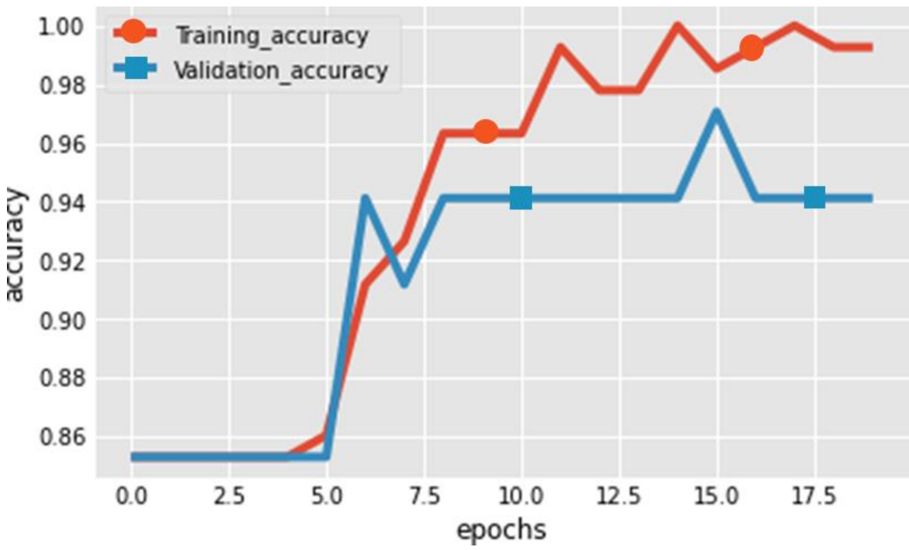

Figure 6. Training and Validation Accuracy.

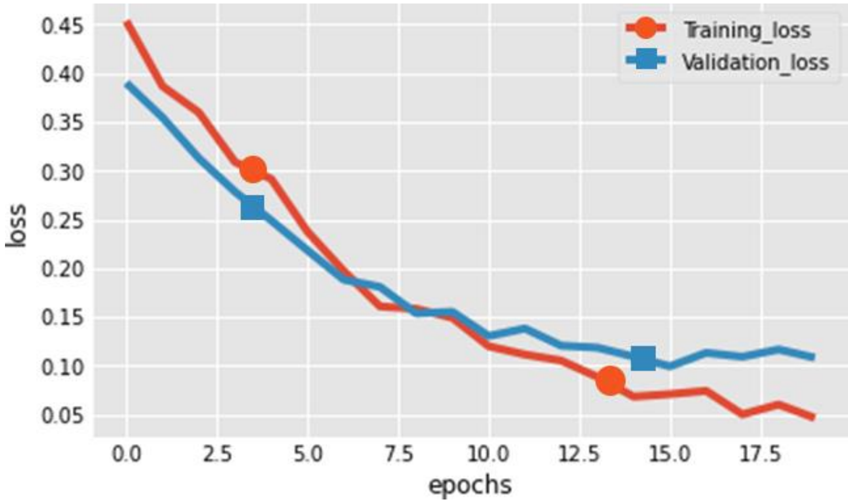

Figure 7. Training and Validation Loss.

In order to diagnose pneumonia, patients may not need to visit a doctor or spend a lot of money on clinical tests and exams using the suggested model; instead, they only need a chest X-ray and a supporting mobile app [27]. As a result, the findings of the current research will greatly benefit the less fortunate, poorer, or rural segments of society. Following the app's diagnosis of pneumonia, they only need to adhere to the doctor's instructions and take the necessary medications.

Figure 8 represents the probability of the disease in an chest x-ray image, the disease in an image is COVID-19 prediction with an probabilty of an 100%.

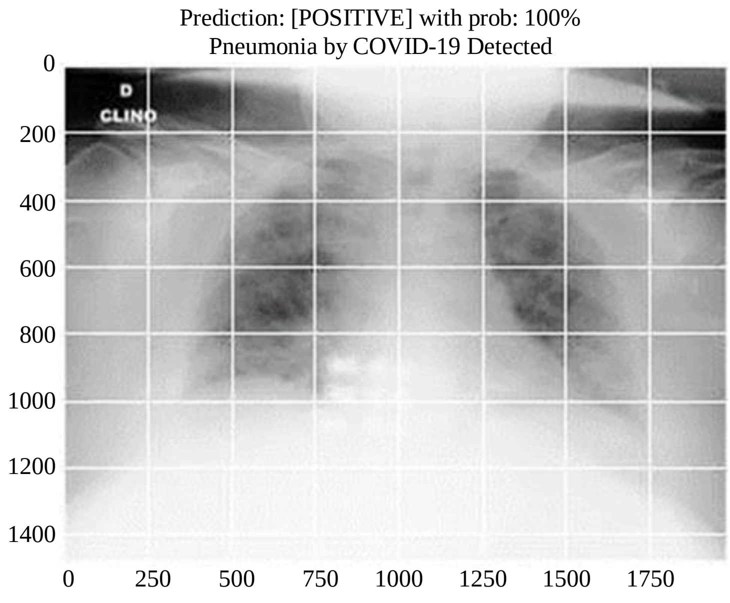

Figure 8. X-Ray COVID-19 Detection.

Application of deep learning-based techniques using chest X-rays for COVID-19 categorization has come a long way. The COVID-19, normal, and pneumonia detection were the primary areas of focus for the researchers. The evaluation of the suggested models is significantly hampered by the lack of big datasets. Transfer learning techniques have been used to address the issue of small samples [20, 21, 28–32]. On the ImageNet collection, the models are pretrained [13]. COVID-19 detection also uses using ensemble learning approaches [19, 33, 34], which aggregate data from many models to produce accurate predictions. The predictions and results of the model are improved by lowering the generalisation error and variation. Another method for using chest X-ray images to identify COVID-19 individuals is domain adaptation. This method was used by Zhang et al. [35] to manage data by adapting feature adversarial and a novel classifier approach. The process yielded noticeably improved results.

Enables the detection of COVID-19. The lack of data makes radiography-based COVID-19 identification difficult. For detecting COVID-19, a cascaded network was also developed. To detect COVID-19, LV et al. [36] employed a cascaded approach by combining two neural networks, namely ResNet-50 and DenseNet-169.

CONCLUSION

The present study introduces a novel two-stage deep residual learning approach for the identification of COVID-19-induced pneumonia through the analysis of lung X-ray images. The utilisation of the VGG16 model yielded satisfactory results in distinguishing patients afflicted with COVID-19 from those suffering from COVID-19-induced pneumonia. With an average sensitivity of 60%, specificity of 100%, and accuracy of 94.12%, the model accurately identified pneumonia. Accuracy is raised while training waste is decreased. In the present situation, parallel testing can be used to stop the infection from spreading to front-line personnel and to produce initial diagnoses that show whether a patient has COVID-19. In order to identify cases of pneumonia, the suggested technique can be used as an alternative diagnostic tool. The efficiency of the CNN architecture can be enhanced in the future by modifying the hyperparameters and transfer learning combinations. An improved, complicated network structure might be a viable alternative to decide which model for pneumonia and COVID-19 is the most appropriate.

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