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Detection of Post COVID-Pneumonia Using Histogram Equalization, CLAHE Deep Learning Techniques

Sujatha Rajkumar, Mure Vamsi Kalyan Reddy, Vaishnav Janesh, M. Vinodhini
School of Electronics Engineering, Vellore Institute of Technology, India.

Abstract Pneumonia, also known as bronchitis, is caused by bacteria, viruses, or fungi. Pneumonia can be fatal to an infected person because the lungs cannot exchange air. The disease primarily affects infants and people over the age of 65. Every year, nearly 4 million people are killed by the disease, affecting an estimated 420 million people. Detecting and diagnosing the condition as soon as possible is also critical. Diagnosing the condition using the patient's X-ray is the most effective method. Experienced radiologists will use a chest x-ray of the affected patient to make an informed decision. Recently, coronavirus has been a contagious viral disease caused by the SARSCoV2 virus and affects the human respiratory system. The virus also causes pneumonia (COVID pneumonia), which is far more dangerous than ordinary pneumonia. The primary purpose of the work is to study and compare several deep-learning enhancement techniques applied to medical x-ray, and CT scan images to detect COVID-19 (pneumonia).

A convolutional neural network (CNN) is used to design a model that can distinguish between COVID-19 pneumonia and ordinary pneumonia. In addition, image enhancement techniques (Histogram Equalization (HE), and Contrast-Limited Adaptive Histogram Equalization (CLAHE) have been processed against the dataset to find more efficient methods and models for detecting pneumonia. A dataset of 6432 CXRs was used - 576 COVID pneumonia CXRs, 1583 ordinary pneumonia CXRs, and 4273 healthy lung CXRs. The proposed results proved that the equalized histogram and the equalized dataset of CLAHE run faster than the original dataset. A computer-aided diagnosis (CAD) system is influenced by the framework that can distinguish between COVID pneumonia, ordinary pneumonia, and healthy lungs. In addition, the improved VGG16 achieved 96% accuracy in detecting X-ray images of COVID-19 pneumonia.

Keywords: Convolution Neural Network, Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Covid-19 (Pneumonia), Visual Geometry Group (VGG16).

1 Introduction

Radiology is a branch of medicine that diagnoses diseases using X-ray images and scans are used to evaluate any complications from pneumonia, such as infections or pulmonary effusions (fluid surrounding the lungs). Consequently, radiologists must carefully interpret each X-ray image, which requires time. Computer-aided systems have evolved to reduce human eye error in diagnosing the condition for better diagnosis. In recent years, machine-learning approaches have produced impressive outcomes in the medical field. This study uses a machine learning approach to diagnose pneumonia from a chest X-ray. Convolutional neural networks are used to develop models from scratch. A model created from scratch aids in fine-tuning hyperparameters to meet our needs.

Furthermore, when compared to any pre-trained model developed for various purposes, training the model from the ground level is more efficient in terms of size and training time because there are fewer layers. According to UNICEF data [3] approximately 2,200 children under five die from pneumonia daily. More than 1,400 children per

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100,000 are infected with pneumonia. Lower respiratory tract infections, including pneumonia, are ranked second in the top 10 causes of death based on the Global Burden Disease Survey. According to the latest report from the John Hopkins Bloomberg School of Public Health, India has the highest number of deaths from pneumonia, with children under the age of 5 dying from pneumonia and diarrhea at about 2.97 lakhs in 2015.

The COVID-19 pandemic has had a significantly detrimental impact on countries worldwide and has led to the loss of lives at an alarming rate. According to a report by the Ministry of Statistics, India's growth slowed to 3.1% in the final quarter of 2020. So far, the total number of cases in India has exceeded 3.47 crores and the case fatality rate has exceeded 47.4 lakhs. India alone accounts for 13% of the total COVID cases in the world, almost 9% of the real death rate due to coronavirus. Chest X-rays are mainly used to detect pneumonia. The proposed framework uses a convolutional neural network (CNN) to design a model distinguishing between COVID-19 pneumonia and ordinary pneumonia. In addition, image enhancement techniques including Histogram Equalization (HE), and Contrast-Limited Adaptive Histogram Equalization (CLAHE) have been processed on the dataset to find more efficient methods and models for detecting pneumonia. As shown in Fig1, here propose a methodology to create a model to determine the presence/absence of pneumonia using the different hyperparameters mentioned above. This document leverages one of the best end-to-end open-source machine learning platforms: TensorFlow. Tool libraries and community resources are part of this rich and flexible ecosystem. Keras [4] is the backend for the program with Python API for deep learning and run-on TensorFlow. This machine learning platform is highly efficient and scalable, allowing the program to export to different devices. VGG16 is the convolutional neural network model used in the proposal for large-scale image recognition. After testing with ImageNet, a dataset of over 14 million images, 96 percent accuracy was achieved.

The principal endowment of the work is as follows:

For the routine analysis of Covid-19 utilizing chest radiographs, the capabilities of several highly developed pre-trained CNNs were examined. Applying a small number of images allowed for excellent accuracy results; hence transfer learning TL is induced. Figure 1. Shows the block diagram of the proposed methodology.

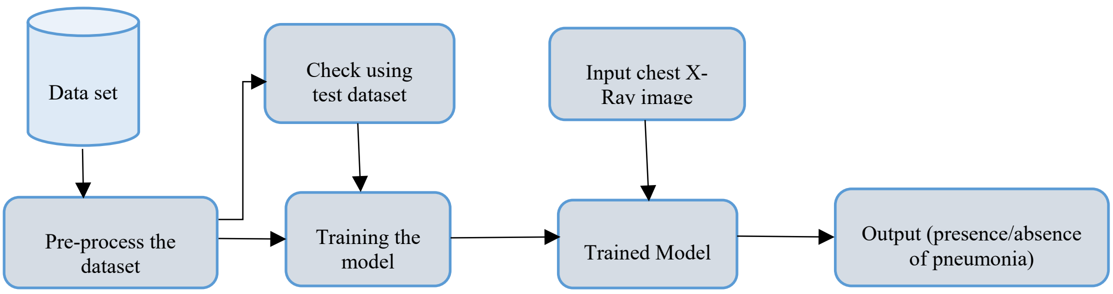


Figure 1: Block Diagram for Proposed Methodology

2 Related Works

Significant research has been done on pneumonia detection in recent years. The author [1] employed a low-complexity dilated barrier that integrates into the FPN network and bypasses the processing delay associated with network depth and the difficulties connected with the high number of parameters related to network width. [2] proposes the design, development, and deployment of a Convolutional Neural Network model that detects the presence of Pneumonia in a patient based on their X-Ray images. The model is trained from scratch using Python and different libraries associated with Python, so it separates itself from the already pre-trained models. Using feature-based extraction using a bagged tree, SVM, logistic regression, decision tree, and KNN classifications to distinguish the recent coronavirus pneumonia from general pneumonia based on machine learning (2020) lectures on the differentiation of COVID-19 from prevalent pneumonia [5] include preprocessing the images, which are further sent over to a transfer learning-based CNN model. [6] used a minimalist automatic approach to detect pneumonia with energy-efficient medical equipment, which enhances healthcare quality while lowering costs and speeding up response times. [7] Using Supervised Learning, the network anticipates the outcome based on the dataset's quality. Transfer learning is utilized to fine-tune deep learning models to enhance training and validation accuracy. Xception and Vgg16 are standard convolutional models for pneumonia diagnosis. [9] transfer learning and fine-tuning were implemented. [10] The classification is influenced after the image is passed through a sequence of convolutional and max-pooling layers initiated using the ReLU activation function, which is then fed into the neurons 62 in the dense layers. Eventually, the sigmoidal function enables the output neuron. The author [10] developed an algorithm – 121 layered CNN trained over ChestX-ray14 (database) and the model achieved higher accuracy.

Tatiana Gabruseva et al. [11], in which a single-shot detector (SSD), and squeeze-and-excitation deep CNNs are utilized. Chest X-rays [12] can be used to diagnose and follow up patients with COVID-19 pneumonia (2020). One particular model deals [13] with a classification challenge that involves determining if a chest X-ray reveals alterations compatible with pneumonia or not, and then categorizing the X-ray images into two categories based on the detection findings. [14] For feature extraction, chest radiographs are considered input and influence in several convolution network architectures. After the extraction process, images were apportioned into various machine-learning classifiers, which could capture the pneumonia-affected lungs or standard. The datasets were forced into VGG16, VGG19, and Inception V3 models for extraction purposes. The author [15] utilized the 194 X-rays of COVID-19-affected patients and 194 normal people's datasets fed into different convolutional networks. MobileNet architecture collaborates with the Support Vector Machine to present an accuracy of 98.5% in the pair of extractor-classifier. Adam optimizer [16] is used to predict the COVID-19-affected person. Capturing pneumonia-affected person's lungs X-ray images for doing feature extraction. [17] By influencing the transfer learning algorithm (AlexNet, GoogleNet, VGG16, VGG19, and Dense NET) for classifying the bunch of person's chest X-ray images and diagnosis of the pneumonia-affected images. Lung opacity, typical nasal problems, COVID-19, and viral pneumonia are suffered by people and could be used as datasets for classifiers. Artificial Intelligence [18] techniques are applied for detecting pneumonia-affected persons with the help of X-ray, CT, and US images. Prevalent transfer learning [19] has been used to detect the early stage of pneumonia and do a comparative study for other models such as AlexNet, DenseNet121, InceptionV3, GoogLeNet, and ResNet18.
The paper is correlated as follows: Section III presents the proposed methodology of the work like histogram equalization steps, CLAHE for color images, and other pre-processing methods, Section IV describes the result analysis of the trained datasets, Section V shows the conclusion and Section VI presents future of the work.

3. Proposed Deep-Learning Techniques to Detect Post-Covid Pneumonia

In the proposed work, Dataset generation is done by enhancing and pre-processing the original database as required. A deep neural network is created and the model is trained with different data sets. The data set is divided into training, validation, and testing sections. The model is then trained with the training and validation dataset, tested on the test dataset, and evaluated for accuracy. Pre-processing techniques such as histogram equalization (HE), and contrast-limited adaptive histogram equalization (CLAHE) are applied to the data set, and their accuracy and runtime are recorded in the work. In this section, we investigate the outcomes produced by fusing the features that Convolutional Neural Networks extracted using transfer learning and classifiers.

3.1 Pre-processing Methods

3.1.1 Histogram Equalization Steps

Histogram equalization frequently creates artificial appearances in the pictures; however, it is highly beneficial for scientific images in nature such as thermal, satellite, or X-ray images, and false color-like images are applied. Suppose to influence the false color pictures with low color depth, histogram equalization can cause undesirable effects (such as noticeable image gradation). In addition, applying an 8-bit image presented with an 8-bit grayscale reduces the image's color depth (number of distinct shades of gray). When used for images with a color depth significantly higher than the palette size, such as 16-bit grayscale images or continuous data, histogram equalization suits well at the time. Histogram equalization can be viewed and managed in two different ways: as an image modification or as a palette change. The activity can be determined using P(M(I)), where I is the 'original image', M is 'histogram equalization mapping', and P is the 'palette'. If we create a new palette with P' = P(M) and leave the I 'image' as is, we can do histogram equalization as mapping or palette modification. If the palette P is unchanged and the image is changed to I' = M(I) then the implementation is completed by changing the images for the original data to be preserved.

$$\mathcal{f}_i\left(i_\kappa\right) = \frac{n_\kappa}{\mathcal{N}} \quad (1)$$

$$\mathbb{F}_\kappa(i_\kappa) = \sum_{j=0}^{\kappa} \mathcal{f}_i(i_j) \quad (2)$$

The probability of pixel-level occurrence can be calculated by the above equation (1) where i_k is the grayscale image in discrete form and gray-level occurrence, and N is the image's pixel count. Equation (2) calculates the cumulative distribution function of the image. $F_i(i_k)$ is the histogram image of the pixel. The approach done in this work fails in myocardial nuclear imaging because the gray levels of the image are physically separated. As a result, histogram equalization produces inadequate results in myocardial images. The following steps are followed in histogram equalization:

1. Determine the pixels of a histogram for mapping or palette modification
2. Determine the normalized sum of a histogram.
3. The input image changed into an output image M(I) with pixel brightness.

3.1.2 Contrast Limited Adaptive Histogram Equalization for Color Image

Contrast Limited Adaptive Histogram Equalization (CLAHE), works with tiles presenting small areas of the image rather than the entire image to improve the quality of cloudy images visibility and videos. The surrounding tiles are merged using bilinear interpolation to remove the artificial boundaries.

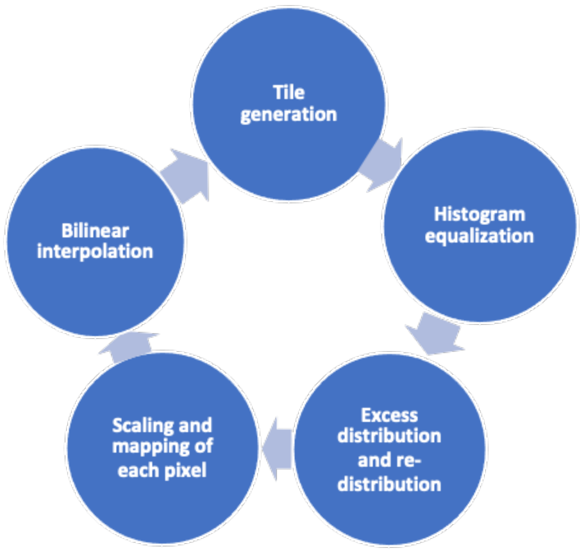


Figure 2: CLAHE algorithm steps for improving contrast

CLAHE algorithm steps are presented in Figure.2 for improving the quality of pixels. Fig 3. The Schematic Structure of the Convolution Neural Network determines the number of rectangular context tiles in which the image will be split for each chrominance channel

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.000 \\ 112.000 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (3)$$

The method can be handed down to improve the image's contrast and bid into color images. Generally, most commonly used for luminance channels, and the result of equalizing only the luminance channel of an HSV image is significantly better than all of the equalized channels of a BGR image. Because the two chrominance channels are separated, the system can determine the number of rectangular context tiles in which the image will be split for each chrominance channel. Experimentation is used to identify the best value for accuracy. The uniform distribution is used to build the contrast transform function. In equation (4) Set ic min and ic max to the minimum and maximum intensity levels allowed and, the appropriate clip limit value. For the input contextual tile I(c-in), the cumulative distribution function is Fk (ic in). Then the uniformly distributed altered chrominance channel tile expression is given in equation (4).

$$i_{c\_out} = [i_{c\_max} - i_{c\_min}] * F_k(i_{c_{in}}) + i_{c_{min}} \quad (4)$$

3.1.3 Other Pre-processing Methods

Image pre-processing is a factor to be of concern in the original datasets. Tensor flow provides a section for adding visual data that aid in training the data. At each epoch, the Image Data Generator class ensures that the model receives new image variations. The model would be trained multiple times with the same image set without the image generator class, resulting in model overfitting. The Image Data Generator class can rotate, shift, flip, brightness variation, zoom the image and provide randomized variation of a similar image during different epochs. The variations performed in workflow model training – are rotation, shifting, rescaling, zoom, and flips.

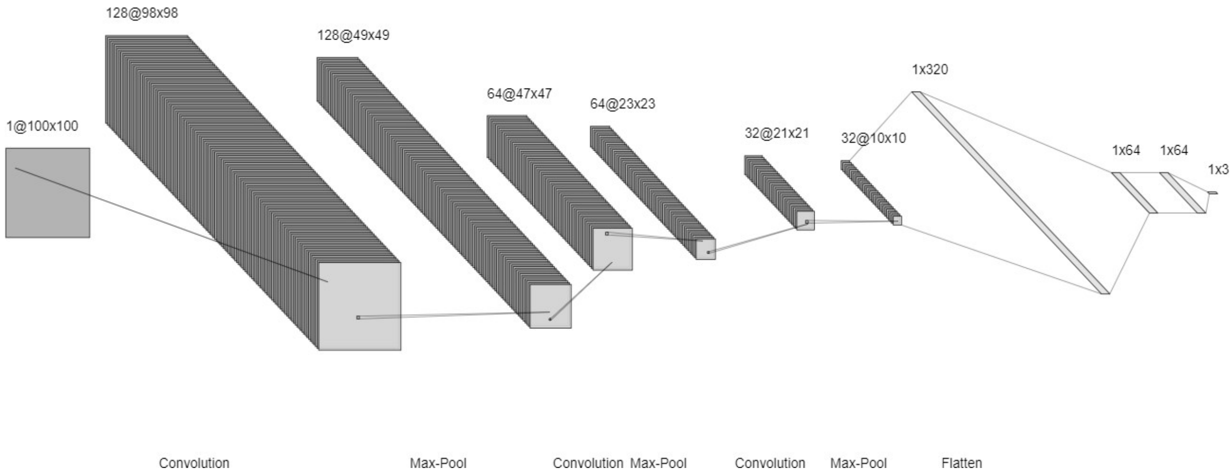


Figure 2: Schematic Structure of Convolution Neural Network.

3.1.4 Feature Extraction Steps with ConvNet

Convolutional neural networks (ConvNet/CNN) can utilize input images to assign relevance (the learnable weights and the biases) to different aspects/objects in an image and distinguish between them. CNN is typically used if the input is in the form of an image, as seen in Fig 2. The problem set's constructed model includes three sets of Convolutional and Max-Pooling layers, and flattened, Dense, and Dropout layers. The input image is 100x100 pixels in size and has only one channel – grey and assists in minimizing the model's processing capacity, Most chest X-rays are recorded in the grey channel. The activation function for the Convolutional layers is 'ReLu.'

$$f(x) = x^{+} = \max(0, x) \quad (5)$$

ReLu Activation Function

The Convolutional layer's kernel size is 3x3, and each Max-Pooling layer's pooling size is 2x2 with a stride of 2. Maximum pooling, or max pooling, is a technique that determines the largest or maximum value for each feature map patch. The pooling layer creates a new set of pooled feature maps with the same number of features set by working on each feature map individually. Flattening transforms the data into a one-dimensional array that can be used in the next layer and smooths the output of the convolution layer to build a single-long feature vector. Dropout is a technique for avoiding the overfitting of the CNN models. Each time the training phase is updated, the dropout works by setting the output edge of the hidden unit (the neurons that form the hidden layer) to 0.
The last layer of dense has a " Soft Max" activation function. When compiling the model, categorical cross-entropy is used to monitor losses; with Adam as an optimizer. The dataset is divided into training, validation, and testing. The model is trained in the training and validation part while being tested on the test dataset. The "Early Stopping" function is used to check the validation dataset of the scanned image, on the monitor for validation loss. Early stopping is a technique that specifies any number of training epochs and stops training when the holdout validation

dataset no longer improves the model's performance. The model output of 3 categorical types – COVID19 Pneumonia, Normal Pneumonia, and Healthy lung. The proposed work utilized the VGG16 CNN architecture for feature image (healthy lungs and pneumonia-affected lungs) classification. The VGG16 network consists of 16 layers, with 13 convolutional layers stacked with a 3x33x3 filter and a 2x22x2 maximum pooling layer. A Relu activation function is applied between these layers. The three fully connected layers contain most of the network parameters. Finally, the softmax function generates the probability of each pulmonary symptom classification. The VGG16 model has been a successful application for convolutional neural networks.

4 Experimental Results

Google Colab Software for training the model: The work utilized Google Colab for compiling the code. Google Colab is an online platform that allows users to compile python code arbitrarily. The tensor flow was used as the platform for training the model. The model was trained using Nvidia Geforce MX130 GPU.

Dataset: The same model was trained under four different conditions of the image dataset – Original dataset, Histogram Equalized dataset, CLAHE dataset, with VGG16 model – and their performances were noted. Each dataset is subdivided into 3 – train (60%), validation (20%), and test (20%) as shown in Table 1.

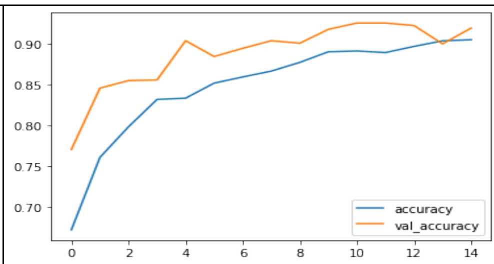
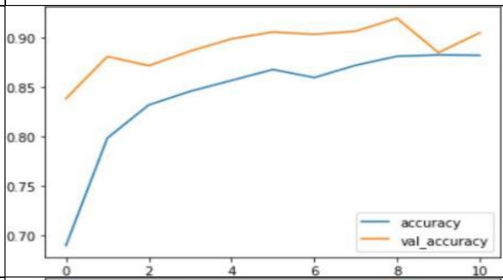
A total of 6432 images existed in the dataset, of which 5144 were used for training and 1288 were left for testing.

Table 1: Trained and Tested Dataset Representation

Train (80%)	COVID Pneumonia	460
	Normal Pneumonia	1266
	Healthy Lung	3418
Test (20%)	COVID Pneumonia	116
	Normal Pneumonia	317
	Healthy Lung	855

The proposed system can test the model using HE and CLAHE pre-processing methods to get the accuracy, precision, and F1 score. The framework detects COVID-19 (pneumonia) from X-ray images, and the proposed VGG16 with an improved model achieved more accurate performance with the larger dataset compared to previous works. It gives out an accuracy of 95%, as shown in Fig 3.

Dataset	Train accuracy and Validation Accuracy	No of Epochs

<table>
<tr><td>Original dataset</td><td>
</td><td>16</td></tr>
<tr><td>HE dataset</td><td>
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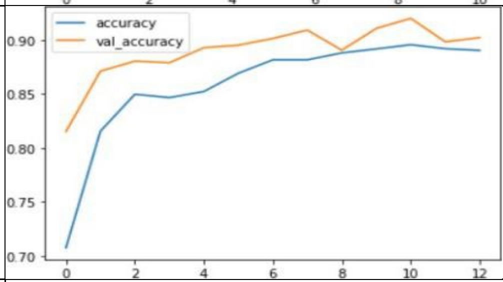
<tr><td>CLAHE dataset</td><td>
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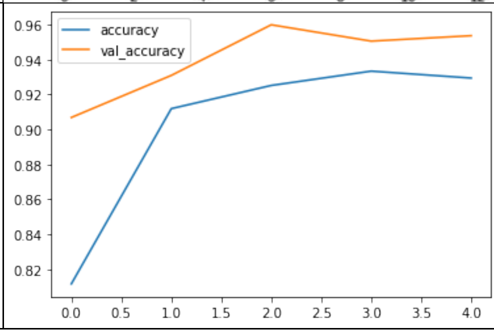
<tr><td>VGG16</td><td>
</td><td>5</td></tr>
</table>

Figure 3: Train and Validation Accuracy of Different Datasets concerning Epoch

5 Conclusion

In the section, analyzing the X-ray Prompt and accurate diagnosis of highly contagious COVID-19 is essential to prevent the spread of the virus. The framework can select Chest X-ray pictures in this investigation because X-ray imaging is less expensive, more accessible, and faster than other regularly used procedures namely RT-PCR and CT and the effect of different image enhancement techniques in the detection of COVID-19 chest x-ray images by using deep Convolutional Neural Networks was also tested. From the results obtained as shown in Table 2, The proposed system can find that the image enhancement techniques – HE, CLAHE – have a minimal effect on the model accuracy that of using the original dataset, but in turn, speeds up the prediction process by almost twice. The accuracy of the datasets is more or less the same – The original dataset (92%), Histogram. Equalized dataset (91%), Contrast Limited Adaptive Histogram Equalized dataset (91%).

Table 2: Face Recognization Values of the Model Under Each Datatype

S.No	Enhancement Technique used	Accuracy	Precision	FI-Score	Support	Time taken
1	Original dataset	0.92	0.91	0.89	0.9	34s
2	Histogram equalized dataset (HE)	0.91	0.89	0.89	0.89	17s
3	Contrast Limited Adaptive Histogram Equalized dataset (CLAHE)	0.91	0.91	0.88	0.9	18s
4	Original dataset with VGG16 infrastructure	0.95	0.96	0.95	0.95	45s

The reduction in time can help radiologists to get to a conclusion at a faster rate. Generally using the VGG16 architecture in the CNN model has drastically increased the accuracy to 95%. The deep CNN-based technique can serve as a screening tool fastly to save lives and avoid deaths, especially during pandemics where delays and misdiagnosis can lead to death.

6 Future Work

The Proposed DL-based detection of post-COVID-19 pneumonia has achieved an accuracy of 95% by utilizing the wide dataset. Different enhancement techniques like Histogram Equalization methods, Contrast Limited Adaptive Histogram Equalization method (CLAHE), and VGG16 deep learning infrastructure are implemented to achieve the targeted accuracy (95%), Precision (96%), and FI-score (95%). Thus, the obtained outcome shows the accurate segmentation of pneumonia-infected and healthy lungs from CXRs. As a future study, LSTM-based deep learning architectures can distinguish images from the patient dataset, with lung issues and COVID-19. In addition, the performance of the proposed system can be improved by using a distinct variant of denseNET-201 (CLAHE) with various encoder methods along with 3-D scans. The rising of deep learning-based diagnostic methods in the medical field should concern the practical aspects for better results.

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Not Applicable.

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