Advanced Medical Images Recognition and Diagnosis of Respiratory System Viruses

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Research Article

Keywords: Biomedical imaging, COVID-19, Viral Pneumonia, Computed tomography, feature extraction, MFCC, image classification, CNN

Posted Date: May 31st, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1561622/v1

Abstract

Respiratory infections are a confusing and time-consuming task of constantly looking at clinical pictures of patients. Therefore, there is a need to develop and improve the respiratory case prediction model for Covid-19 and Viral Pneumonia as soon as possible to control the spread of disease. Deep learning makes it possible to discover that respiratory viruses such as Covid-19 and Viral Pneumonia can be effectively acquired using its classification tools such as CNN (Convolutional Neural Network). MFCC (Mel Frequency Cepstral Coefficients) is a common and effective method of signal processing. In this research, MFCC - CNN's learning model is proposed to speed up the prediction process that assists medical professionals. MFCC is used to extract image features related to the presence of Covid-19 and Viral Pneumonia or not. Prediction is done using a convolutional neural network. This makes the time-consuming process easier and faster with more accurate results for radiologists and this reduces the spread of the virus and saves lives. Experimental results show that using a CT image converted to Mel-frequency cepstral spectrogram as input to CNN can achieve high accuracy results; with the classification of validation data of 100% accuracy of the appropriate Covid-19 and Viral Pneumonia categories and images with the normal healthy (NON COVID) label. Therefore, it can probably be used to detect whether Covid-19 orViral Pneumonia are present in the CT images. The work here provides evidence of the idea that high accuracy can be achieved with a moderate dataset, which can have a significant impact on this area.

1. Introduction

Respiratory virusesare the most numerous contributory agents of disease in humans, with considerable impact on morbidity rate and humanity globally, that leads to significant cause of illness and death around the world. Regarding twenty-five percent of all deaths worldwide related to Covid-19 (corona virus) metabolism infections, particularly in innocent folks round the world wherever Covid-19cases are fatality remarkably higher than before. Covid-19 is presently a worldwide communicable disease caused by a pestilence known as SARS-CoV-2, initial introduced in urban center, China in 2019 and later in several components of the world; on three January 2020, the planet Health Organization declared COVID-19 to be a world Emergency Medical Concern (PHEIC), and declared it a deadly disease on March eleven, 2020 [1]. The virus is unfold chiefly through shut contact with the tract delivered once a patient sneezes or coughs. Symptoms of the virus are coughing, shortness of breath, abdominal pain and fever which are close enough to that of Viral Pneumonia. No antibiotics, antibodies or correct treatment for COVID-19 infection area unit given. Analysis efforts afoot on numerous aspects of COVID-19, as well as diagnostic tools for early detection of the virus.

Today, Artificial Intelligence (AI) may be a wide used force worldwide, which can scurtinize a method for speedy detection and high detection rates of Covid-19 virus and Viral pneumonia, and differentiate the chance and cruelty of these viruseson patients exploitation advanced learning (DL) [2].

DL a part of machine learning (ML) that focuses on designing of deep neural network (NN) network models that browse knowledge exploitation from data using algorithms of feed-forward and back-propagationalgorithms. However, it takes a large quantity of knowledge to know. DL algorithms generally embrace Deep Belief Networks (DBN), Deep Neural Network (DNN), and Deep Convolutional Neural Networks (Deep CNN) [3].

In this study, the accomplishment of high accuracy of imaging classes was assessed on the COVID-19 and Viral Pneumonia X-radiation scan (CT) pictures compared with the presence of normal healthy CT scan images. CT pictures (PNG and JPEG formats) area unit used as quick, the power to produce pictures of tissues, organs, bone formation and area unit quick, painless, and painless. The CT image is transferred to the MFCC part extraction section wherever the features are extracted from the image. This image is transmitted to CNN designed by python (Tensor Flow environment) to predict the presence of Covid-19 in an exceedingly patient or not. during this field, a diagnostic computer code application will be obtained for a a lot of correctness and quicker designation for the presence of Covid-19 or viral pneumonia or not.

Respiratory viruses are the foremost common pathogen-causing diseases in humans, having a profound impact on the standard of health and therefore the world temperament, resulting in a serious reason for health problem and death worldwide. Regarding twenty-five percent of all deaths worldwide area unit related to Covid-19 (corona virus) metabolism infections, particularly in innocent folks round the world wherever Covid-19 cases area unit on top of ever. Corona-Virus is presently a worldwide communicable disease caused by a pestilence known as SARS-CoV-2, initial introduced in urban center, China in Gregorian calendar month 2019 and later in several components of the world; on three January 2020, the planet Health Organization declared COVID-19 to be a world Emergency Medical Concern (PHEIC), and declared it a deadly disease on March eleven, 2020 [1]. The virusesare unfold chiefly through close contact with the tract delivered once a patient sneezes or coughs

2. Chest Ct Scan Image

The role of respiratory viruses in analysis these days is growing to boost imaging for treatment and designation. CT pictures are two-dimensional pictures representing three-dimensional objects. Images are created by changing power (moving electrons) into X-ray photons, transferring photons to the total object, and so changing measured photons back to electrons. It may also sight advanced bone fractures and tumors. If a patient has cancer, emphysema, cardio-pathy or liver and mass tumors, CT scans will mark or facilitate specialists diagnose any changes [4].The infection triggers a huge spectrum of CT scan imaging discoveries, most typically respiratory lung periphery consolidations and ground-glass opacities. The sensitivity of Chest CT to diagnose respiratory viruses is found to be appreciably higher with high-quality resolution and might occur before a positive infectious viral laboratory test. Therefore, hospitals with massive quantities of patients use CT for its pros with conceivable respiratory viruses malady in epidemic territories, wherever the fundamental attention system is besieged. Chest CT plays a vital role within the estimation of respiratory viruses patients with rigorous and compound metabolic process symptoms. supported CT scans, it's potential to see however defectively the lungs are compromised and the way the illness of the individual progresses, that is effective in creating medical choices. Based on CT scans, it is possible to determine how defectively the lungs are compromised and how the sickness of the individual progresses, which is effective in making medical decisions. There is a growing consideration of the sudden occurrence of lung defects that are such as abdominal CT scans for bowel disorders or patients without respiratory symptoms [5]. During this pandemic, by reducing the strain on clinicians, the analysis of AI could become the foremost vital issue. AI will analyze the pictures in but ten seconds. Therefore, advanced image process with MFCC and artificial neural network has the chance to considerably improve the role of CT in respiratory viruses detection by permitting an outsized proportion of patients to spot malady simply and quickly with high accuracy. A chest CT image (JPEG) is shown in Fig. 1.

3. Methodology

Covid-19 CT image is producing decent data for good Covid-19 discrimination. Capturing this data in form and size that permits efficient modeling is important. Many feature extraction techniques are utilizedby signal recognition system such linear prediction coefficients. This paper tends to propose a MFCC-CNN model to additional quicken the prediction method of respiratory viruses (Covid-19 & Viral Pneumonia) recognition technique supported with the Mel-Frequency Cepstral Coefficients (MFCCs) for extracting features composite inside wavelet transform of the image that may assist in achieving a superior recognition rate by passing it to a CNN. Once passing the image to CNN, this can yield to predict whether or not the patient features predicting whether a Covid-19 virus or viral pneumonia is present or not.

3.1 Extraction of CT image using Mel Frequency Cepstral Coefficients

Feature extraction can be defined as the process of reducing the amount of data present in a given image sample while retaining the discriminatory image information. The concept of feature extraction offers the goal of identifying the Covid-19 CT image for the purpose of generating sufficient information on the positive effects of Covid-19 and capturing this information in a form and size that allows for effective modeling. Various decoding methods are used in the signal recognition system, such as Linear Predictive Coefficients (LPC), Linear Predictive Cepstral Coefficients (LPCC), Perceptual Linear Predictive Parsing (PLP), and Mel frequency Cepstral Coefficients (MFCC) which is currently very popular and will be discussed in this article. MFCC are used to represent signal distribution and often used as elements in speech recognition systems. Also its features are derived from Cepstral analysis and distorted according to Mel-scale scale, which emphasizes the components of the lower frequency than the components of the higher frequency. The steps from the image to the MFCC coefficient (Fig. 2) are:

1. Slicing of the original waveform into predetermined window size.

2. Performing Fourier Transformation (FFT) on the sliced signal.
3. Mapping the log amplitudes of the spectrum onto the Mel scale, using triangular overlapping filters.
4. Performing Discrete Cosine Transformation (DCT) on the Mel log amplitudes.
5. The resulting amplitudes of the spectrum are the MFCCs.

Calculation of MFCC features proceeds similarly to the Cepstral transformation process: the input converted image is first of all framed and windowed. Then Fourier transform is applied and therefore the magnitude of the ensuing spectrum is represented on by the Mel-scale. The log of this spectrum is then taken and a discrete cosine transform is applied. The Mel is a unit of measure of perceived pitch or frequency of a tune. The Mel- scale is thus a mapping between the real frequency scale (Hz) and the perceived frequency scale (Mels). The name Mel comes from the word melody to point that the scale relies on pitch comparisons. The Mapping is virtually linear below 1 kilohertz. The formula used to convert f hertz into m Mel is given in (1). The output of MFCC extraction of a Covid-19 image is shown in Fig. 3.
$m = 2595 \log_{10} ((f/700) + 1)$ (1)

3.2 MFCC-CNN classification

MFCC-CNN architectures are effectual for classifying image data. Images extracted from MFCC is represented as an image as shown in Fig. 4. This is done to each image used in the training, validation and testing samples. A block diagram representing the proposed system is shown in Fig. 5.
We used a deep convolutional neural network, with multiple hidden layers and a binary dense output layer for label classification. The layers are shown in following model summary in Fig. 6:

4. Experimental Results

The dataset used in this research consists of 1200 CT-image is collected from various trustful sources. It consists of 400 covid1-19 images, 400 viral pneumonia images and 400normal (healthy) images by which a MFCC feature extraction is done to each of the dataset image. The resulting MFCC image samples are divided into 840 training images as 280 of Covid-19, 280 Viral Pneumonia and 280 training images as normal (healthy). Also 180 validation samples (60 images of Covid-19, 60 of Viral Pneumonia and 60 images of normal healthy patients), 180 test samples (60 images of Covid-19, 60 of Viral Pneumonia and 60 images of normal healthy patients) batch size of 32, epochs number of 10 epochs and 27 steps per epoch (calculated by ceil dividing the number of training samples by batch size). The performance metrics token in considerations in each epoch were:

Accuracy: the relation of correctly classified patients (tp + tn) to the total number of patients (tp + tn + fp + fn).

Validation loss: Controlled by using early stopping to prevent over fitting.

Precision: The ratio of correctly classified cases with respiratory virus (tp) to the total number of patients predicted to have the virus (tp + fp), and correctly predicted by the classifier.

Recall: is the ratio of correctly classified patients with respiratory virus (tp) divided by total number of patients who have actually have a respiratory virus.

This CNN modeling and training produced a training accuracy of 100% using early stopping call back for full epochs training and a classification report as shown in Figs. 7and Fig. 8 with the metrics token in considerations with a precision of 100% with recall value of 99% and 100% sensitivity.

Covid1-9, Viral Pneumonia and normal labels for the MFCC images in the validation dataset were correctly classified. The plotting of accuracy (train accuracy) against validation accuracy (val accuracy) results of the viral comparisons using MFCC image cases is shown in Fig. 9.

The plotting of train loss against validation loss results of the viral comparisons using MFCC image cases is shown in Fig. 10.

The model evaluation of our proposed system is shown in Fig. 11 obtaining an accuracy of 99.44%

The confusion matrix of the proposed system model is shown in Fig. 12.

A comparison of the proposed system results against similar research work can be seen in Table 1 below.

Table 1
Table of Comparisonagainst similar research work

Classifier	*Accuracy*	*Reference*
Logistic Regression	65%	[6]
Random forest	70%	[7]
SVM	82%	[6]
CNN(Covid images)	96.76%	[8]
MFCC of coughs	70.58%	[9]
CNN (MFCC of Covid images)	98.93%	This Research
CNN (MFCC of Respiratory System viruses using early stopping call back)	100%	This Research

5. Conculsion

This researchaffords an advancedtechnique for respiratory system viruses (Covid-19 and Viral Pneumonia) prediction based on converting the CT- Scan image into a signal, and then extracting MFCCs features of this modeled signal in the form of an image. The deep learning technique applied to clinical images of different types of respiratory viruses (COVID-19& Viral Pneumonia) which showed the knowledge gained by model trained for detecting and identifying the respiratory system viruses is pretty good. This makes the extraordinary work easier by using existing model for prediction ofrespiratory system viruses. It is difficult to detect the abnormal features from images due to the noise impedance from lesions and tissues. For this reason, Mel Frequency Ceptral Coefficient (MFCC) feature extraction is consummated which focus only on the area of interest to detect respiratory system viruses out of CT image. The classifier used in this research demonstrated a high accuracy of 100% for full epoch training and 99.44% testing accuracy compared to the other studies, marginally outperforming good acceptable results. In the field of biomedical, respiratory system virusesdetection is an essential and promising technology. Boundless work has been reported on respiratory system viruses identification and verification although the importance of both respiratory system viruses(Covid-19 and Viral Pneumonia) features. Respiratory system virusesimages recognition based on extracting features is tedious work and requires high computational complexities. The obtained accuracy is better than that obtained of Logistic Regression, Random forest, SVM, CNN (applied to Covid images), CNN (applied to MFCC of Covid coughs). These results are highly encouraging and provide further opportunities for research by the academic community on this important topic.

6. Future Work

As a future work, the direction for this research would be to use this methodology to diagnose the severity of illness, and differentiate between possible diagnoses and similar diseases. Taking in considerations to apply this proposed method on various biomedical cases such as Alzheimer cases, breast cancer ECT.

7. Declarations

• Ethics approval and consent to participate

Not applicable

• Consent for publication

Not applicable

• Availability of data and materials

Dataset used would be provided by the authors upon a reasonable request.

• Competing interests

The authors declare that they have no competing interests

• Funding

The authors had received no funding.

• Authors' contributions

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version of the manuscript.

• Acknowledgements

Not applicable.

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Figures

Figure 1

Chest CT-Scan Image

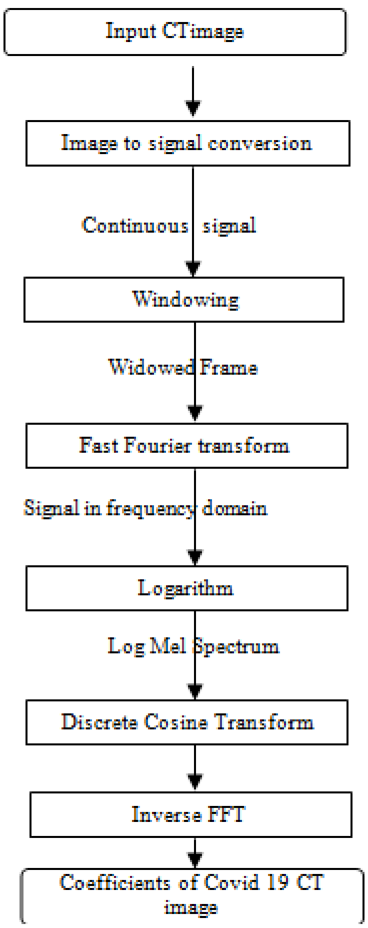

Figure 2

MFCC stages diagram

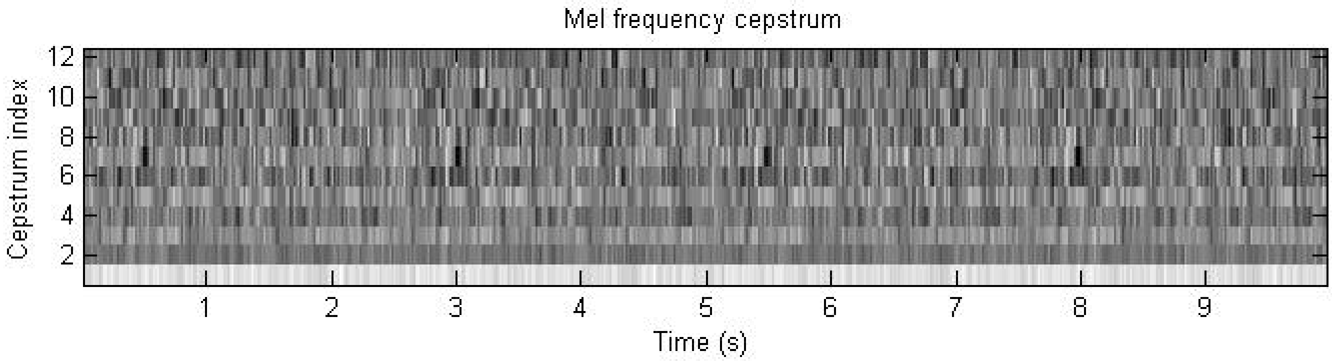

Figure 3

MFCC Output of Covid-19 image

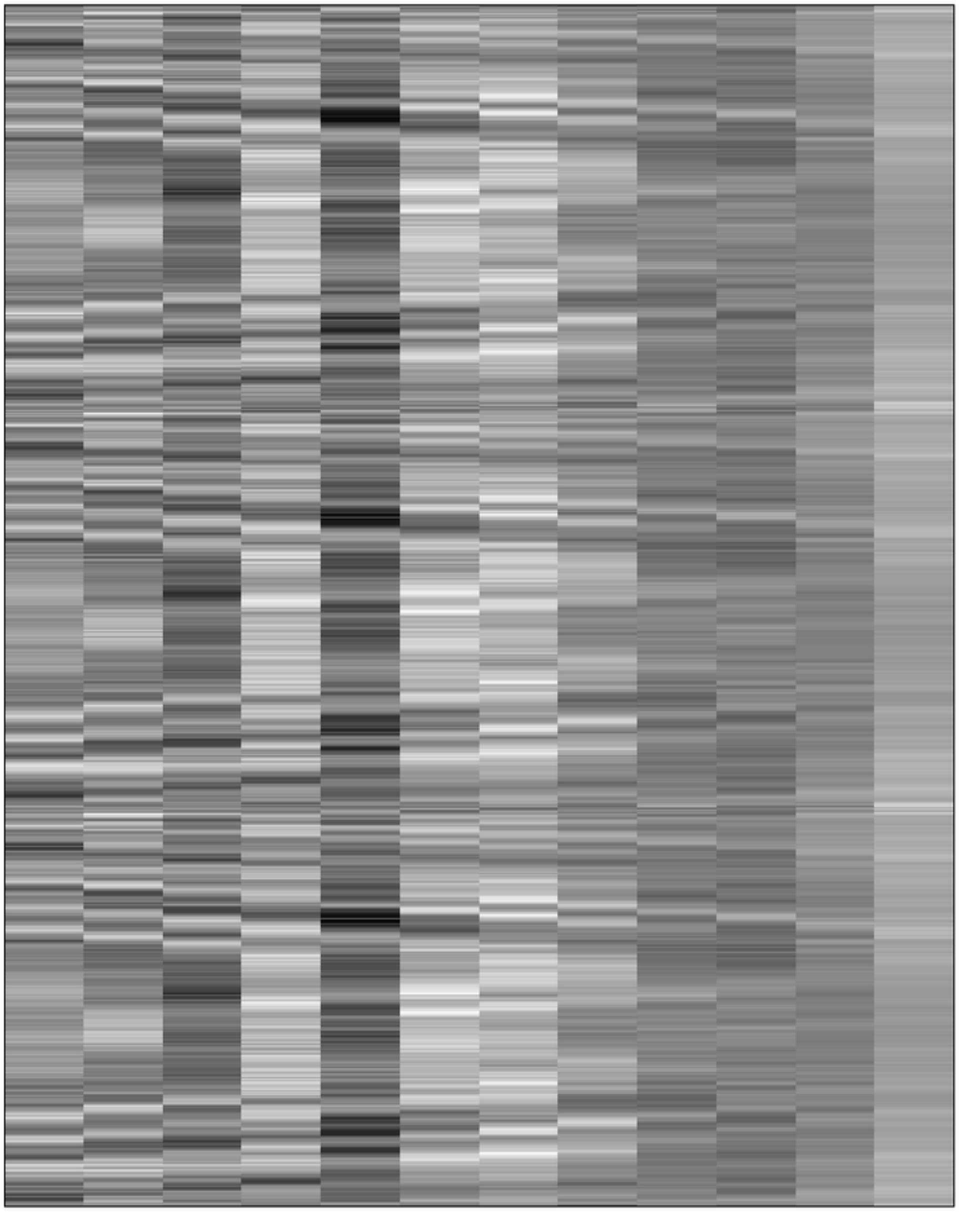

Figure 4

MFCC of Covid-19 image

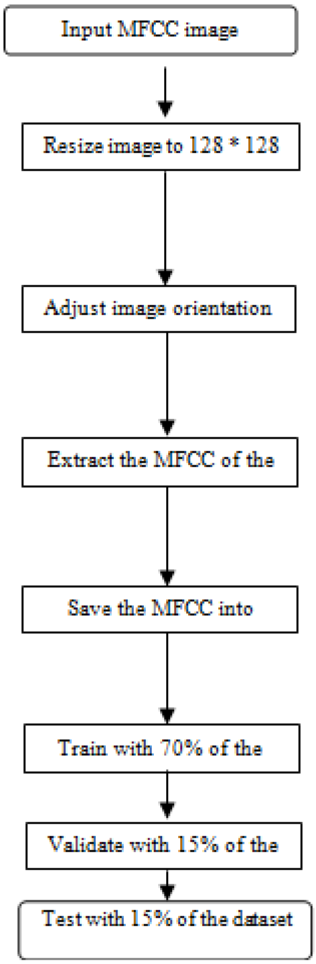

Figure 5

Proposed system block diagram

```
_________________________________________________________________
Layer (type)                 Output Shape
=================================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)
_________________________________________________________________
block3_conv4 (Conv2D)        (None, 56, 56, 256)
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)
_________________________________________________________________
block4_conv4 (Conv2D)        (None, 28, 28, 512)
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)
_________________________________________________________________
block5_conv4 (Conv2D)        (None, 14, 14, 512)
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)
_________________________________________________________________
flatten (Flatten)            (None, 25088)
_________________________________________________________________
dense (Dense)                (None, 3)
```

Figure 6

Model Summary

```
Epoch 10/10
27/27 [==============================] - 16096s 596s/step - loss: 0.0019 - accuracy: 1.0000 - val_loss: 0.0310 - val_accuracy: 0.9833
```

Figure 7

Resultant Accuracy using early stopping call back

```
#get classification report
print('Classification Report')
target_names = ['Covid', 'Normal', 'Viral Pneumonia']
print(classification_report(y_pred,test_y, target_names=target_names))
```

```
Classification Report
                 precision    recall  f1-score   support

          Covid       0.98      1.00      0.99        59
         Normal       1.00      0.98      0.99        61
Viral Pneumonia       1.00      1.00      1.00        60

       accuracy                           0.99       180
      macro avg       0.99      0.99      0.99       180
   weighted avg       0.99      0.99      0.99       180
```

Figure 8

Classification Report

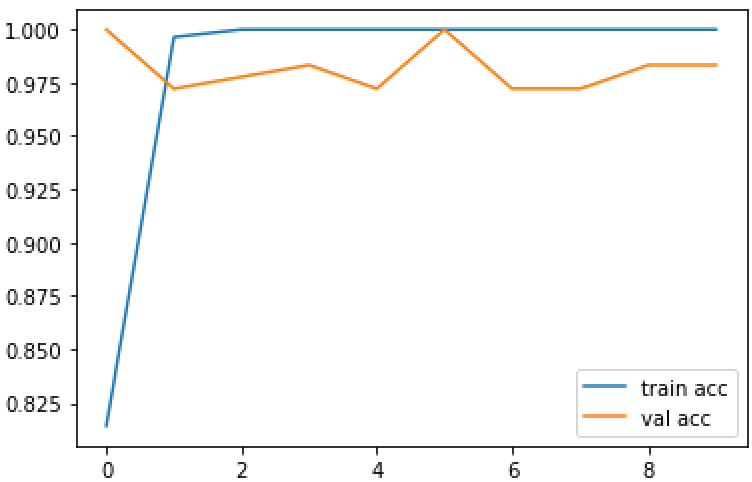

Figure 9

Accuracy against validation accuracy

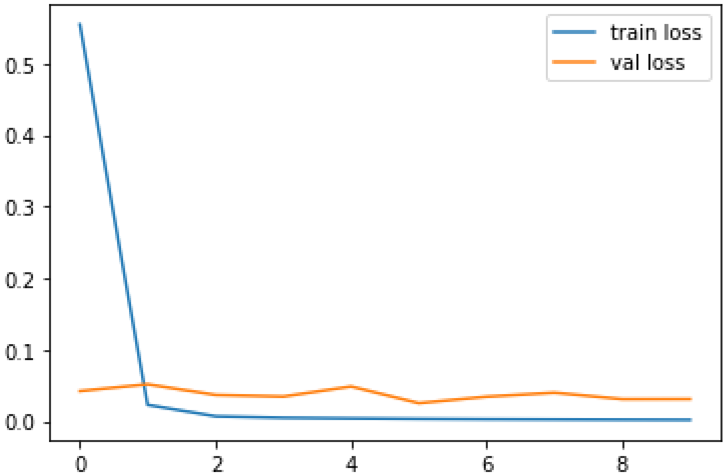

Figure 10

Train loss Vs. Val Loss.

```
model.evaluate(test_x,test_y,batch_size=32)
```

```
6/6 [==============================] - 2424s 404s/step - loss: 0.0355 - accuracy: 0.9944

[0.03550466522574425, 0.9944444298744202]
```

Figure 11

Model Evaluation

```
#Get the confusion matrix
```

```
print('Confusion Matrix')

print(confusion_matrix(y_pred,test_y,))
```

```
Confusion Matrix
[[59  0  0]
 [ 1 60  0]
 [ 0  0 60]]
```

Figure 12

Confusion Matrix