Multi-class Classification for the Identification of COVID-19 in X-Ray Images Using Customized Efficient Neural Network

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Abstract During the global urgency, experts from all over the world searching for a new technology that supports the COVID19 pandemic. The deep learning and artificial intelligence application used the researchers on the previous epidemic, which encouraged a new angle to fight against the COVID19 outbreak. The limited number of COVID19 kits available in hospitals is due to the increasingly high number of cases. Therefore, it is necessary to implement an alternative system that detects and diagnoses the COVID19 and stops spreading among people. This chapter aims to detect and classify COVID19 infected, normal, and pneumonia patients from X-ray images using deep learning techniques (proposed CNN, AlexNet, and VGG16 models). The experiment was performed by combining two datasets, which are available on the Kaggle repository. The result analysis shows that the proposed CNN model achieved the highest accuracy of 95% from other deep learning models (AlexNet 90% of accuracy, and VGG16 94% of accuracy).

Keywords Classification · Deep learning · COVID19 · Pneumonia · X-ray images · CNN AlexNet · VGG16

1 Introduction

In December 2019, the COVID19 pandemic began in Wuhan, China, and spread worldwide. The cause of the COVID19 pandemic disease infection was the acute severe respiratory syndrome coronavirus (SARS-CoV-2) and Middle East Respiratory Syndrome (MERS-CoV). The COVID19 pandemic is spreading throughout the world at an unprecedented rate for any infectious illness. One of the effective approaches offered by the World Health Organization (WHO) to control the spread of viral disease is social distance and contact tracing [1, 2].

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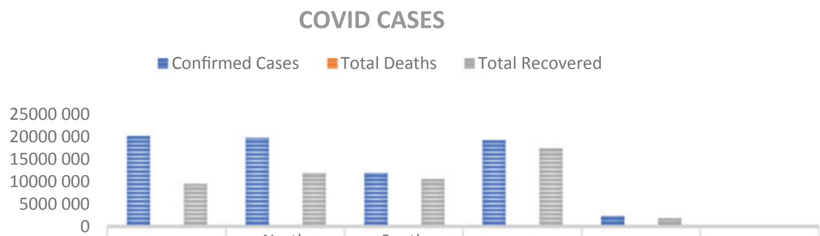
According to the World Health Organization (WHO), 9,919,725 cases were reported, while 1,623,064 have died from the COVID19 diseases. In many developed countries, the health framework falls due to the synchronous flare-up of COVID19 and the expanding interest for serious consideration units loaded up with the infected patients [3]. The sign of infection, including respiratory symptoms of the COVID19, are fever, cough, and sore throat. The disease can also be caused by severe acute respiratory syndrome, pneumonia, multi-organ failure, septic shock, and death in some serious cases [4].

It has been determined that women are less affected than men, and children between the ages of 0 and 9 are not affected. In Respiratory rates, the COVID19 have been observed to be infected faster than healthy people. COVID19 is associated with a highly Intensive Care Unit (ICU) due to a rapid transition rate which requiring an urgent quest for fast and precise diagnosis treatments [5]. WHO reported the distribution of COVID19 cases worldwide as of 16 December 2020. Europe, North America, and Asia are the most highly infected countries. Figure 1 shows the region-wise confirmed, total-death, and recovered cases ("Coronavirus", 2021).

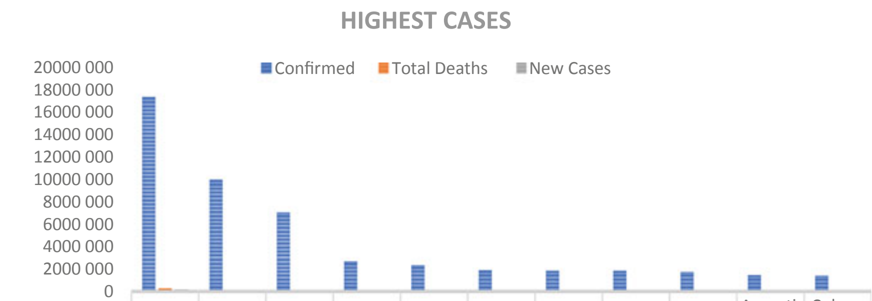
The United States, Spain, Italy, United Kingdom, India, France, Turkey, Russia, Brazil, and Colombia are the highly infected countries with many registered cases of COVID19 patients. According to the WHO, there are currently 17,361 confirmed cases in the United States, rising sharply, and the loss of life has ascended to 314.36. In India, Spain, Italy, Turkey, Argentina, and different nations, by observing serious lockdown and full consideration, mortality and new cases are declining, as presented in Fig. 2 ("Coronavirus", 2021).

Radiological imaging, such as CT scans and chest X-rays, can help people with scars to cope with the epidemic in a timely manner [6]. These methods may, without limitation, differ in the radiological properties of COVID19. The best option for a radiologist is a chest X-ray, as most emergency clinics are equipped with X-ray. As it may be, chest X-ray images obtained from X-ray machines cannot be clearly separate delicate tissues [7]. CT scan of the chest is used to eliminate this problem



	Europe	North america	South america	Asia	Africa	Oceania
Confirmed Cases	20275 974	19769 685	12079 717	19318 114	2422 789	46 865
Total Deaths	469 876	457 898	342 500	315 865	57 170	1 040
Total Recovered	9591 202	12008 486	10714 273	17522 098	2047 235	33 251

Fig. 1 Region-wise COVID19 cases



	USA	India	Brazil	Russia	France	Turkey	UK	Italy	Spain	Argenti na	Colom bia
Confirmed	17361 6	9954 76	7042 69	2734 45	2409 06	1928 16	1913 27	1888 14	1782 56	1517 04	1456 59
Total Deaths	314 364	144 487	183 822	48 564	59 361	17 121	65 520	66 537	48 596	41 365	39 560
New Cases	216 208	21 861	68 437	26 509	17 615	29 718	25 161	17 572	11 078	6 843	11 953

Fig. 2 Country-wise COVID19 highest cases

and effectively identify the delicate tissues. CT images are needed to examine the chest by Radiologists [8]. In this epidemic, COVID19 requires numerous radiologists to diagnose. Even so, owning one is still beyond the reach of the average person.

As the core technologies of the advancement of artificial intelligence (AI) in recent years, deep learning and machine learning have been reported with significantly improved diagnostic accuracy in medical imaging to detect and classify COVID19 [9]. It surpassed human-level- performance to classify the imageNet dataset, which consists of millions of images in 2015 [10]; also, detection and classification of a skin lesion with machine learning deep learning and obtained impressive results with the help of X-ray images [11].

As a result, COVID19 needs automatic identification. For that machine learning techniques such as, deep learning is widely used for automatic examination of chest radiological images. AI analysts and computer researchers played a key role when COVID19 spread around the world [12].

The rest of the chapter is organized as follows: Sect. 2 reviews and discusses the COVID19 detection and classification. Section 3 discussed the data collection and methodology of COVID19. Section 4 presents the implementation and results of the classification. Finally, Sect. 5 concludes the work.

2 Related Work

Sarker et al. [13] proposed a method based on deep learning. They used Desnet-121 and transfer learning to classify COVID19 patients. They used the exchange learning strategy to eliminate the problem of angles and train deep learning networks. The accuracy of this strategy was 92%.

Öztürk et al. [14] presented a method for covid classification. They use four distinctive feature extraction techniques to extract features from chest CT images. The SVM technique has been used further for classification. For classification purposes, these separated pictures are applied to support vector machines (SVM). They utilized 10-overlap cross approval during the characterization cycle, which is obtained 99% of precision.

Zhang et al. [15] Presented a method for COVID19 classification with greater efficiency based on deep learning models using chest X-ray images leading to faster and more reliable scanning.

Adhikari [16] proposed a network “Auto Indicative Medical Analysis” attempting to discover an irresistible region to help the specialist distinguish the ailing part better. CT and X-rays images were utilized during investigation. The DenseNet technique has been used to eliminate and check the infected area of the lungs.

Narin [17] Proposed a method based on different deep learning models such as InceptionResNet-V2, InceptionV3, and ResNet50 for classification on COVID19 using X-ray images.

Wang [18] presented a technique, COVID19Net, which is implemented on the COVIDx dataset. The dataset consists of 266 COVID19 infected patients with CXR images. The framework was first developed on ImageNet and then achieved the best score of 0.9480 in three-class order.

Shan et al. [3] proposed a method based on deep learning for automatic categorization of infected areas in the lung. The data is consisting of 300 COVID19 positive cases images. This model achieved of 91% accuracy.

Chen et al. [19] Design UNetþþ to differentiate COVID19 and pneumonia. The samples for this model consist of 106 COVID19 and pneumonia patients.

Li et al. [20] created the ConVNet Detector Neural Network (CONVNet) to recognize Covid infection in patients by extracting the features from chest CT images. The COVNet technique was trained on 3322 patients of CT images. The model has been achieved of 95% precision rate.

Xu et al. [5] segmented the infected regions from CT scan and utilized a three-dimensional profound learning model. The model is used to classify COVID19 from normal and Influenza-A viral pneumonia.

Sethy and Behera [21] uses chest X-rays presented a deep learning model with SVM. The SVM and Resnet 50 perform better than other pre-trained models.

Horry et al. [22] presented a technique for analysis of COVID19 using X-ray images. Two methods MobileNet, AOCTNet and shuffleNet with CNN has been used and highlight the extraction feature in the images. The KNN, SVM, RF, and SoftMax classifier has been used further for classification.

Khan [23] presented a pre-trained model Xception to identify the COVID19 infected patients. The dataset consists of COVID19, viral pneumonia, and bacterial cases.

Shi et al. [24] examined the patients who have been harmed from coronavirus pneumonia and have been admitted to a clinical center in Wuhan, China. The CT images of patients with their behavioral characteristics were also analyzed and considered for recognition of Covid 19 diseases.

Table 1 Dataset distribution in classes

Labels	Number of images
COVID19	1266
Normal	1266
Pneumonia	1266
Total	3798

Yadav and Jadhav [25] used CNN-based pre-trained models such as inspirationV3 and VGG16 with SVM using chest X-ray images to perform better. Thejeshwar [26] proposed a KE Sieve Neural Network structure that uses chest X-ray images to find estimates of Covid 19.

Ullah et al. [27] presents a machine learning technique to detect and classify COVID19 from X-ray images. The feature is extracted from a Histogram of oriented gradients and then classify it using a support vector machine and logistic regression. The result shows that the SVM provide better performance than logistic regression.

3 Material and Methods

This section presents a detailed description of the dataset and evaluation of the proposed method, such as pre-processing, augmentation, and experimental setup for classification.

3.1 Dataset

Chest X-ray images from the two datasets combined, which contain a total of 3798 images for training and testing. The dataset is obtained from the open-source Kaggle repositories. The dataset contains a mix of chest X-ray images (COVID19, normal, and pneumonia). In addition, 1266 images of COVID19 infected patients, 1266 for normal, and 1266 for pneumonia patients are presented in Table 1. 70% of the dataset has been used for training purposes and 30% for testing [30].

X-ray images are different in gray surface, features, and dimensions. Figure 3 presents a sample of COVID19 infected, normal, and pneumonia images.

3.2 Image Pre-processing

The pre-processing technique is used to resize the X-ray images from the input data with a fixed size of $224 \times 224 \times 3$, which shows the height, width, and channel. The

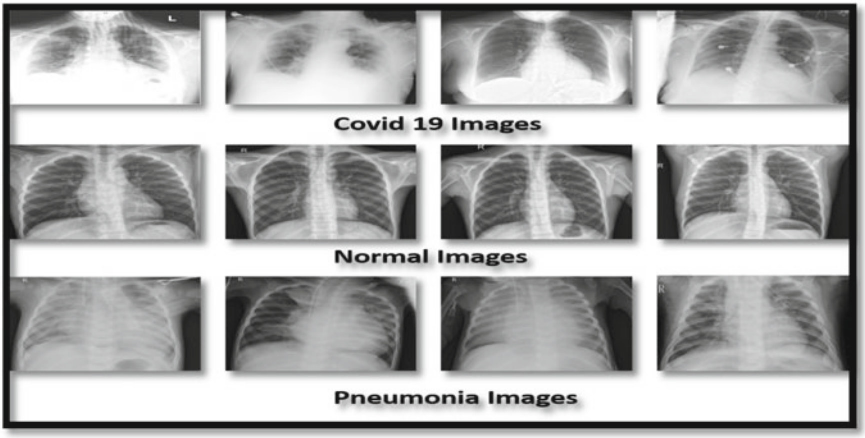


Fig. 3 Sample of COVID19, normal, and pneumonia using X-ray images

performance of the deep learning framework enhances by speeding and anticipating time from the pre-processing.

3.3 Image Augmentation

The data augmentation is applied on an inadequate date during the training process. All images consist of different styles like rotation, horizontal, vertical flip, and zoom-out. The aims are to provide an adequate amount of data into the CNN model to develop the performance and efficiency of the model. Figure 4 presenting the data augmentation with different rotations.

3.4 Classification

In classification, two different convolutional neural networks Alexnet and VGG16 (pre-trained architecture) are used and compared with the proposed model.

3.4.1 AlexNet Model

The AlexNet model is CNNs most illustrative model, which consists of three main points: superior, low training parameters, and solid robustness.

AlexNet is a deep virtual neural organization model comprising hidden layers, including one input and output layer, five polling, and three fully connected layers.

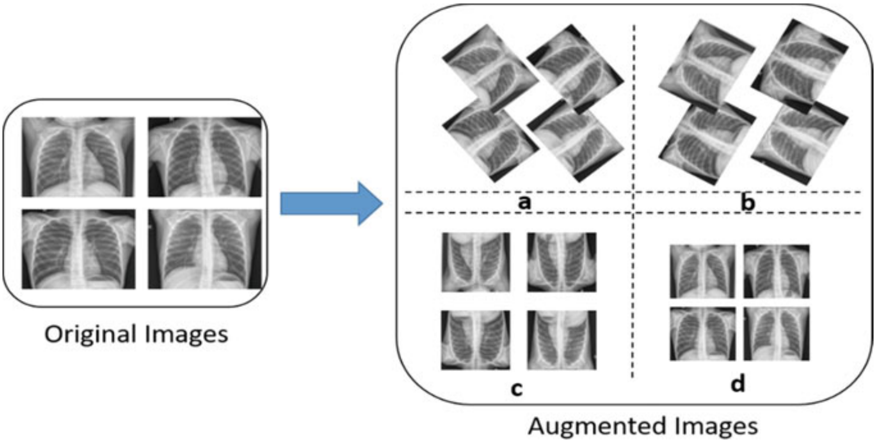


Fig. 4 Data augmentation

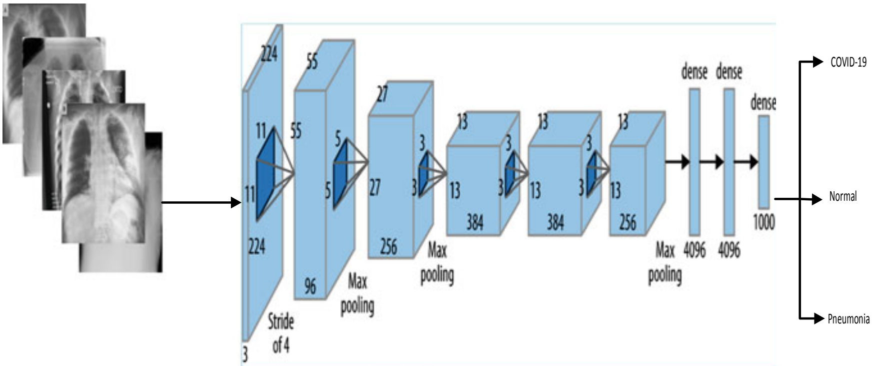


Fig. 5 AlexNet architecture

The learning feature is completed in the approved layer with two channels and passed to the third feature's extraction layer. The fully connected layer is cross-blending for the properties of the two groups, correspondingly. Figure 5 shows the design of the AlexNet architecture [28].

3.4.2 VGG-16 Model

VGG16 is a convolution neural net (CNN) architecture used to win ILSVR(ImageNet) competition in 2014. The VGG16 has a large number of hyper-parameters that focused on having convolution layers of 3 × 3 filter and 16 connection layers. The max-pooling layer consists of five layers, and the size of the layers is 2 × 2. The arrangement of convolution and max pool layers consistently throughout

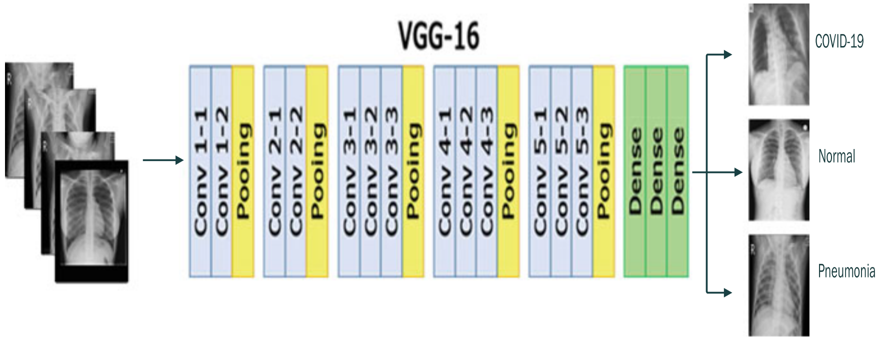


Fig. 6 VGG16 model

the whole architecture and considered one of the excellent vision model architectures. In the end, 2 FC (fully connected layers) followed by a SoftMax for output. A schematic graph of the VGG-16 architecture is presenting in Fig. 6 [29].

3.4.3 Proposed Architecture

The CNN network architecture consists of multiple conventional layers (CONV), subsampling layer (polling layer), and fully connected layers. The proposed CNN model takes image is an input with (128, 128, 3) size. The proposed network consists of four Blocks; each block contains convolutional and pooling layers. In the first block, the convolutional layer having 32 filters with (3, 3) size and the same padding, while the Maxpooling size is (2, 2). The second block contains one convolution layer having 64 filters of size (3, 3) and the same padding, while the Maxpooling size is the same. The third and Fourth blocks contain one convolution layer having 128 filters of size (3, 3) with the same padding and max-pooling size (2, 2). 66,128 features are extracted from the convolution, and max-pooling layers, which is converted into a 1D array called feature vector with 1,4608 sizes: the two fully connected layers (FC) and one out layer. Two layers have (1512) features and a ReLU activation function. In contrast, the output layer has (1,3) classed and SoftMax activation functions which are presented in Fig. 7.

4 Results and Discussion

The performance of each deep learning model has been evaluated using a confusion matrix which is illustrated in Eq. (1) to Eq. (3). Different performance metrics such as accuracy, sensitivity, specificity, precision, and F1-score. have been applied to measure the misclassification of COVID19 during diagnosing from X-ray images. The four term used to describe confusion matrix as follows; True Positive (TP), True

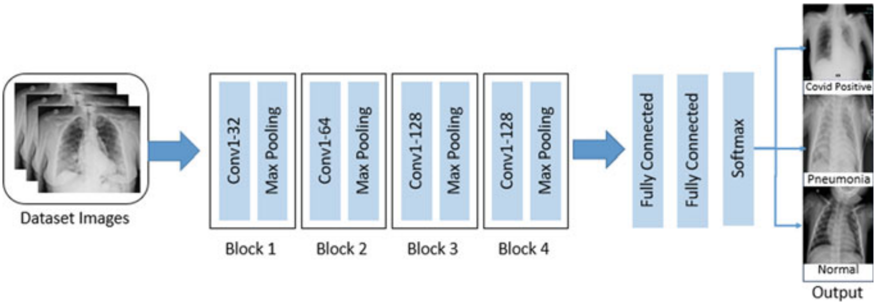


Fig. 7 Proposed CNN model

Negative (TN), False Positive (FP), False Negative (FN). True Positive (TP) refers that the images are correctly predicted and diagnosed. True Negative (TN) is number predicted negative class correctly. False Positive is the number wrongly classify COVID19 images. False Negative (FN) is number of non-detected occurrence of COVID19 ("Evaluating a machine learning model", 2021).

$$\text{Precision} = \frac{\text{Truepositive}}{(\text{Truepositive} + \text{Falsepositive})} \tag{1}$$

$$\text{Recall} = \frac{\text{Truepositive}}{(\text{Truepositive} + \text{Falsenegative})} \tag{2}$$

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FN}) + (\text{TN} + \text{FP})} \tag{3}$$

In this study, chest X-ray images have been used to predict COVID19, normal, and pneumonia. The study examined the performance of three different deep learning models to identify Normal, COVID19, and pneumonia based on CNN, VGG 16, and AlexNet. The performance of different pre-trained models is illustrated in Tables 2, 3 and 4. The proposed CNN model has been achieved 95% of accuracy among other models such as VGG 16 (94%) of accuracy and AlexNet (90%) of accuracy.

The training loss, training accuracy, validation loss, and validation accuracy of the proposed CNN model are illustrated in Fig. 8. The training has been carried out up to 100 epochs to avoid the overfitting of the proposed CNN model. However, it is seen that the Proposed CNN Model shows a fast-training process with low training loss and validation loss.

Table 2 Performance Accuracy of Deep Learning Models

Model	Accuracy
AlexNet	90%
VGG-16	94%
Proposed Model	**95%**

Table 3 Performance of deep learning models using precision and recall

Precision			
Classification	AlexNet (%)	VGG-16 (%)	Proposed model (%)
COVID19	97	99	99
Normal	93	94	95
Pneumonia	82	90	92
Recall			
Classification	AlexNet (%)	VGG-16 (%)	Proposed model (%)
COVID19	96	95	98
Normal	83	93	93
Pneumonia	93	95	95

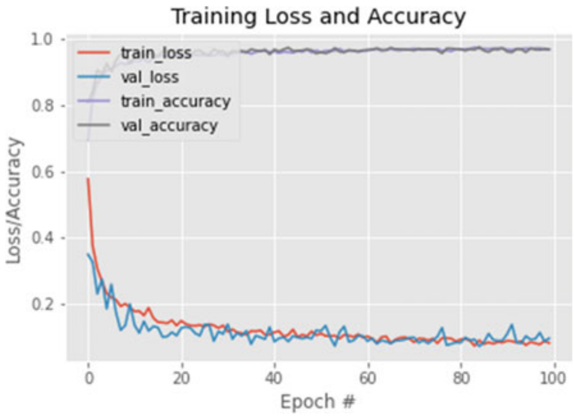


Fig. 8 The performance accuracy of the proposed CNN model

In another detailed performance, comparisons of three models using the test data are shown in Table 3.

The proposed model has achieved the highest precision 99%, 95%, and 92%, and recall 98%, 93%, 95% for COVID19, normal and pneumonia respectively than other which is illustrated in Table 3. As a result, the proposed CNN model provides superiority over the training and testing stage of the other two models.

Moreover, Fig. 9 and Table 2 depicts the graphical representation of three deep learning classifiers with accuracy. The proposed model achieved the best performance accuracy (95%), while the lowest accuracy is 90% achieved by the AlexNet model.

Further, Figs. 10, 11 and 12 represent the confusion matrix for each model. The confusion matrix illustrates the exact number of COVID19, normal, and pneumonia samples.

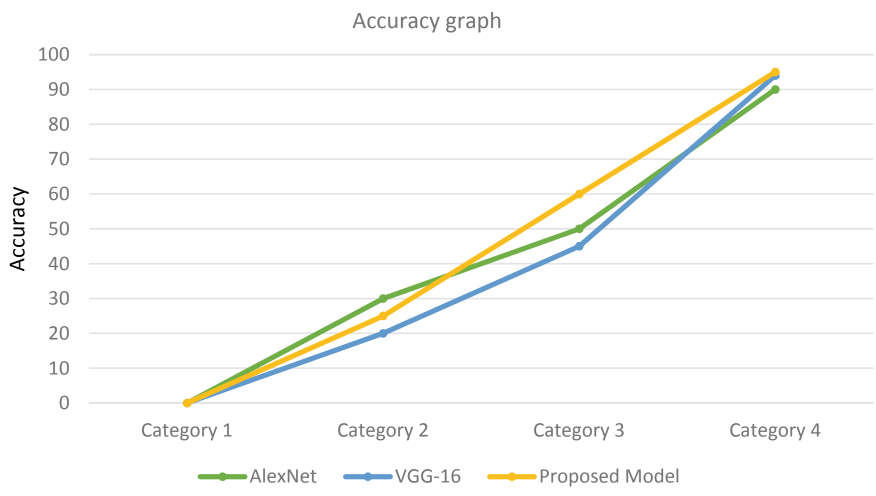
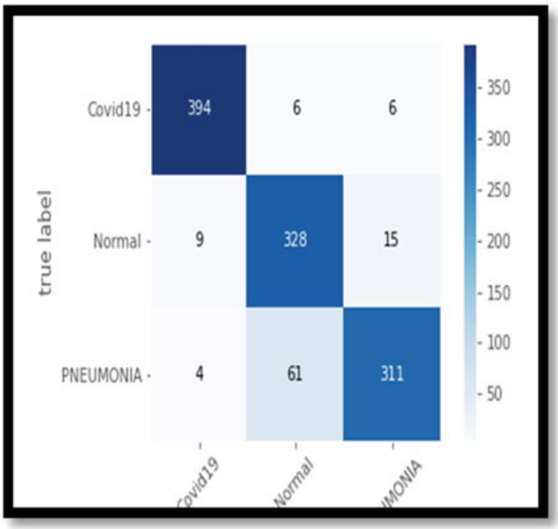


Fig. 9 Accuracy graph of all three models

Fig. 10 Confusion matrix of AlexNet model



5 Conclusion and Future Work

X-ray is the imaging technique that plays a vital role in diagnosing COVID19 and preventing disease among people from the spread. In this study, we used deep learning-based pre-trained models (AlexNet, VGG16) and compared them with fine-tuning of the CNN model. The X-ray dataset consists of COVID19, normal, and pneumonia which differentiate by pre-trained models. The experimental results shows that

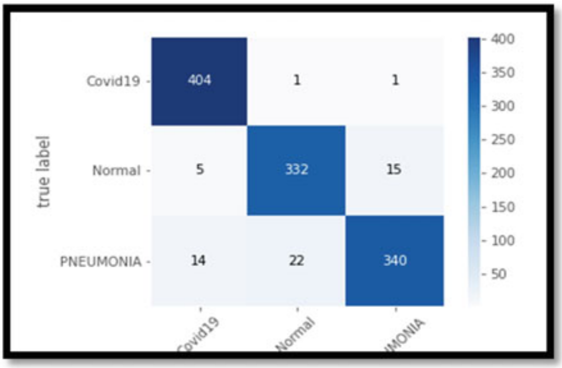


Fig. 11 Confusion matrix of VGG-16 model

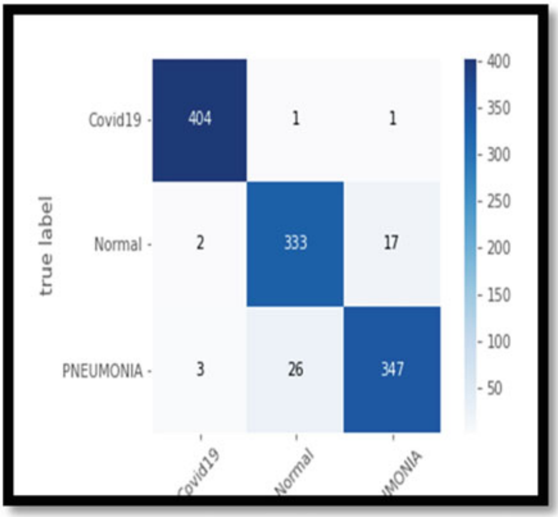


Fig. 12 Confusion matrix of proposed CNN model

our proposed CNN model achieved highest accuracy of 95% among the other two models (AlexNet 90% of accuracy, VGG16 94% of accuracy). In the future, we aim to extend the experimental work using a large dataset of CT and X-ray images. We also aim to use other pre-trained models to enhance performance accuracy and increase efficiency.

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