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Diagnosis of Coronavirus Disease (COVID-19) from Chest X-Ray images using modified XceptionNet

Krishna Kant SINGH[1], Manu SIDDHARTHA[2], Akansha SINGH[3]
[1]Department of ECE, KIET Group of Institutions, Delhi-NCR, Ghaziabad, India
E-mail: krishnaiitr2011@gmail.com
[2]Digital training department, Kolkata, West Bengal, India
E-mail: manu.siddhartha289@gmail.com
[3]Department of CSE, ASET, Amity University Uttar Pradesh, Noida, India
E-mail: akanshasing@gmail.com

Abstract. A beta coronavirus named Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) was identified recently. This virus caused pneumonia of unknown etiology and is named as Coronavirus Disease 2019 (COVID-19). The disease is novel and hence no medicine to cure the infected patients is available. The only way to control the pandemic is by breaking the chain of the virus. The chain can be broken by massive diagnosis and social distancing. Radiological examinations, included computed tomography is identified as an effective way for disease diagnosis. CT and Chest X-ray images are considered to be an effective way for making clinical decisions. The X-ray facility is available even in the remotest parts and thus X-ray images can be easily acquired for patients. These images can help in prevention of infection, diagnosis and control. In this paper, an initial investigation report on the various aspects of COVID-19 is presented. An automated method for diagnosis of COVID-19 from X-ray images is proposed. The proposed model is based on XceptionNet that uses depth wise separable convolutions. The results obtained from the proposed model have high accuracy. The proposed method is compared with four other state of the art methods. The comparative study reveals that the proposed method performs better than the existing methods. Thus the method can be effectively used for diagnosis of the novel coronavirus.

Keywords. Computer Vision and Pattern Recognition, Artificial Intelligence, Medical Informatics, coronavirus, COVID-19, deep learning, convolution neural network, X-ray images

1. Introduction

The latest coronavirus disease known as COVID-19 has appeared and spread extremely fast. According to Huang et al., on January 2, 2020, 41 patients admitted in hospital identified as laboratory confirmed COVID-19 infection out of which six died [1]. The major observation is that all patients had serious pneumonia with abnormal observations on chest CT examination. The virus is novel and scientists around the world are trying to develop the medicine for the disease. As of now no specific medicine is available to prevent or cure COVID-19. Therefore the development of effective methods for diagnosis will be a breakthrough in reducing the effect of the disease. With the advancement in medical imaging and computer aided diagnosis many diseases can be effectively diagnosed. In case of COVID-19, chest X-ray images are being used for diagnosis [2]. Deep learning is a subset of machine learning techniques. It is emerging as an effective machine learning technique and is being used in multiple applications. The major areas where deep learning is successfully used are computer vision, speech recognition and natural language processing. The reason of the wide spread success of deep learning is the way in which computes the output. A major advantage of deep learning over traditional techniques is that it does not require an explicit feature extraction phase. The network takes raw input and maps it to the desired output. The features are automatically learned by the network without manual intervention. These models require high processing power but with the advancement in hardware processing power is not a limitation. Deep learning models are an advancement of the traditional networks with increased number of hidden layers. The hidden layers improve the performance of these networks drastically. In computer vision, Convolution Neural Networks (CNN) is being widely used. Numerous medical imaging researches have also used CNN for image processing operations liking segmentation and classification [3].

Depth wise separable convolution is the building block for many advanced CNNs. Xception network type of convolution originated from the idea that depth and spatial dimension of a filter can be separated which results in fewer parameters than regular convolutional layers, and thus are less prone to over fitting [4]. With fewer parameters, the computational complexity becomes low and hence the resource usage is also reduced.

Xu et al. have used pre-trained network ResNet for classifying image patches into three types: COVID-19, Influenza-A-viral-pneumonia and healthy cases from chest CT images [5]. They have concatenated the results of ResNet based network and another customized CNN model to improve the overall accuracy rate. UNet++ deep learning architecture is used for detecting COVID-19 induced pneumonia from chest CT images [6]. In this method, raw images were firstly input to the model and after pre-processing of the model, prediction boxes framing suspicious lesions were produced as output.

In the recent past, convolutional neural networks (CNNs) showed higher capability in diagnosing pneumonia from chest X-ray images. Deep convolutional neural network having 121 layers named as DenseNet-121 with transfer learning method is used for detecting pneumonia from chest X-ray images [7]. In another study, researchers proposed a 121-layer CNN based on DenseNet called CheXNet [8]. In this study, they have trained a 121-layer convolutional neural network on chest X-ray 14 dataset. The dataset is presently the largest publicly available chest X-ray dataset, consisting over 100,000 frontal-view chest X-ray images with 14 diseases [9].

In this paper, a deep learning model for detection of COVID-19 from chest images is proposed. A large number of deep learning based methods are available for analysing chest images, but the overlapping symptoms of COVID-19 with pneumonia require a tuned network. The existing methods are not capable of classifying the COVID-19 images accurately. The proposed network is capable of classifying pneumonia and COVID-19 into separate classes despite overlapping features. Early diagnosis in case of COVID-19 plays a significant role in the treatment of the disease. Currently the diagnosis is done for patients by a set of laboratory tests. These tests include Reverse-transcription polymerase chain reaction (RT-PCR), Real-time RT-PCR (rRT-PCR) and Reverse transcription loop-mediated isothermal amplification (RT-LAMP) test [10]. These tests are time consuming and require commercial kits. Therefore, alternative ways of diagnosis are significant in case of COVID-19. The patients in which common symptoms are observed can be diagnosed using chest computerized tomography [11]. The abnormalities in chest X-ray images can be used as a diagnosis method. The combination of imaging methods along with clinical observations can help in early diagnosis of the diseases.

2. Diagnosis using Chest X-ray Images

Medical imaging field has grown exponentially in the last few decades. The development of automated methods for clinical decision making have received wide acceptance by the medical community [3]. In case of COVID-19, chest X-ray images can play a vital role in early diagnosis of the disease. Thus, in this paper, an automated method based on Convolution Neural networks is proposed for diagnosis of COVID-19 using chest X-ray images. In this section, a background of depth wise separable CNN is presented. Thereafter the proposed method, implementation details and experimental results are discussed.

2.1 Depth-wise Separable CNN

The main idea of CNNs is that it takes biological inspiration from the visual cortex in the human brain. The visual cortex has small regions of neuron cells that are sensitive to specific regions of the visual field. CNN's are the replica of neuron cells in the human brain that makes it capable of extracting more detailed features from the entire image and helps in classifying image in a particular class just like the human brain. The basic architecture of CNN is explained in Figure 1. CNN consists of multiple convolutional layers, where the initial layer is responsible for capturing the low-level features such as basic shapes, edges, colour, gradient orientation, etc. As the number of layers increases, the architecture adapts to the high-level detailed features. CNN possesses properties like translation invariance, parameter sharing sparse connectivity and implicit feature extraction. These properties have made CNN one of the most popular deep learning models for different applications [12].

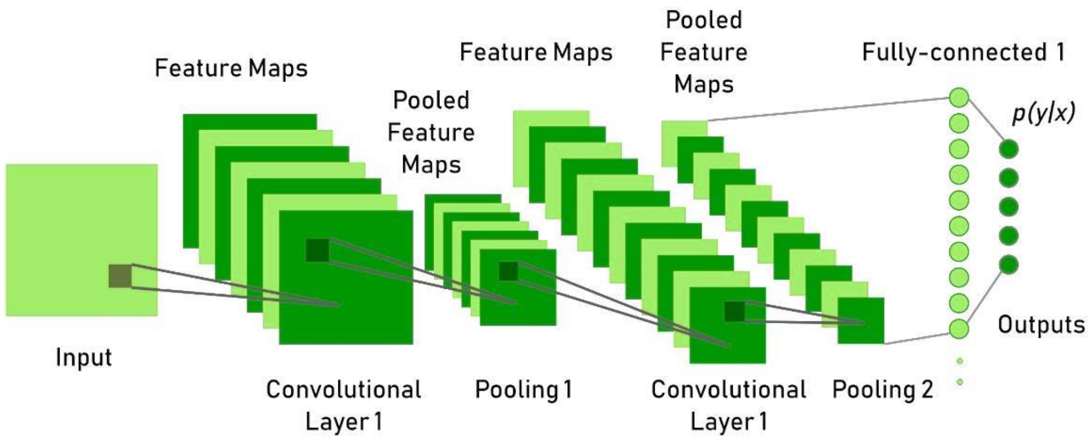
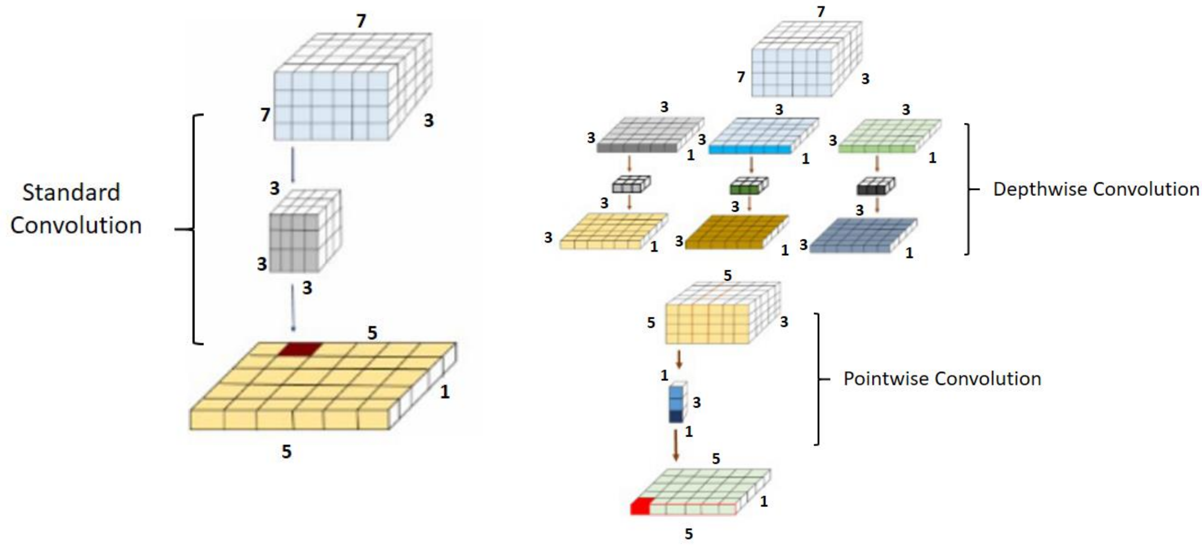


Fig. 1. Basic architecture of convolutional neural network

Convolutional Neural Networks (CNNs) have shown distinguished results in various computer vision tasks, such as image classification, object detection, and image segmentation. CNNs have the capability of automatically extracting the features and thus the model performs with high accuracy. However, the CNNs have some limitations also including the computation cost due to the high number of parameters extracted. Secondly, due to large number of parameters the network results in over fitting. The limitations of CNN can be overcome by using depth wise separable convolution (DSC). DSC breaks the regular convolution operation into two separate operations depth wise or spatial convolution and sequential point wise convolution. The basic operation of a traditional CNN and DSC is shown in Figure 2. The depth wise convolution operation applies a 2D filter to each input channel. The concept of depth wise separable convolution is used in the architecture of XceptionNet [4]. In this paper, a modified XceptionNet architecture using 12 depth wise separable convolution layers in combination with 6 regular convolution layers is proposed.



(a) (b)

Fig. 2. Working principle of a) Regular convolution operation b) depth wise separable convolution operation [Source: https://eli.thegreenplace.net/2018/depthwise-separable-convolutions-for-machine-learning/]

3. Proposed Method

In the proposed method, we have trained 41 layers deep model whose architecture is inspired from XceptionNet architecture. The proposed model comprises of six convolution layers at the top and twelve depth wise separable convolution layers in the middle. In the end, fully connected dense layers with no repetition of convolution block are built. The process flow of the proposed method is shown in Figure 3.

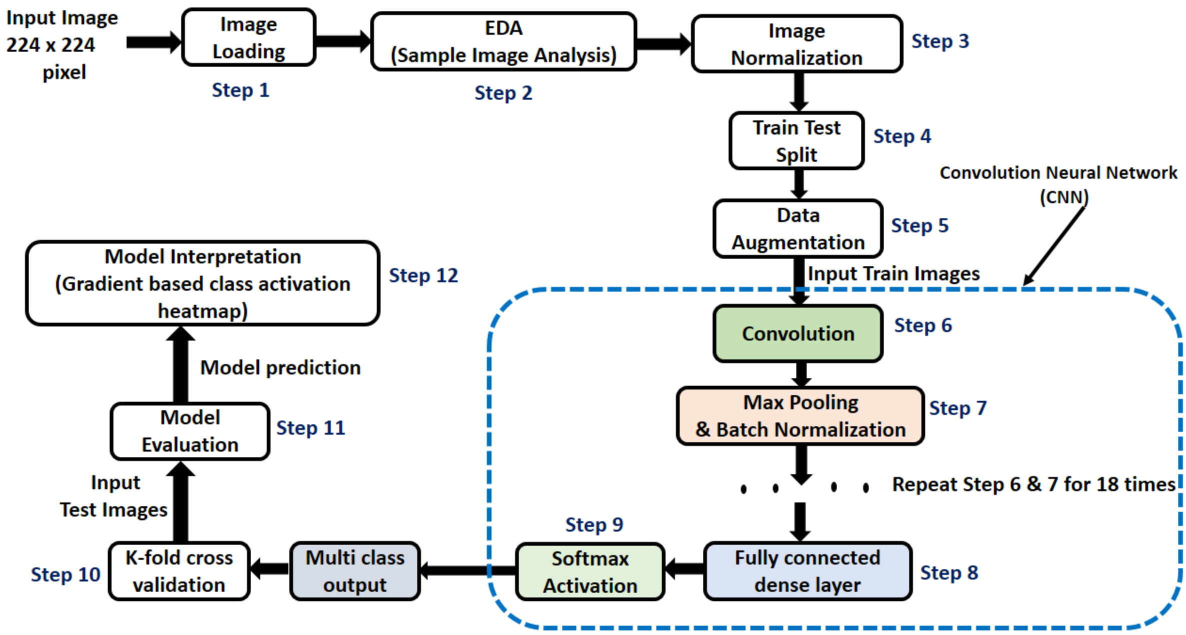


Fig. 3. Process flow of the proposed method

The steps involved in the proposed method are as follows:

Step 1: In this step, we have collected images from different sources based on our research objective and label them with appropriate class type.

Step 2: Exploratory Data Analysis (EDA) by visualizing sample images of each class type for visual understanding of the images is performed.

Step 3: Image normalization by converting the images into array and dividing them by 255 is done. It helps in describing the range of image in a scale of 0.0 -1.0. It helps in removing distortions caused by lighting and shadows in an image.

Step 4: In this step, we split the images into training and test set in the ratio of 80:20, where 80% train set for training deep neural network (DNN) and 20% test set for validating the DNN.

Step 5: Data augmentation is performed. Data augmentation helps in increasing the training set for improving the model training.

Step 6: The augmented training set images is fed into the convolutional neural network which comprises of 3 blocks of standard convolution.

Step 7-9: Max pooling and batch normalization is performed. Thereafter depth wise separable convolution is performed followed by drop out layer. Softmax optimizer is applied which outputs the prediction of classes in terms of probabilities.

Step 10: k-fold cross validation is performed. The training set is divided into k folds or groups and the model is trained on k-1 parts. The evaluation is done on the remaining 1 part as test set. This step is repeated k times and the performance of the model is reported by taking the average of k fold predictions.

Step 11: Model evaluation by input test images is performed. The model is validated by plotting confusion matrix and computing the different metrics. The metrics computed are F1-score, precision, sensitivity, specificity and average area under the curve (AUC).

Step 12: In the last step, we perform model interpretation by randomly evaluating test images prediction by plotting gradient based class activation map which highlights the important patterns in the image which the model used for classifying different classes.

3.1 Data Set Used

In this research, we have used the dataset by scraping images of annotated poster anterior (PA) view of chest X-ray images of COVID induced pneumonia cases from two sources [13,14]. The chest X-ray dataset is used for viral pneumonia and healthy cases [9]. The dataset consists of 1419 images comprising 132 images of COVID cases, 619 cases of viral pneumonia and 668 healthy cases. The mean age of COVID infected patients in our dataset was 55 years where most of the patients were men (83 (63.15%) of 132). Most of the patients (78 (59.2%) of 132) didn’t survive. Top five countries comprising most of the patients in the dataset are Italy (26.15%), Spain (10.6%), China (10.6%), Taiwan (9%) and USA (7.5%), while (8.5%) patients belongs to Canada, Israel, Vietnam, Sweden, U.K., and remaining 27.65% of the patients belong to unidentified locations. For model building process, we split the dataset into training and test set in ratio of 80% for training the model and 20% for validation purpose. The distribution and specification of the images present in the dataset is detailed in Table 1 and Table 2 respectively. The sample images depicting normal, viral pneumonia and COVID-19 patients are shown in Figure 4.

Fig. 4. Sample images of Normal, viral Pneumonia and COVID-19 infected patients [9]

Table 1. Distribution of images in train and test set

Image Type	Train	Test
Normal	534	134
Viral Pneumonia	495	124
COVID-19	106	26
Total	1135	284

Table 2. Specification of images in the dataset

Image Type	Minimum Width	Maximum Width	Minimum Height	Maximum Height
Normal	1040	2534	650	2534
Viral Pneumonia	438	2304	190	2304
COVID-19	256	4095	237	4095

3.2 Architecture

The architecture of the proposed network is shown in figure 5. The input layer of the network is fed with chest X-ray images. These images pass over 18 convolution layers out of which six are regular convolution layers and twelve are depth wise separable convolution layers. The network consists of combination of two separate convolution blocks. The batch size is not specified and therefore the output shape is 3D. In the first block, two convolution layers are followed by max pooling layer of size 2×2. In the second convolution block, two convolution layers are followed by batch normalization. This is further followed by max pooling layer of size 2×2. The batch normalization overcomes the problem of local minima by mapping the activations to the mean of zero and unit variance. It enables larger steps of gradients which results in faster convergence [15]. The dropout layers are added after sixth separable convolution layer with a dropout ratio of 0.2 [16].

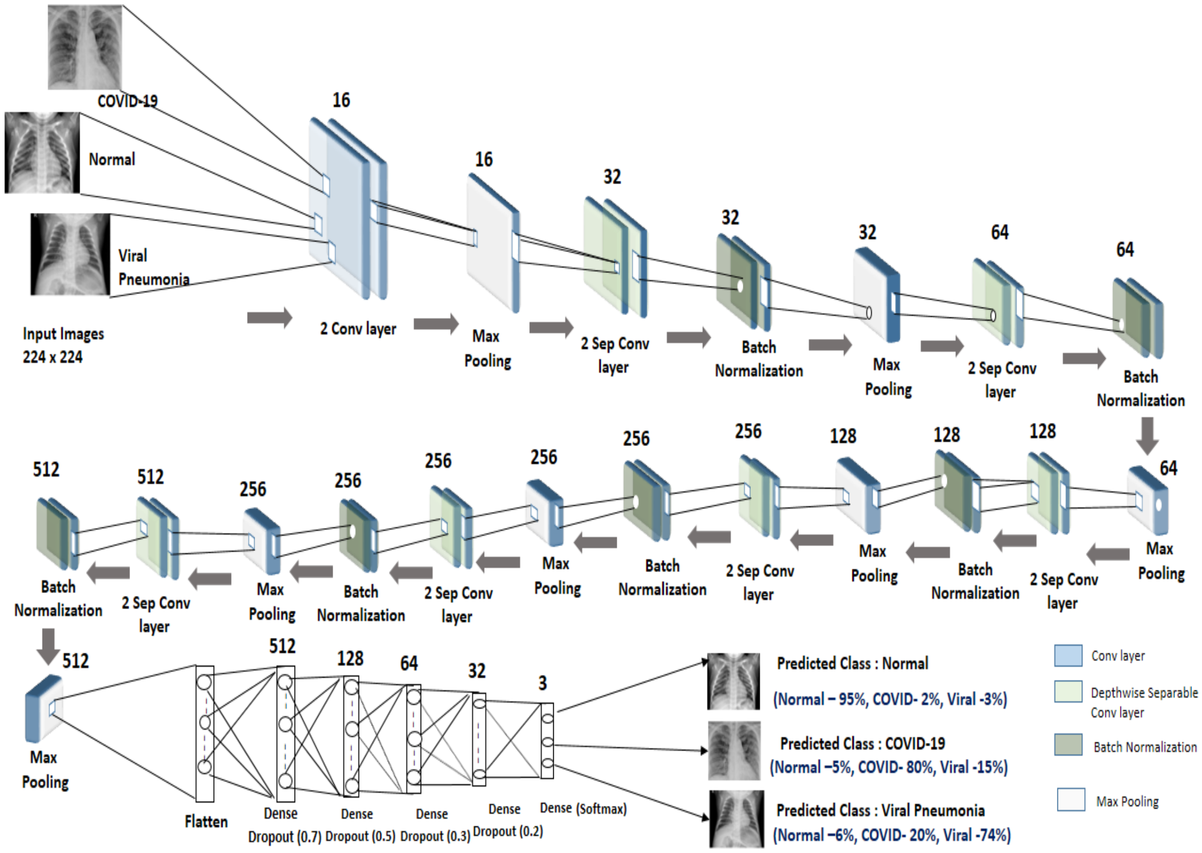


Fig. 5. Schematic diagram of the proposed deep learning architecture

3.3 Activation Function

The convergence of the neural net largely depends on the choice of activation function. The most effective activation function used in hidden layers of deep neural network is ReLU function. ReLU is an activation function which works by thresholding values at 0, i.e. $f(x) = \max(0, x)$. It simply outputs 0 when $x < 0$ while outputs a linear function when $x \geq 0$. In the last layer of the network, we have used softmax activation function which normalizes the output of the network in interval of (0,1).

Table 3. Detailed Architecture of Deep CNN Models Utilized in Proposed Method

Layer Type	Output Shape	# Parameters	Kernel size	Dropout	# Filters
Input	(224,224,3)	0	-	0	-
Conv 2dx2 (ReLU)	(224,224,16)	2768	3×3	0	4
Maxpooling 2d	(112,112,16)	0	-	0	-
Separable Conv 2dx2 (ReLU)	(112,112,32)	2032	3×3	0	32
Batch Normalization	(112,112,32)	128	-	0	-
Maxpooling 2d	(56,56,32)	0	-	0	-
Separable Conv 2dx2 (ReLU)	(56,56,64)	7136	3×3	0	64
Batch Normalization	(56,56,64)	256	-	0	-
Maxpooling 2d	(28,28,64)	0	-	0.2	-
Separable Conv 2dx2 (ReLU)	(28,28,128)	26560	3×3	0	128
Batch Normalization	(28,28,128)	512	-	0	-
Maxpooling 2d	(14,14,128)	0	-	0.2	-
Separable Conv 2dx2 (ReLU)	(14,14,256)	102272	3×3	0	256
Batch Normalization	(14,14,256)	1024	-	0	-
Maxpooling 2d	(7,7,256)	0	-	0.2	-
Separable Conv 2dx2 (ReLU)	(7,7,256)	136192	3×3	0	256
Batch Normalization	(3,3,256)	1024	-	0	-
Maxpooling 2d	(3,3,256)	0	-	0.2	-
Separable Conv 2dx2 (ReLU)	(3,3,512)	401152	3×3	0	512
Batch Normalization	(3,3,512)	2048	-	0	-
Maxpooling 2d	(1,1,512)	0	-	0.2	-
FC1 (ReLU)	(512)	262656		0.7	512
FC2 (ReLU)	(128)	65664		0.5	128
FC3 (ReLU)	(64)	8256		0.3	64
FC4 (ReLU)	(32)	2080		0.2	32
FC5 (ReLU)	(3)	33		0	3

3.4 Training Method

The optimization algorithm minimizes the loss function by updating the weights of the network. In this paper, categorical cross entropy loss function is used. It is used for multi-class classification problem to output the probabilities over the n number of classes for each image. Data Augmentation is used for handling imbalanced dataset problem [17]. With data augmentation the training data is enhanced to improve the training of the model. The data augmentation in this work is done by the following technique. Initially, the training images are rescaled which reduces or magnifies the dimension of the image. A rotation range of [-15, 15] is used. Images are generated by rotating them in the given range. Adam optimization algorithm with weight decay in terms of initial learning rate / total number of epochs to train the network is used. Adam with customized weight decay helps in faster convergence and improving the performance. After relevant experiments, the number of samples per batch was set to eight. We have used 100 epochs for training, cross validating and validating our deep neural network. The performance of the models is assessed with different evaluation metrics such as F1-score, Precision, Validation Accuracy, Sensitivity, and Specificity etc. which is detailed in results section.

4. Implementation

The implementation of the proposed method is done using Python programming language. The keras module of python with tensorflow is used for implementation. All the experiments are performed in Linux operating system on a machine with CPU Intel Xeon @2.30 GHZ in-built with NVIDIA K80 GPU and 128 GB of RAM. The evaluation of the proposed method is performed using training-cross validation - test scheme i.e., the actual training of the model performed on training set, whereas 5-fold validation is used for tuning model's hyper-parameter and final testing of the model performed on test set. The evaluation metrics used for assessing the proposed method are F1-score, accuracy on test set, precision, sensitivity or recall, specificity, and average area under the curve (AUC).

5. Experiments and Results

This section is divided into two parts. In the first part, the details of experimental findings and the choice of suitable hyper-parameters is discussed. In the next section, the evaluation of the proposed method is done using different evaluation metrics.

5.1 Tuning of hyper-parameters

In this section, we demonstrate the effect of hyper-parameters in our proposed method in the training procedure and during evaluation stage. In the experiments, initially the image size for input was 224×224. The input size was reduced to 100×100 to tune the network and improve the performance. By modifying the number of convolution layers, we found that the number of optimal separable convolution layers is 12 and regular convolution layers are 6. The optimizer algorithm used is Adam optimizer with weighted decay.

5.2 Evaluation

In this section, we demonstrate the performance of the proposed method using different evaluation metrics. Table 4 demonstrates the performance of the proposed method on various evaluation metrics. The confusion matrix of the model's prediction is shown in Table 5. The weighted average F1-score for the three categories is 95.88%. The class accuracy for normal class is 96.48%, COVID-19 is 98.94% and viral pneumonia is 96.13%.

Table 4. Accuracy Results

Disease Type	Accuracy (%)	Precision	Sensitivity	F1-score
Normal	96.48	0.96	0.97	0.96
COVID-19	98.94	0.93	0.96	0.94
Viral Pneumonia	96.13	0.97	0.94	0.96

Table 5. Confusion matrix

		Predicted Result		
		Normal	**COVID-19**	**Viral Pneumonia**
Actual Result	**Normal**	**130**	1	3
	COVID-19	0	**25**	1
	Viral Pneumonia	6	1	**117**

The Receiver Operating Characteristics (ROC) curve for three classes i.e., normal, COVID-19 and viral pneumonia is shown in Figure 6. The ROC curve is the plot of True Positive Rate (TPR) against False Positive Rate (FPR). It represents the diagnostic ability of the model by measuring the degree of separability among different classes. Higher the area under the curve (AUC) better is the model in distinguishing among different classes. The AUC of ideal model is 1.0, whereas poor model is 0, the value of 0.5 indicates that the model is equivalent to random guessing. The average area under the curve (AUC) for normal class is 0.99, COVID-19 class is 1.0 and viral pneumonia class is 0.99 while the micro-average AUC is 1.0 and macro-average AUC is 0.99. The major reason that AUC of class normal and viral pneumonia is 0.99, as our model has predicted 3 False positives in case of Viral pneumonia and 1 False negative in case of normal patient whereas, there are no false positives and false negatives in case of COVID due to which AUC of COVID-19 is 1.0.

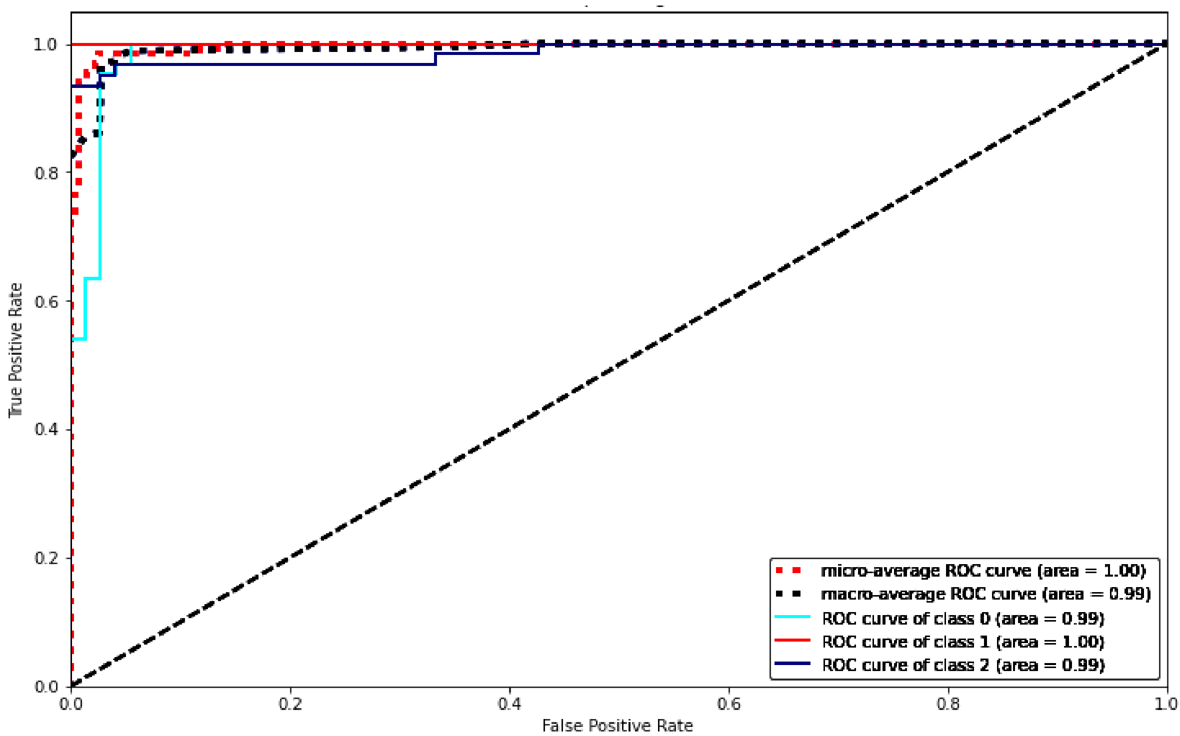
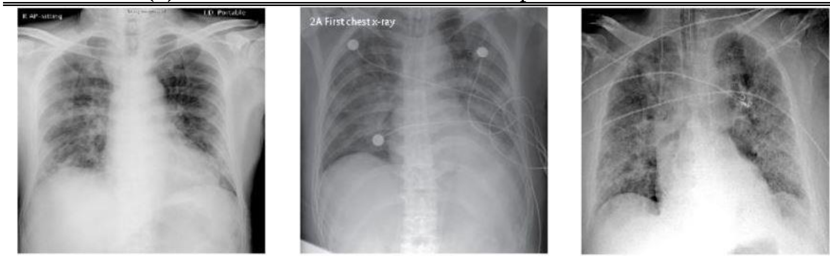


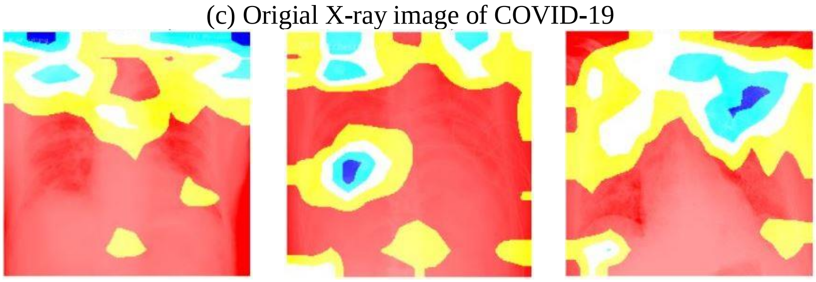
Fig. 6. Receiver Operating Characteristics (ROC) Curve (Class 0: Normal, Class1: COVID-19, Class2: Viral Pneumonia)

(a) Original Image of No infection

(b) Grad Cam Class Activation Map of No Infection

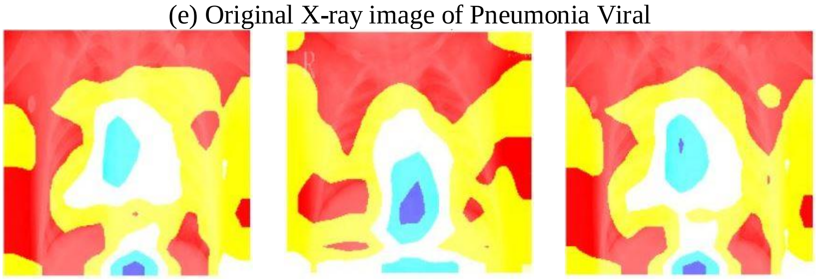


(c) Origial X-ray image of COVID-19



(d) Grad Cam class activation map of COVID-19

(e) Original X-ray image of Pneumonia Viral



(f) Grad Cam class activation Map of Pneumonia Viral

Fig. 7. GRAD-CAM class Activation Map

Gradient based Class Activation Map (Grad-CAM) is a class-discriminative localization map that highlights the relevant regions of image by computing class gradient [5]. It is a weighted combination of forward activation maps followed by ReLU operation [18]. The Grad-CAM visualization heat map of sample test images of the three classes are shown in Figure 7. The Grad-CAM utilizes the concept of gradient by visualizing its flow into the final convolutional layer. This produces a coarse localized heatmap for highlighting the important regions in the image. This is used for predicting the class. The class activation map of normal X-ray highlights full image focusing on middle region whereas in case of COVID-19 images upper region of the image is highlighted with greater density and in the case of viral pneumonia images bottom region of the image is highlighted. The highlighted part in the class activation map is the important regions in the image used by the model for predicting the concept. Figure 7 shows GRAD-CAM heat map of the final convolution layer of the model. The GRAD-CAM highlights important regions in the image for predicting the three classes of image i.e., normal, COVID-19 and viral pneumonia.

5.3 Comparative Study

The proposed method is compared with the existing state of the art methods available for detection of COVID-19 from chest X-ray images. The results obtained from other state of the art methods [19-21] are compared with the proposed method. In [19], a deep neural network with seventeen convolution layers with LeakyRelu as activation function is used. The researchers have used their model for you only look once (YOLO) real time object detection system. The second method shown in the table employed DeTraC deep convolutional neural network. In this study, researchers have developed a variant of CNN named DeTraC i.e., decompose, transfer and compose for detecting COVID-19 images by identifying class boundaries using class decomposition mechanism [20]. The other two methods used for comparison are presented in [21]. They use an EfficientNet family of deep learning models with flat and hierarchal approach respectively. In hierarchal approach, researchers have used two classifiers one at root node of the tree for discriminating Normal and pneumonia cases while the other one at next level to discriminate between pneumonia types COVID-19 and viral Pneumonia cases. The comparative analysis is shown in table 6.

Table 6. Comparative Analysis

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)
DarkCovidNet[19]	87.02	89.96	85.35	87.37
DeTraC-ResNet18 [20]	95.12	93.36	97.91	95.58
Flat - EfficientNet B3 [21]	93.34	93.93	93.96	93.94
Hierarchical - EfficientNet B3 [21]	93.51	93.93	93.55	93.73
Proposed	**95.80**	**96.16**	**95.60**	**95.88**

DarkCovidNet achieved an accuracy of 87.02% and F1-score of 87.37. The low accuracy is due to the use of regular convolution layers and absence of dropout layers within the network. DeTraC-ResNet18 achieved an accuracy of 95.12% and F1 score of 95.58% which is higher than the first method. The hierarchical method has an accuracy of 93.51 and F1-score of 93.73. The performance of the flat method is almost similar to the Hierarchical method. The best results are obtained in the proposed method. The accuracy of the proposed method is 95.80% and F1-score of 95.88.

6. Conclusion and Discussion

Laboratory tests are available that are being used for the identification of the virus from throat and nose swab. The limitation of these tests is the availability of testing machines and kits. On the other hand, X-ray machines are more easily and readily available. Therefore the use of chest X-ray images for diagnosis of coronavirus will be helpful. The model designed in this paper is trained on chest X-ray images and is able to successfully identify all the test images of COVID cases. The proposed method can also be applied to CT images for identification of the diseases. The model can be effectively used to assist doctors in the diagnosis of the disease. The novel architecture captures low-level feature maps from pre-processed chest X-ray images. The model automates the process of recognizing complex patterns from medical images at a level comparable with experienced radiologists. Moreover, we can further enhance the performance of our method by including more COVID cases and lateral view of chest X-ray images in our training data. The proposed method is experimentally tested and evaluated. The results obtained are compared with four existing methods. The different metrics like Accuracy, Precision, Sensitivity, Specificity, F1-score are computed. The proposed method has shown significant improvement over the other methods. The accuracy obtained for the proposed method is 95.80% with a precision of 96.16%.Therefore it can be concluded that the proposed method can be used for the detection of coronavirus from chest X-ray images.

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Conflict of Interest: The authors declare that they have no conflict of interest.

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