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► **To cite this version:**

Arnab Dey. COV-XDCNN: Deep Learning Model with External Filter for Detecting COVID-19 on Chest X-Rays. 6th International Conference on Computer, Communication, and Signal Processing (ICCCSP), Feb 2022, Chennai, India. pp.174-189, 10.1007/978-3-031-11633-9\_14. hal-04388158

**HAL Id: hal-04388158**

**<https://inria.hal.science/hal-04388158v1>**

Submitted on 11 Jan 2024

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# COV-XDCNN: Deep Learning Model with External Filter for Detecting COVID-19 on Chest X-rays

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**Abstract.** COVID-19 is a highly infective viral disease and it is observed that the newest strains of the SARS-CoV-2 virus has greater infectivity rate. Due to the present pandemic, the economy of the country, the mental and physical state of the people and their regular lives are being affected. Medical studies have shown that the lungs of the patients who are infected by the corona virus are mostly being affected. Chest x-ray or radiography is observed to be one of the most effective imaging techniques for diagnosing problems which are related to the lungs. The study proposes a novel COV-XDCNN model with external filter for diagnosing diseases such as COVID-19, Viral Pneumonia, automatically which can assist the healthcare workers, mainly during the time of outbreak. The motivation of this research lies in designing an automated system which can aid the healthcare workers. The proposed model with external filter gives 97.86% test accuracy in classifying the chest radiography images. The model performance is examined with various other models such as NASNetMobile, ResNet50, MobileNet, VGG-16 etc and analyzed. The model proposed in this study shows better performance than most of the existing traditional methods.

**Keywords:** COV-XDCNN, COVID19, Deep Learning, External Filter, Chest X-ray, Data Processing.

## 1 Introduction

The World Health Organization (or WHO) have announced the COVID-19 as a pandemic during the month of March in the year 2020 after the virus has affected a large number of countries across the globe. COVID-19 disease is still a matter of huge concern as a large number of people are getting affected and many of them are also losing their lives daily across the globe. Numerous number of countries are still going through the pandemic phase. The bronchitis, common cough and cold, tuberculosis, chronic pulmonary disease, pneumonia, asthma etc. are the most commonly observed chest infections. Coronavirus disease is a kind of disease that is mainly related to chest infection. The novel corona virus disease is also familiar as severe acute respiratory syndrome coronavirus 2 (SARS- CoV-2). [5] As of 23 Jan. 2022, the corona virus has affected more than 35.1 crore people, about 56 lakh people died and also many people have been recovered as well. Generally, the COVID-19 disease comes

into the human body as a throat infection and then the lungs gets infected. The Corona virus disease is mostly been detected with the utilization of the frequently utilized Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR) method. [7] Although this procedure has a high specificity, but the RT-PCR test kits are limited, the diagnosis process is slow as it takes about one or two days for the report to come and also very costly. The RT-PCR tests may sometimes also produce an incorrect result. Chest X-rays are a commonly utilized diagnosis method which is cheaper and faster. Medical imaging [11] is considered as one of the most powerful techniques for predicting and analyzing the effects of the corona virus on the human body. With the aid of the chest radiography images and the CT images, various kinds of chest related infections or diseases can be classified. The healthcare industry needs to undergo some major technological transformation. [25] The technological innovation with the utilization of Artificial Intelligence (AI) in the healthcare will decrease the anxiety and hindrance from most of the recurring or repetitive tasks instead of replacing the trained healthcare worker or doctor. Chest x-ray can also be utilized for observing the effect of the virus on the chest after getting recovered from COVID-19 disease. The aim of this study is to classify and detect the chest x-ray images into 3 categories, namely Viral Pneumonia, Normal and COVID utilizing the Proposed COV-XDCNN model with the utilization of the external Gabor filter and other filters. For performing this research, the chest radiography images of the pneumonia, COVID affected, normal patients were collected from different sources. The proposed work is also being investigated with the deep learning models - NASNetMobile, VGG-16, MobileNet, VGG-19 and ResNet50 model for testing the performance with respect to the proposed model. It is found that utilizing the Gabor filter in the proposed COV-XDCNN model, learning duration gets reduced. Thus, it is also energy efficient. The proposed trained model is also investigated with some random labelled chest radiography images.

## 2 Literature Review

The literature [1] brings together numerous studies related to the field of the medical imaging technological advancements and its numerous applications. It also indicates that the ultra-modern medical imaging systems mostly comprise of the Chest radiography, Magnetic Resonance Imaging (MRI), CT scan, Ultrasound etc. and the data processing methods. In [4], the authors have utilized various Machine Learning (ML) based models for detecting COVID-19 on the chest x-ray scans. They have achieved 92% accuracy with the Random forest and 96% accuracy utilizing the SVM-based classification model. In [6], the authors have utilized the ResNet18 model for classifying disease based on CT scan images with 97.32%. In [8], various deep learning frameworks that are being utilized in medical imaging are discussed. In [10], authors mostly gave emphasis on demonstrating the coronavirus disease on the lungs of human beings and its impact. They have taken into account the chest CT images of twenty-one COVID patients in Wuhan (a popular city in China). Cohen et al. [13] have proposed a COVID-RENet model dependent on CNN and extracted the edge and region-based features for classification. Here, the authors extract the features by

applying CNN, then they have utilized SVM for improving the classification performance. The authors have utilized 5 fold cross-validation on the dataset that is gathered for predicting Covid-19 disease. Table 1 shows a comparative study of various machine and deep learning-based methods that already exist to detect COVID-19 disease.

**Table 1.** Comparative Study of various methods that are existing to detect COVID-19

S. No.	Title / Existing Work	Feature(s)	Classifier Used	Dataset	Accuracy (%)
1.	Identification of COVID-19 using Chest X-ray images with voting classifier [2]	Augmented Image, Majority Voting classifier, x-ray based	SVM (RBF Kernel)	Chest X-ray	82.90%
2.	Recognizing COVID-19 Pneumonia on Chest X-Ray and CT utilizing DL [3]	Glorot weight initialization, Single CNN Layer, ReLU	CNN	Chest X-ray and CT Scan	94%
3.	COVID-19 classification with the Chest X-Ray images using ML [4]	Chest X-Ray, Binary classification (Covid and Normal)	Random Forest (ML based)	Chest X-ray	92%
4.	Transfer learning-based automatic detection of COVID-19 with CT scan [6]	Stationary wavelet decomposition, Normalization, Lung CT	ResNet18 (Deep Transfer Learning)	CT Scan	97.32%
5.	Deep neural network model to recognize COVID-19 with chest radiography scans [7]	DCNN based, Pre-trained on Imagenet, 4-fold cross validation	Xception - CoroNet	Chest X-ray	89.6%
6.	AI on COVID-19 pneumonia detection with chest x-ray [9]	Data Aggregation, Hyper parameter tuning.	CNN Based	Chest X-ray	90%
7.	Finding covid19 on chest x-rays utilizing Deep Learning [15]	Small Dataset, Binary classification (Covid and Pneumonia)	ResNet50 and VGG-16	Chest X-ray	89.2%
8.	Detect Covid-19 with chest x-ray [17]	Pre-trained CNN model, Classification (Covid, Pne. and Normal)	CheXNet and DenseNet	Chest X-ray	90.5%
9.	Efficient model for corona virus patterns detection [18]	Pre-trained CNN model, Imbalanced dataset.	Efficient-Net	Chest X-ray	93.9%
10.	Recognizing covid-19 utilizing Deep Learning based model [23]	DL Framework, Two step transfer learning mode, limited data size	COVID19X rayNet	Chest X-ray (189 images)	91.92%

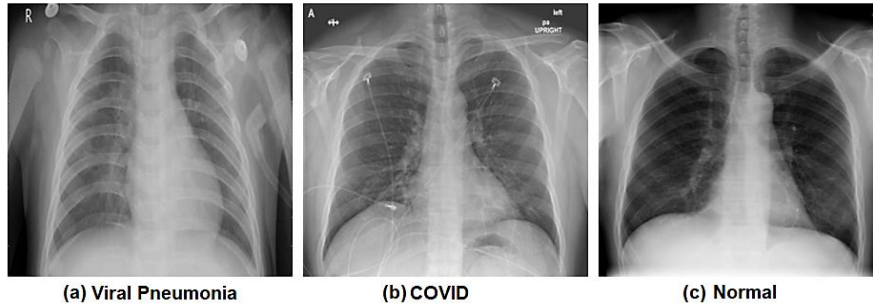
In [14], the authors have recommended a hybrid system dependent on deep learning with Convolutional Neural Network (CNN) and the softmax classifier and implemented it for predicting COVID cases with chest radiography scan images. Another study [18], the authors utilized Efficient-Net, a pre-trained convolution neural network model and classified chest radiography images into three disease classes namely the Normal, the viral Pneumonia and Covid-19 with 93.9% accuracy. They have considered an imbalanced chest x-ray dataset for performing the study. In study [19] the authors have proposed a new deep learning based architecture to automatically diagnose Covid-19 disease with the chest radiography images to help the doctors. The authors have explored how the COVID-19 disease was exhibited as novel pneumonia infection in the Wuhan. In [20], the authors have discussed various techniques that can be used for detecting the Covid-19 disease and its challenges. There is a huge demand for developing an automated method for recognizing the Covid infection which will help to check the further spread of the disease with contact. Hemdan et al. [21], have discussed the chest x-ray based method for identifying abnormalities in the lungs. They have also shown that the healthcare industry will depend on chest radiography because of its availability and minimized infection control. Zhang et al. [23], have utilized Covid19-XrayNet framework dependent on a transfer learning approach that comprises 2-additional layers, namely Feature Smoothing layer (FSL) and another is the Feature extraction Layer (FEL) to predict the chest radiography images in 3 categories, namely viral pneumonia, normal and Covid-19 with accuracy of 91.92%. The dataset size is too small. They also have analyzed the performance of the model with the pre-trained ResNet34 model. It is observed from various existing works that the Deep Learning (DL) methods [27] performs better in most of the recognition related activities as compared to the humans beings, that showcases its numerous applications in the healthcare industry, mostly in the domain of medical imaging.

### **3 Materials and Methods**

#### **3.1 Dataset**

The dataset selected for performing the present research has been collected from RICORD [22], Mendeley data repository [16] and [24] that comprises of the Chest radiography images of Viral Pneumonia, COVID infected and Normal patients.

The dataset taken for performing the research utilizing deep learning methodology consists of 8965 chest radiography image samples. Fig. 1 shows a sample image of the chest radiography dataset of (a) person having Viral Pneumonia infection (b) COVID-19 positive person and (c) normal person. This database has been split into train set which comprises of 7968 image samples and the validation set having 997 samples of normal, COVID and viral pneumonia classes, has been utilized for analyzing the performance of the proposed model.

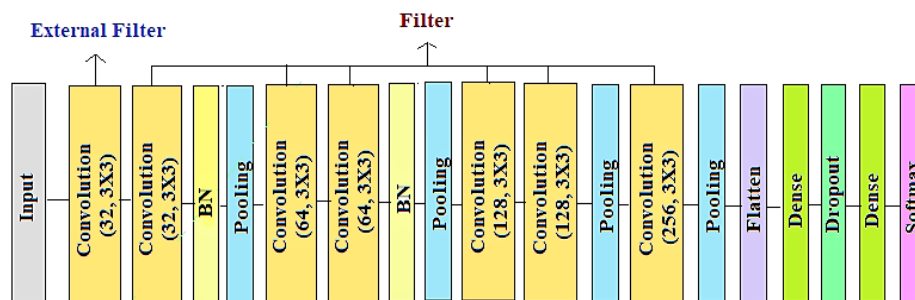


**Fig. 1.** Image sample taken from each class of the chest radiography dataset is shown.

The image size considered for this study is  $224 \times 224$  that is scaled down from the original size of  $299 \times 299$  for boosting the training process to some extent.

### 3.2 Proposed COV-XDCNN Model

The proposed COV-XDCNN model is being implemented with external Gabor filter in the first convolution layer for better and efficient feature extraction and the Gaussian and Sobel filters are utilized in successive convolution layers. The proposed model recommended in this study consists of 18 layers having 7 conv. layers, 2 BN layers, 4 pooling layers, 2 dense layers, 1 fully connected layer, 1 dropout layer and 1 Softmax layer. BN layer normalizes and regularizes the input layer making the training process faster. BN is the Batch Normalization. The pooling layers are utilized in the proposed model for decreasing the dimension of the feature maps. ReLU activation is utilized for introducing non-linearity in the model. In proposed model, conv. layer is considered to be the base layer. This layer with the utilization of some filter which slide across the image for extracting the low level and high level image features. The size of the input image is  $224 \times 224$ . The filter of size  $3 \times 3$  is being utilized. The model also has a dropout layer for eliminating the overfitting effect. The parameters utilized for training the model are selected after performing various experiments. The architecture of the model proposed in this study with external filter is indicated in Fig. 2.



**Fig. 2.** Proposed COV-XDCNN Model Architecture

The output of the conv. layer is represented in the eqn. 1. In the equation, the (\*) represents the vector convolution process,  $c_j^l$  denotes the jth feature map in the layer l,  $f$  represents the function,  $m_r^{l-1}$  denotes the rth feature map in (l-1) layer,  $k_j^{l-1}$  denotes the jth kernel in the (l-1) layer,  $b_j^l$  denotes the bias factor in layer l of the jth feature map and the variable N denotes the total no. of features in the (l-1) layer.

$$c_j^l = f \left( \sum_{r=1}^N k_j^{l-1} * m_r^{l-1} + b_j^l \right) \quad (1)$$

The categorical cross-entropy loss function is being utilized to train the proposed model. The equation of loss function is highlighted in eqn. 2. In the equation, the term  $y$  represents the True Label and the term  $\hat{y}$  denotes the Predicted labels. It is being utilized for optimizing the value of the parameters that are being utilized in the proposed model. The aim is to decrease the loss function in successive cycles of training.

$$L(y, \hat{y}) = - \left( \sum y * \log(\hat{y}) + (1 - y) * \log(1 - \hat{y}) \right) \quad (2)$$

For compiling the model, Adam optimizer is being utilized. It is a stochastic gradient descent method [29] that integrates the good features of both the AdaGrad and RMSProp algorithms for providing optimization which has the capability of handling sparse gradients on the noisy problems. To automate the training process and to control the learning process, the callback functions are being utilized.

### 3.3 Deep Learning Models

Some of the deep learning models which are taken for performing the efficacy testing on the chest radiography dataset are described below. The efficiency of various deep learning models is investigated by varying the base model that is shown in Fig. 3 and keeping the other layers same. The base models taken for the experiment include – NASNetMobile, VGG-16, VGG-19, ResNet50 and the MobileNet model. The models are being trained on ImageNet [28] weights.

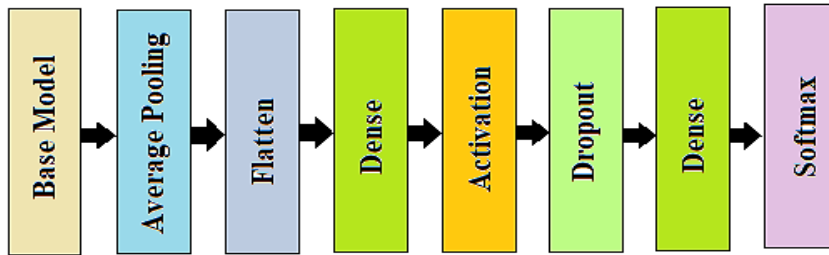


Fig. 3. Proposed Deep Learning Base Model Architecture



**A. NASNetMobile:** It is a mobile architecture dependent on CNN known as Neural Architecture Search Network (NASNet) Mobile. The Google brain team initially developed the design of this model. The model is based on an algorithm which searches the best method for achieving the best performance on a definite task. The control architecture in NASNet is dependent on Recurrent Neural Network (RNN) that is being utilized in this model for predicting the entire structure of the network based on the two initial hidden states. Here, the base model as shown in Fig. 3 is taken as NASNetMobile model for investigating the performance with the chest x-ray images.

**B. VGG-16:** VGG-16 net stands for Visual Geometry Group-16 network and is based on CNN. It is named as VGG-16 due to the presence of 16 numbers of layers. The main idea behind the entire network is that the convolution layers have 3 X 3 fixed sized kernels having a stride value of one and the padding is normally selected as the same so that the size of the input image remains the same. Here, max pool layer is generally utilized after each convolution block having pool size of two and a stride value of two. The number of filter we utilize in this network generally keeps on doubling which is the working principle that is being utilized to design this model. It comprises of 12 convolution layers, 5 pooling layers and 4 dense layers including the output layer. It comprises a total of 16 layers with 5 blocks and each block is accompanied with 1 pooling layer i.e. max. Pool. The model is trained on ImageNet weights.

**C. VGG-19:** VGG-19 net stands for Visual Geometry Group - 19 network. It is based on Convolution Neural Network. It is named as VGG-19 due to the presence of 19 numbers of layers in the net. This model is deeper than that of VGG-16 and requests more amount of memory. The main idea behind the entire network is that the convolution layers have 3 X 3 fixed sized kernels having a stride value of one and the padding is normally selected as the same so that the size of the input image remains the same. It comprises of 14 convolution layers, 5 pooling layers and 4 dense layers. The model is being trained on ImageNet weights. Here, max pool layer is generally utilized after each convolution block having pool size of two and a stride value of two.

**D. ResNet-50:** It stands for Residual Neural Network-50. It is a 50-layer deep Residual Neural Network (RNN). This model is an enhanced form of CNN and also an extension of the deep ResNet model. The model is dependent on the split - transform - merge approach. For solving some certain problem, the model adds shortcuts between the layers which have the capability to check the distortion that may happen when the model becomes deeper or more complex. Additionally, in this model the bottleneck blocks are being utilized for making the process of training faster.

**E. MobileNet:** It is 28-layer deep neural net including the depth-wise separable convolution which comprises of two layers namely the counting widthwise and pointwise convolution layers. In the model, the depth-wise conv. layer is being utilized to filter the input channels and the pointwise conv. layer is utilized for combining them for creating a new feature. It is a simple, lightweight but efficient Neural Network-based

model for mobile vision applications. [12] This model is widely being utilized in various works such as fine-grained classifications, object detection etc.

### 3.4 Proposed Algorithm

The technique utilized to implement the COV-XDCNN model that is being proposed in this study for classifying the chest x-ray images is mentioned below:

Step 1: The data is imported from the directory

Step 2: Data is split into the Training and Test set.

Step 3: Data Augmentation approach is being applied. The parameters used in this study are shown in Table 2. Pre-process image X (utilizing Keras data generator).

**Table 2.** Selected parameters utilized for data augmentation

Parameters	Value
Brightness Range	0.1-0.2
Shear range	0.1
Rotation range	15
Width and height shift range	0.1
Zoom Range	0.2
Horizontal Flip	True

Step 4: Give the image (224,224) as the input to the first convolution layer with an external Gabor filter in the proposed model. And then activation (A) is applied.

Step 5: Followed by the BN, max pooling layer and various successive convolution layers. And activation function (A) is also applied after each conv. layer.

Step 6: Features are extracted in other layers using filters such as Sobel, Gaussian etc.

Step 7: Result of the ultimate conv. layer of the model is being fetched.

Step 8: Then flatten the dimensions utilizing the Flatten layer for decreasing the dimension from n to n-1.

Step 9: A dense layer is added to the model. In equation 3, w represents the weights and b denotes the bias.

$$Z = w * A + b \quad (3)$$

Step 10: Then Activation function (A) is applied. The activation function and its range is highlighted in equation 4 and 5.

$$A = \text{ReLU}(Z) \quad (4)$$

$$\text{where, } \text{ReLU}(Z) = \max(0, x) \quad (5)$$

Step 11: A dropout (20%) is being performed.

Step 12: An additional Dense Layer is added for introducing non-linearity.

Step 13: Softmax function is applied for classifying the chest radiography images. The equation of this function is shown in 6.

$$\text{Softmax } (\sigma_z)_j = \frac{e^{z_j}}{\sum_1^N e^{z_N}} \quad (6)$$

Step 14: Model is compiled with 0.001 LR and the loss function Categorical cross-entropy and Adam optimizer is used. (LR denotes Learning Rate)

Step 15: The proposed model has been trained in 15 batches for 30 epochs with Callback functions - Early Stopping, ReduceLRonPlateau and Model Checkpoint.

Step 16: Chest x-rays are classified into 3 categories, namely COVID, Normal and Viral Pneumonia.

Step 17: The proposed model is validated on Test data

Step 18: Plot Train and Test Accuracy curve

Step 19: Generate the Classification report, Plot Confusion Matrix and analyze the model performance

### 3.5 Data Augmentation

For the artificial creation of newer train data from the existing data, this technique is being incorporated into this research. The data augmentation methods, namely the height shift, width shift, rotation, zoom, horizontal flip and brightness are utilized before training the model. It is known that the deep neural networks require large sized database for proper training, so this method helps to overcome this issue as well.

### 3.6 Feature Extraction and Classification

The features of the Chest radiography images are extracted utilizing the Sobel filter, Gaussian filter, custom Gabor filter and some common edge detection filters with the proposed COV-XDCNN model. The pixel data is being converted into a higher form of representation of the texture, spatial configuration, motion and shape of the chest or its components utilizing various feature extraction approaches. Due to the use of additional filters, the features of chest X-rays are extracted more efficiently. The filters that are utilized for extracting chest radiography image features are discussed below:

**A. Gaussian Filter (GF):** It is a filter that is having the shape of the function Gaussian distribution (curve) for defining the weights in the kernel, that are being utilized to compute the weighted average of the neighboring points (pixels) in an image. GF also helps in extracting useful features from the chest radiography images. The canny edge detection utilizes a GF for the eliminating the noise from the image, as this noise can be presumed as edges due to sudden change in intensity with the aid of the edge detector. In this study, kernel of size 3 X 3 and std. deviation taken as 1.4 that blur the image and eliminate the noise from it. The equation 7 shows the equation of Gaussian filter kernel. In the equation,  $\sigma$  represents the std. deviation of Gaussian filter and x and y are the two components as it is a 2-D filter.

$$G_{\sigma} = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad (7)$$

**B. Sobel Filter:** At present, the sobel filter is being considered as the most popular edge detection filter. It gives much better performance than most of the other edge detection approaches due to its efficient extraction of edge features from the image. [26] Utilizing edge features will definitely aid in training the proposed COV-XDCNN model and improve the disease classification performance as it is found that the edges in an image have discriminatory information.

$$K_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -3 & 0 & 1 \end{pmatrix}, \quad K_y = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -3 & 0 & 1 \end{pmatrix} \quad (8)$$

The derivatives  $I_x$  and  $I_y$  are being computed w.r.t x and y axis when the image is being smoothed. It is being achieved with the utilization of the Sobel-Feldman kernels convolution with image as given. Thereafter, apply the kernels  $K_x$  and  $K_y$  as represented in eqn. 8, the gradient magnitudes and the angle can be utilized for further processing. Utilizing the eqn. 9 and eqn. 10, the magnitude and angle can be computed respectively. The Sobel filter detects the edges at the regions of the chest radiography image where there is a high gradient magnitude.

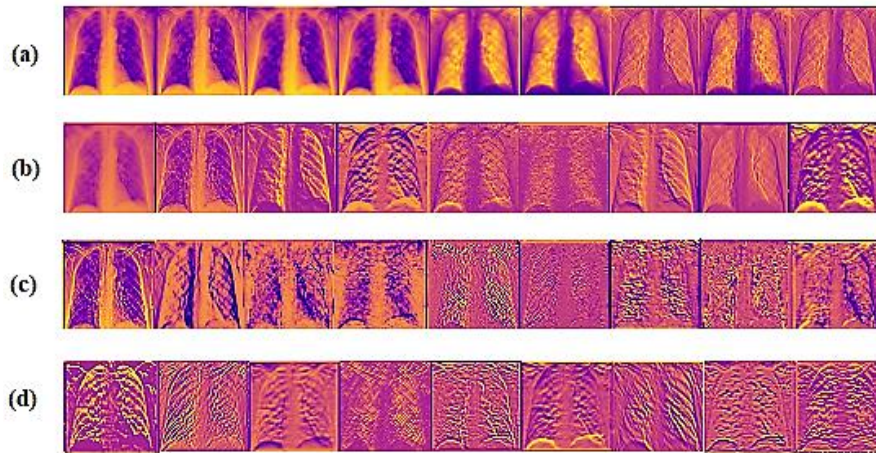
$$|G| = \sqrt{I_x^2 + I_y^2} \quad (9)$$

$$\theta(x, y) = \left( \frac{I_y}{I_x} \right) \quad (10)$$

**C. Gabor Filter:** These filters are mostly utilized for feature extraction, edge detection and in texture analysis. Gabor filter banks are considered to be one of the most powerful approaches for processing the chest radiography images of human beings. It is a dynamic filter.

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2+y'^2}{2\sigma^2}\right) \exp(i(2\pi \frac{x'}{\lambda} + \psi)) \quad (11)$$

The filter finds a specific frequency that exists in the image along a certain orientation at a zone (local) around the region of analysis. The proposed COV-XDCNN model extracts the image sub-features utilizing this filter. It improves in extracting the features of various components of the chest and thus improves the disease detection rate. The complex form of a 2-D Gabor filter is shown in eqn. 11, it comprises of both the real and imaginary component. The orientation and frequency representations of the Gabor filters are identical to those of the human visual system. In the equation 11,  $\sigma$  represents the std. deviation of the Gaussian function utilized,  $\lambda$  represents the wavelet of sinusoidal factor in the eqn.,  $\gamma$  denotes the special aspect ratio,  $\psi$  here denotes the phase-offset,  $\theta$  here denotes the orientation of normal to parallel strips,  $x' = x \cos \theta + y \sin \theta$ ,  $y' = -x \sin \theta + y \cos \theta$  and  $k$  is the size of Gabor Kernel. The proposed model have been trained using varied orientations and scales.



**Fig. 4.** Output of the Intermediate feature maps of (a) First Layer (b) Fourth layer (c) Sixth Layer (d) Ninth Layer

The selected images from the color feature map output of some intermediate layers are shown in Fig. 4. Initially, the low level features of chest radiography are extracted and at the successive levels more complex and useful features are being extracted. It shows the responses of the filters, the activation function and pooling operations in some of the layers of the COV-XDCNN model (ext. filter) that is being proposed.

Prior to the extraction of the vital chest radiography image features, the next process is to classify the disease utilizing the trained model. The classification is carried out utilizing the Softmax function at the ultimate layer of the proposed COV-XDCNN model. The classification is considered to be a vital process. For implementation of the work, the trained COV-XDCNN model is utilized to detect random chest radiography data into 3 categories, namely COVID, Viral Pneumonia and the Normal.

## 4 Results and Discussion

### 4.1 Experimental Setup

The proposed work is implemented using the Python programming language on Spyder, Anaconda platform. The experiments and analysis were carried on a 64-bit Win. 10 Operating system having the Core i3 Processor with a clock speed of 2.0 GHz and an Intel Inbuilt GPU.

### 4.2 Performance Measurements

Accuracy of the Chest x-ray classification model can be described as the capacity of the model to rightly predict or classify the disease classes. The mathematical expressions of the Accuracy, Recall (Sensitivity) score, Precision score and the F1- Score or measure that are being utilized for measuring the performance of the models are shown in eqn. 12, 13, 14 and 15 respectively:

$$Accuracy = \frac{Total\ Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad (12)$$

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)} \quad (13)$$

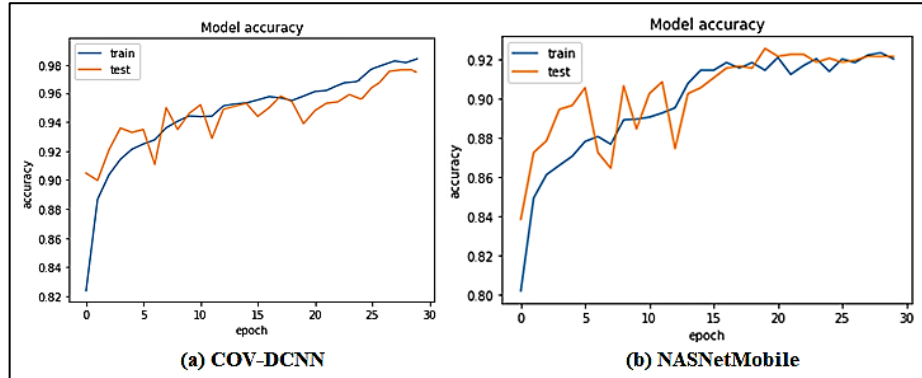
$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)} \quad (14)$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (15)$$

The F1-measure is the harmonic mean of two measures, namely the Recall Score and the Precision score. Apart from the Precision and Recall score, this score is found to be very useful classification metric for understanding the performance of the model.

### 4.3 Accuracy Plot

The output of the Training and Test Accuracy plot of the proposed COV-XDCNN model and NASNetMobile model is shown in Fig. 5. As per the experimental observation, the proposed model in this study outperforms the NASNetMobile model.



**Fig. 5.** Train and Test Accuracy of the (a) Proposed COV-XDCNN Model and (b) NASNetMobile Model

#### 4.4 Classification Performance

The classification report highlighted in Table 3 indicates that the proposed model has high Net Recall and Precision score of 0.97 and 0.96 respectively. Moreover, it also has a high Net F1-measure of 0.96.

All the target classes namely Normal, COVID and Viral Pneumonia are classified effectively as noticed from the classification performance report of the proposed COV-XDCNN model with the external filter.

**Table 3.** Classification Report of the proposed COV-XDCNN model

Class	Precision	Recall	F1-Measure
COVID	0.96	0.97	0.96
Normal	0.98	0.99	0.98
Viral Pneumonia	0.94	0.95	0.94
Avg / Total	0.96	0.97	0.96

#### 4.5 Experimental Results

The proposed COV-XDCNN model and MobileNet model perform much better in terms of classifying the chest radiography images than the other deep learning-based models being experimented as found from Table 4. The NASNetMobile and VGG-16 models also show good results. But, the proposed COV-XDCNN model with an external Gabor filter shows better performance in terms of classification, with test accuracy of 97.86% and training accuracy of 98.24% and has the highest Net F1 score.

**Table 4.** Experimental Results of classification of the Chest Radiography images

S. No.	Model Considered	Training Accuracy (%)	Test Accuracy (%)	Net F1-Score
1.	NASNetMobile	91.98	92.13	0.90

2.	VGG-16	92.63	94.38	0.92
3.	MobileNet	94.86	95.16	0.94
4.	VGG-19	87.38	89.40	0.86
5.	Proposed COV-XDCNN model (with ext. filter)	98.24	97.86	0.96
6.	ResNet50	89.40	90.80	0.88

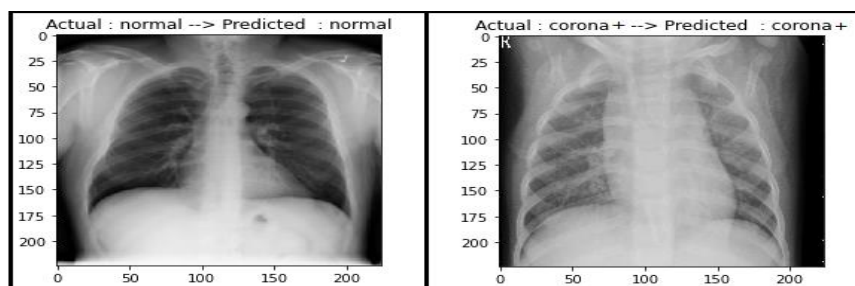
The activation function is used to help the model for learning complex patterns. Utilizing the ReLU activation function in the proposed model better results are obtained as observed from the Table 5. Here, the LeakyReLU and SeLU activation function also performs well but it does not perform better than the ReLU activation function.

**Table 5.** Experiment with different Act. Functions in the proposed COV-XDCNN model

Epochs (No.)	Kernel used	Initial Learning Rate (LR)	Activation Selected (A)	Training Accuracy (%)	Test Accuracy (%)
30	3X3	0.001	ReLU	98.24	97.86
30	3X3	0.001	LeakyReLU	96.53	94.60
30	3X3	0.001	SeLU	89.46	90.30

#### 4.6 Detection Result

The output of the detection performed with the proposed COV-XDCNN Model on two sample chest radiography scans is shown in Fig. 6. It is observed that the predicted result matches exactly with the actual result in both the cases.



**Fig. 6.** Screenshot of the detection output of two sample image with the Proposed Model.

## 5 Conclusion and Future Scope

In this study, the COV-XDCNN model with external Gabor filter is being proposed for classifying the chest radiography images. The proposed model classifies and detects the chest x-ray images of human beings in three categories, namely COVID, Normal and Viral Pneumonia with 97.86% test accuracy. The Gabor filter extracts the features of chest radiography images more efficiently. Moreover, the classification



performance of the model proposed is analyzed with other popular deep learning models and it is seen from experimental analysis that the proposed model shows much better performance. So, it can be employed to classify the COVID-19 affected patients using their radiography images of chest. It is also observed that the proposed COV-XDCNN model, NASNetMobile and MobileNet model takes very less training and testing time in comparison to other models being experimented. Therefore, these models are energy efficient and fast. Deep learning is a powerful method that needs to be widely utilized for automating various diagnosis tasks in the healthcare industry. In future, the classification may be carried out utilizing a more efficient model and a much bigger sized chest x-ray image dataset may be considered for training and validating the proposed model. The proposed approach may be investigated further for proving the actual case-based implementation. This research will influence new research findings on medical imaging and can be utilized as a strong reference.

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