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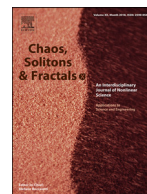
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Frontiers

A deep learning and grad-CAM based color visualization approach for fast detection of COVID-19 cases using chest X-ray and CT-Scan images

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ABSTRACT

The world is suffering from an existential global health crisis known as the COVID-19 pandemic. Countries like India, Bangladesh, and other developing countries are still having a slow pace in the detection of COVID-19 cases. Therefore, there is an urgent need for fast detection with clear visualization of infection is required using which a suspected patient of COVID-19 could be saved. In the recent technological advancements, the fusion of deep learning classifiers and medical images provides more promising results corresponding to traditional RT-PCR testing while making detection and predictions about COVID-19 cases with increased accuracy. In this paper, we have proposed a deep transfer learning algorithm that accelerates the detection of COVID-19 cases by using X-ray and CT-Scan images of the chest. It is because, in COVID-19, initial screening of chest X-ray (CXR) may provide significant information in the detection of suspected COVID-19 cases. We have considered three datasets known as 1) COVID-chest X-ray, 2) SARS-COV-2 CT-scan, and 3) Chest X-Ray Images (Pneumonia). In the obtained results, the proposed deep learning model can detect the COVID-19 positive cases in ≤ 2 seconds which is faster than RT-PCR tests currently being used for detection of COVID-19 cases. We have also established a relationship between COVID-19 patients along with the Pneumonia patients which explores the pattern between Pneumonia and COVID-19 radiology images. In all the experiments, we have used the Grad-CAM based color visualization approach in order to clearly interpretate the detection of radiology images and taking further course of action.

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1. Introduction

Two frailties affect human beings greatly i.e., ill-health and economic slowdown. Unfortunately, this novel coronavirus has brought them to the fore. As we know, the COVID-19 virus targets the lungs of a suspected patient and mutates there promptly. In such a scenario, the infected lungs become inflamed and get filled with fluid. If we perform CT-Scan or X-ray imaging of an infected person then the obtained results show shadowy patches in the lungs called Ground Glass Opacity [1]. Due to the communicable nature, its spread rate is much higher than its prediction or detection rate.

During the various experimental findings performed in this paper, it is revealed that the condition of lungs infected with COVID-19 often relates to another common lung infection known as Pneumonia. Usually, pneumonia is an infection caused by either a virus, bacteria, or fungi. Similar to COVID-19, pneumonia can also be life-threatening for the age group below 2 and people above 65. It is contagious just like COVID-19 with several similar symptoms. However, COVID-19 has proved itself to be more fatal than Pneumonia, as it can lead on to cause Acute Respiratory Distress Syndrome (ARDS). In other words, we can say that it happens as a result of progressing Pneumonia in the lungs.

In the absence of an intelligent diagnosis method, there is a great requirement for fast and accurate detection of COVID-19 suspected patients. However, the contemporary techniques available for the detection of this raging pandemic are moderately accurate and costs a range of time. Currently, there are three different types of COVID-19 testing mechanisms are available known as Reverse Transcription Polymerase Chain Reaction (RT-PCR), Computed Tomography (CT) Scan, and Chest X-Ray (CXR). Among these

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three, RT-PCR is one of the time-consuming techniques, whereas, CXR can detect inflammation in the lungs along with its position, shape, and size, and CT-Scan is a more effective way to diagnose COVID-19 and Pneumonia as it provides a detailed picture of air sacs. Therefore, in our various experimentations we have selected both CXR and CT-Scan images of lungs.

1.1. Role of deep learning in detection/prediction

Healthcare providers generate and capture enormous amounts of data containing extremely valuable signals and information, at a pace far surpassing what traditional methods of analysis can process. As we know, the RT-PCR test is one of the time-consuming and costly methods used for the detection of COVID-19 suspects. Therefore, it is necessary to look for the optimum solution in which fusion of deep learning classifiers and medical images provide the fast and accurate detection of the COVID-19 virus during the analyses of CXR and CT-Scan images of lungs. In this paper, the proposed method can directly help radiologists for fast detection of COVID-19 which in-turn improves the overall detection time and accuracy rate in CXR and CT-Scan images.

Deep Learning (DL) is a subset of Machine Learning (ML) that enables computers for automatic training or learning of sensible features from the raw data sets [2]. In medical imaging, most of the deep learning breakthrough has happened with the introduction of the convolutional neural network (CNN). It is because, Deep Models such as Stacked Auto-Encoder (SAE), Deep Belief Network (DBN), and Deep Boltzmann Machine (DBM) always have inputs in the form of a vector [3]. However, in medical imaging, vectorization destroys the structural and configurational information available in the neighbouring pixels and voxels is one of the important structural information. CNN considers the input in the form of 2D or 3D images and can better utilize spatial and configurational information [3].

Infection on lungs is one of the major signs of COVID-19 and Pneumonia. Which can be seen while examining the CXR and CT-Scan images of lungs and could provide a breakthrough during diagnosing COVID-19. Therefore, we have considered the application of deep learning classifiers and proposed a novel algorithm for extracting the features from various radiology images to detect the presence of infection. The proposed algorithm ensures the use of deep transfer learning on CXR and CT-Scan images of lungs and assesses the report of suspected COVID-19 patients.

In this paper, we have considered the advantage of deep learning classifiers for extracting the features from the taken radiology images of COVID-19 such as CXR and CT Scan and trained them against a combination of Pneumonia, other pulmonary diseases and normal cases. The detection made by our model are visualized by plotting class activation maps using Grad-CAM technique. Thus, our model can be used both independently and alongside a radiologist. The model also focuses on the False Positives (FP) due to the patients with Pneumonia which can create a chaotic scenario. Considering a patient having Pneumonia who is detected falsely by our model as COVID-19 positive will be asked to be admitted in a suspected COVID-19 section of the hospital. Through our experiments it has been suggested to consider the Pneumonia cases in suspected category in order to prevent the further spread of COVID-19.

The main contributions of the paper are listed here:

- We have proposed a new deep transfer learning algorithm and tested it on three different radiology datasets for faster detection of COVID-19.
- With the usage of deep learning and its advantage, it is assumed that proposed model is faster than the traditionally used RT-PCR testing kit.

- We also discover through the experimental by our proposed algorithm that there is a strong relevance between Pulmonary diseases like Pneumonia and COVID-19.
- Grad-CAM analysis has been performed over obtained results provide the colored visualization of the regions of lungs infected by the COVID-19 in both CT-scan and X-ray images.
- We also make the usage of false positive cases e.g., Pneumonia and consider them in COVID-19 suspected category.
- Efficacy of proposed model is more accurate on CT-scan compare to CXR images.
- We used the concept of 'early stopping' in our proposed model in order to overcome the overfitting issue and perform better in real-time.

This paper is further organized into various sections where [Section 2](#) summarizes the various studies on detection of COVID-19 using deep learning approaches. [Section 3](#) discusses about applied datasets, [Section 4](#) presents the proposed approach for fast detection of COVID-19 using binary classification and Grad-CAM approach. [Section 5](#) presents description of proposed Algorithm. [Section 6](#) presents the experimental analysis and their outcomes. Finally, [Section 7](#) concludes this paper.

2. Applications of deep learning for detection of COVID-19

In response to its sudden outbreak, persistent research works are going on in many different perspectives [4–6]. In [7–11], authors have discussed the effective diagnostic methodologies using Artificial Intelligence (AI), deep learning, and machine learning techniques. Recently, deep learning techniques have been widely considered for resolving many healthcare-related issues and the deep learning techniques have proved themselves to be effective in providing significant results. Data scientists have been focusing on improving the detection, analysis, and further prediction of various diseases by taking radiology datasets and apply data science classifiers.

Panwar et al. [12] have proposed the algorithm nCOVnet based on the data leakage concept for fast detection of the COVID-19 cases. In their experiments obtained detection accuracy is 88%, here authors did not provided the clear visualization of detected COVID-19 cases on the CXR images. Kumar et al. [13] have proposed a model called DeQueueNet which classify the patients X-ray images into two categories positive and negative while detecting the COVID-19. The proposed model predicts the possibility of the disease with 94.52% accuracy with the precision of 90.48%, by pre-processing the X-ray images of positive COVID-19 patients and normal cases. Transfer learning has achieved brilliant results in the field of image classification tasks. Luján-García et al. [14], have used chest X-rays for the detection of Pneumonia and further classification between patients infected with Pneumonia or not. The proposed model considers the 36 convolutional layers and has obtained 0.843 precision score. Apostolopoulos and Mpesiana [15] have presented the implementation of transfer learning in COVID-19 detection as there is a very limited amount of data available. They have obtained an accuracy of 96.78%. However, experiments reveal that the dataset was not much balanced. Therefore, feature extraction and classification have turned out to be effective by using transfer learning. In another related work, Toğaçar et al. [16] have considered the chest X-ray images for three different class values known as COVID-19, Pneumonia and normal to reduce the noise by fuzzy technique and stacking. They have considered the SqueezeNet as a model and comprehended the accuracy with varying levels of reconstructed datasets and provided significant accuracy in their obtained results. However, one of the setbacks of this model is that it is not able to work much efficiently with low-resolution images. In Ozturk et al. [17], have presented

another advancement for classification of COVID-19 by proposing a model for binary as well as for the multi-class classification of diseases like COVID-19, regular Pneumonia, and no-findings of any of them. They achieved a 98.08% of accuracy in binary classification and 87.02% accuracy in multi-class along with 17 convolutional layers.

3. Datasets

Computational methods such as AI, Data Science, Machine Learning, and data mining are being used actively to obtain the effective solution of COVID-19 pandemic. These methods are mainly dependent on the datasets for making an effective detection. Since COVID-19 is a new disease therefore the limited amount of dataset is available for the execution of experiments. However, to apply deep learning on radiology imaging, few public datasets are available. Dataset by Cohen et al. [18] is one of the most used data set for performing experiments related to COVID-19. In this work, we have considered the following three datasets for the execution of different experiments.

- *COVID-chest X-ray-dataset* – Cohen et al. [18] have compiled this dataset and is being used widely by many researchers. The recent updated images are timely included in the database. We collected this dataset on 09th Jun, 2020 which consist of 673 radiology images of 342 unique patients. These radiology images includes various CXR and CT-scans of COVID-19 infected patients and with other pulmonary diseases too. After selecting the unique cases of COVID-19 positive patients the total number of patients reduces to 285 along with total number of images to 526. The CXR images available in this dataset can be categorized into three different categories known as Posteroanterior (PA), Anteroposterior (AP), and AP Supine (APS). In experiments, we have used the *PA view* as it provides the *better view of the lungs*. Use of this dataset ensures the issue of data leakage as there are different unique patients, having more than one sample of CXR or CT-Scan images available in the datasets. Therefore, while splitting the dataset for training and testing purpose, we have also addressed the issue of data leakage, then a single patients CXRs or CT-Scans could end up in both testing and training giving false results.
- *SARS-COV-2 CT-scan* Soares et al. [19] have compiled this publicly available dataset. This dataset is collected from a hospital in Sao Paulo, Brazil and approved by their ethical committee. It consists of 1252 CT-Scans of COVID-19 positive patients

and 1230 CT-Scans for NON-COVID patients which are COVID-19 negative but may have other pulmonary diseases.

- *Chest X-ray Images (Pneumonia)*– Kermayn et al. [20] have created this dataset. This dataset has large number of publicly available OCT and CXR images. In the experiments, we have used the X-Rays part of this dataset which consists of 5856 images of Pneumonia and Normal patients [21].

4. Proposed methodology

This section describes the methodology of Convolution Neural Networks (CNNs) and Transfer Learning. The CNNs are very much similar to vanilla Neural Networks except convolution operations which take place in one or more than one layer of CNN [22]. A simple neural network's layer is presented in Eq. 1.

$$z^{[1]} = g(W^{[1]}a^{[0]} + b^{[1]}) \tag{1}$$

where $z^{[1]}$ is the current layer, $a^{[0]}$ is the first or input layer, $W^{[1]}$ represents the weights for the first layer and $b^{[1]}$ is the bias. For VGG19 Conv Layer [23], we have changed the multiplication operation with the convolution operation and updated the weights of a 2-D weight matrix to a 3-D filter tensor. In Eq. 2 each channel of x , there is a corresponding channel in the first filter of $W_c^{[1]}$. The final layer is shown in Eq. 3.

$$z_{(i,j,k)}^{[1]} = (x * W_c^{[1]})(i, j, k) + b_{(k,1)}^{[1]} \tag{2}$$

Or,

$$z_{(i,j,k)}^{[1]} = \sum_{(l,m,n)=1}^3 W_{c(l,m,n,k)}^{[1]} a_{(i+l,j+m,n)}^{[0]} + b_{(k,1)}^{[1]} \tag{3}$$

Where i, j and k corresponds to row, column and channel for $z[1]$ respectively and represents the final product. Whereas l, m, n is the row, column, and channel number of the filter respectively, and k is the symbol which reflects the filter currently being used. Notice how the convolution operation in Eq. 2 becomes just like matrix multiplication in Eq. 3. As shown in Eq. 2 and Fig. 2, the convolution operation generally marked by the (*) sign, here its working is different from mathematics/statistics perspective [22,24]. Technically, it is one of the related function known as cross-correlation but many times in the deep learning literature it is confused with the word *convolution*.

Fig. 1 consists of input, convolution, pooling, fully connected, and output layers. In the input layer, the type of data is CXR or CT-Scan images. Whereas, Fig. 2 separately presents the convolution layer, pooling layer, and connected layer. Fig. 2 also discusses

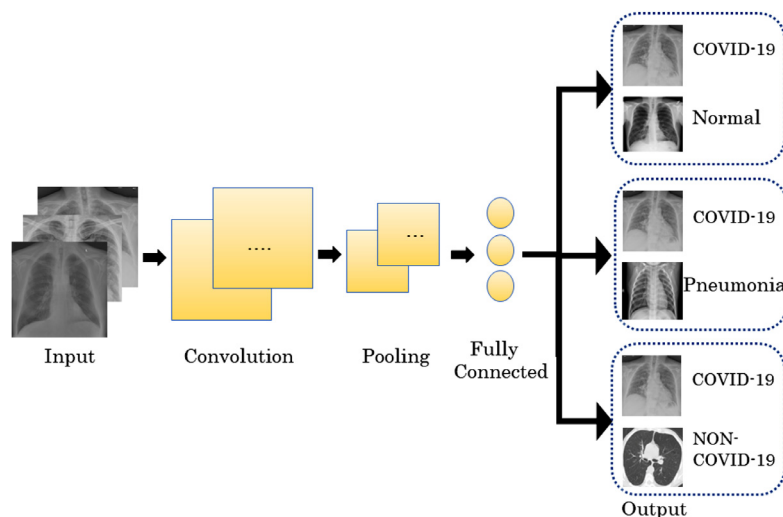


Fig. 1. A basic CNN architecture for the binary classification of COVID-19 images.

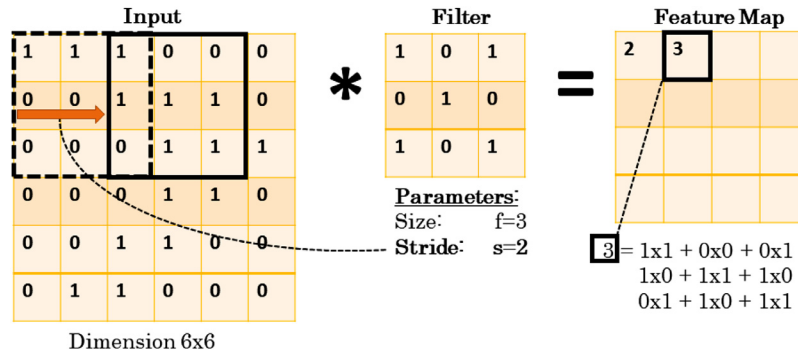


Fig. 2. A sample of the convolution operation with filter size =3, and stride = 2.

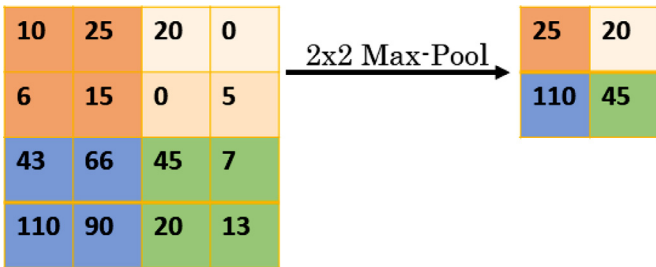


Fig. 3. A sample of maxpooling operation with 2x2 window size.

the sample of the convolution operation on 6×6 matrix using a 3×3 filter and a stride of 2. The movement of the filter window on the input matrix is defined by using a stride value. After the convolutional layer, the next layer is a pooling layer which is used to reduce the computational loss of the network. Some popular pooling functions such as average, L2 norm, minimum, and maximum pooling are considered here. An example of maxpooling operation is shown in Fig. 3. Further, next to the pooling layer is fully connected layer, in which each neuron in fully connected to each neuron of the flattened version of the previous layer and shown in Fig. 4.

Further, the obtained output depends on the classes used to train the proposed model. In this work, we have classified the output into four different classes which can be recognized as follows:

- **COVID-19:** states the identified COVID-19 positive cases by examining the CXR and CT-Scan images.

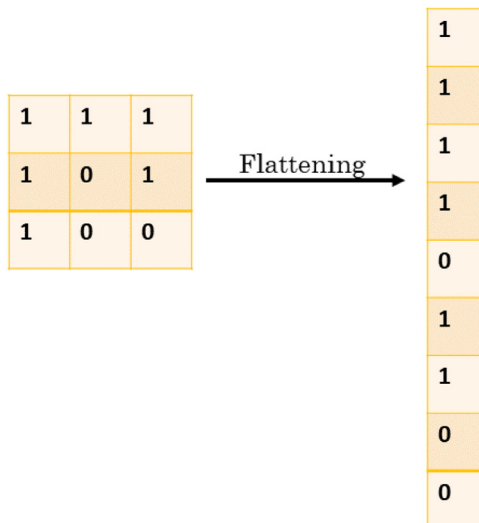


Fig. 4. A sample of the flattening operation.

- **Pneumonia:** states the identified CXR images of patients that consist the patches of Pneumonia infection.
- **Non-COVID-19** includes the radiology images of the patients which are found negative to COVID-19 tests. However, as per descriptions provided for the concerned dataset these patients may have other pulmonary infections.
- **Normal:** Includes the radiology images of various cases which are neutral or negative to COVID-19, Pneumonia and other pulmonary infections.

4.1. Proposed transfer learning model with five extra layers

In this section, we have focused on the problem of binary classification of images with a finite amount of dataset. For addressing the challenges in COVID-19 detection, transfer learning is one of the most considerable methods used for classification of images. In transfer learning, the method of applying the expertise or knowledge is gained from one task to execute another kindred piece of work. The idea turns out to be prominent when working with a limited dataset for the training of the proposed model. We have used VGG-19 as one of the transfer learning techniques as the available dataset of radiology imaging relates to X-rays of COVID-19 patients is limited. In VGG-19, there are 19-weighted layers of deep convolutional neural network using which a comparably outperforming classification accuracy can be achieved. Among these 19-weighted layers, there are 16-convolution layers, and 3-fully connected layers. Here, the proposed model also consists of 5-MaxPool layers and a 1-softmax layer with all hidden layers having rectification non-linearity [23]. The VGG19 model is further trained on ImageNet [25] consisting a big dataset of 14,197,122 images which is categorized into thousands of classes on which it was able to achieve 75.2% top-1 and 92.5% top-5 accuracy. Therefore, we have considered it as one of the base models for the proposed study.

The proposed model consists of 27 layers in which the first layer is the input layer of size $512 \times 512 \times 3$ pixels. Fig. 6 highlights the architecture consisting of an input layer followed by a set of 19-weighted layers accommodating a union of convolutional layers with rectification non-linearity applied and max-pooling layer. In the convolutional layers, filters of size 3×3 consisting of the most user-defined parameters, has been applied to the image. All the Max pooling layers perform the function of obtaining a maximum value in a certain filter patch and result in a reduction of its dimensionality. In VGG-19, Max-Pooling has been performed over a 2×2 pixel window with stride=2 [26]. Here, the fully connected layers are the final set of layers used for flattening the results before the classification of images. Finally, The final layer in this set is the softmax layer which is responsible for the network to run a multi-class function.

Here, the last 5 layers include an Average Pooling 2D layer which also results in dimension reduction by reckoning the aver-

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 512, 512, 3)]	0
block1_conv1 (Conv2D)	(None, 512, 512, 64)	1792
block1_conv2 (Conv2D)	(None, 512, 512, 64)	36928
block1_pool (MaxPooling2D)	(None, 256, 256, 64)	0
block2_conv1 (Conv2D)	(None, 256, 256, 128)	73856
block2_conv2 (Conv2D)	(None, 256, 256, 128)	147584
block2_pool (MaxPooling2D)	(None, 128, 128, 128)	0
block3_conv1 (Conv2D)	(None, 128, 128, 256)	295168
block3_conv2 (Conv2D)	(None, 128, 128, 256)	590080
block3_conv3 (Conv2D)	(None, 128, 128, 256)	590080
block3_conv4 (Conv2D)	(None, 128, 128, 256)	590080
block3_pool (MaxPooling2D)	(None, 64, 64, 256)	0
block4_conv1 (Conv2D)	(None, 64, 64, 512)	1180160
block4_conv2 (Conv2D)	(None, 64, 64, 512)	2359808
block4_conv3 (Conv2D)	(None, 64, 64, 512)	2359808
block4_conv4 (Conv2D)	(None, 64, 64, 512)	2359808
block4_pool (MaxPooling2D)	(None, 32, 32, 512)	0
block5_conv1 (Conv2D)	(None, 32, 32, 512)	2359808
block5_conv2 (Conv2D)	(None, 32, 32, 512)	2359808
block5_conv3 (Conv2D)	(None, 32, 32, 512)	2359808
block5_conv4 (Conv2D)	(None, 32, 32, 512)	2359808
block5_pool (MaxPooling2D)	(None, 16, 16, 512)	0
average_pooling2d (AveragePo	(None, 4, 4, 512)	0
flatten (Flatten)	(None, 8192)	0
dense (Dense)	(None, 64)	524352
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 2)	130
=====		
Total params: 20,548,866		
Trainable params: 5,244,098		
Non-trainable params: 15,304,768		

Fig. 5. Model summary with VGG19 as base model and last 5 layers as a head model.

age values of each region. The average pooling layer is followed by a flatten layer that creates a single feature vector, i.e., it removes all the dimensions except one, in a matrix of features. The single feature vector is then put into a dense layer of 64 units in size. A dropout layer is then applied with a threshold of 0.5, which drops some units to prevent the model from overfitting.

4.2. Explainable deep learning using grad-CAM

A lot of work is being done to make deep learning more sensible and explainable. In various deep learning applications related

to medical imaging, it is very important to make the deep learning model more interpretative. Selvaraju et al. [27], have introduced a Gradient Weighted Class Activation Mapping (Grad-CAM) technique which provides the explainable view of deep learning models. Grad-CAM technique creates the visual explanation for any deeply connected Neural Network and helps in determining more about the model while performing detection or prediction work.

As presented in the Fig. 7, the Grad-CAM takes a simple image as input and detection techniques are applied further by using the proposed model. Once the predicted label has been calculated using the full model, Grad-CAM is applied to any of the Conv layers.

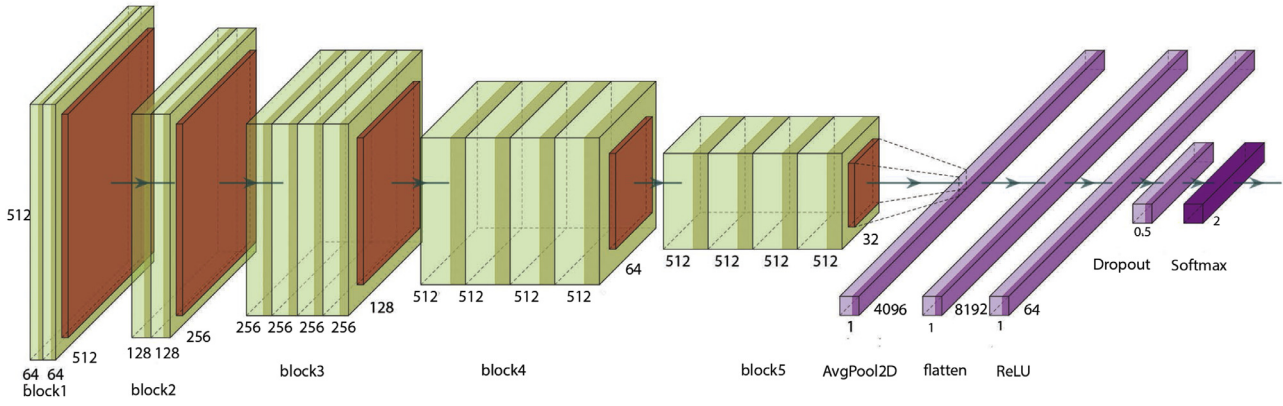


Fig. 6. The Network configuration of VGG19 model for COVID-19.

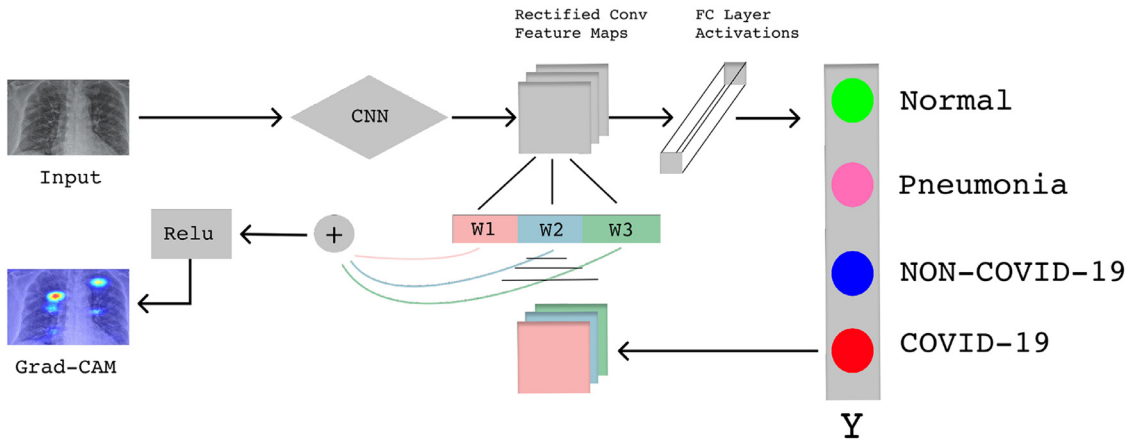


Fig. 7. A simple explanatory diagram of Gradient Weighted Class Activation Mapping (Grad-CAM).

Mostly, the last Conv layer is considered as the layer to be used for applying Grad-CAM.

4.3. Performance evaluation

For evaluating the model we have calculated the precision, recall, F-measure score and accuracy using the confusion matrix as shown in Table 5. These have been calculated by following parameter and equations [28]:

1. **True Positive (TP):** If a COVID-19 infected person is detected as COVID-19.
2. **True Negative (TN):** If a person is correctly detected as NON-COVID-19.
3. **False Positive (FP):** represents incorrect detection where a normal person is detected positive for COVID-19.
4. **False Negative (FN):** represents incorrect detection where a person infected with COVID-19 is detected as normal one.

Based on the confusion matrix parameters, following performance metrics have been computed.

- **Precision** calculates the fraction of correct positive detection of COVID-19. It is calculated by Eq. 4

$$Precision = \frac{TP}{TP + FP} \times 100\% \quad (4)$$

- **Recall** gives how good are all the positives which depends on the percentage of total relevant cases correctly classified by the model. It is calculated from Eq. 5

$$Sensitivity/Recall = \frac{TP}{Predictive\ Results(TP + FN)} \times 100\% \quad (5)$$

- **F-Measure** is a harmonic mean between precision and recall. It is calculated from Eq. 6

$$F - Measure = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (6)$$

$$Specificity = \frac{TN}{FP + TN} \quad (7)$$

$$Accuracy = \frac{TP + TN}{Total\ no.\ of\ predictions} \quad (8)$$

5. Proposed algorithm

The proposed deep transfer learning algorithm mainly focuses on binary classification of images in order to classify the various CXR and CT-Scan images for fast and accurate detection of COVID-19. The proposed algorithm considers the pre-trained weights to extract simple features and then learn the pattern of COVID-19 cases obtained from the patients' CXR and CT-Scan images. The main feature of the proposed technique is that it is fully connected layers with five extra layers in VGG-19 model. Similar to other algorithms it also considers the input dataset. Here, CXR and CT-Scan images which includes the cases of COVID-19, NON-COVID-19, Pneumonia and Normal, have been considered. The dataset is represented using δ_n where n represents the n^{th} class. As, we have considered the binary image classification therefore the value of class will be $n = 2$. For this, Here, we can select any required datasets i.e δ_1 or δ_2 to the input variables in Algorithm 1. However, for multiclass image classification the value of n should be ≥ 2 . The main steps of the proposed algorithm are as follows:

Algorithm 1: Image Classification for COVID-19.

Input : $\delta_1 \rightarrow$ dataset containing class 1 labelled images
 $\delta_2 \rightarrow$ dataset containing class 2 labelled images
 $\mu \rightarrow$ learning rate
 BS \rightarrow batch size
 $\epsilon \rightarrow$ number of epochs

Output: $\omega \rightarrow$ CNN weights

begin;

1. Selecting Train, Test and Validate data split.
2. Calculating class weights for train sets.
3. basemodel - VGG19(weights, imagenet)
4. layers - VGG19(weights, none)
5. newmodel - Output(basemodel)
6. layers- Set CNN(averagepooling2d, flatten, dense, dropout, dense_1) layers on top of VGG19 layers.
7. Initialize the hyperparameters: μ , BS, ϵ
8. Train the CNN model and store the output weight (ω).

for $\epsilon = 1$ **to** *callback* **do**

Forward propagation and compute the binary cross-entropy loss.

Backpropagation and update adam optimizer.

end

- **Step1: Generate the train, validate, and test dataset-** generates three required sub-datasets from the input dataset. Here, the first sub-dataset is a training dataset in which the sample of data is used to fit the model for learning purposes. In the second sub-dataset of validation, a set of samples is considered to tune the various hyper-parameters for an unbiased evaluation of the classifier while selecting the number of hidden units in a neural network. Finally, test sub-dataset which is a random set of samples used to assess the performance of a fully-specified model. The split ratio of training, validation, and testing sub-dataset are considered 64, 20, and 16 respectively.
- **Step2: Prepare the base model and the new model**
 In this step, we have used VGG-19 with pre-trained weights on ImageNet as a base model. The proposed model has been trained for adapting and learning the basic features (e.g., edges and boundaries) of computer vision which ensures that the model needs not to learn every time from scratch while training on CXR and CT-Scan image datasets. After certain attempts of experimentation's we have explored the most suitable hyper-parameters as shown in Table 1 using which the best accuracy for the proposed model has been obtained.
- **Step 3: Update and store the trained weights**
 Finally, these weights have been used to detect COVID-19 cases. Forward propagation does the calculation process and obtains the values of the output layers from the inputs data. It traverses through all the neurons and covers each layer from the beginning. The binary cross-entropy loss function is then calculated

Table 1
Hyper-parameters values used in the experiments.

Hypermeters	Values
Batch Size	15 Samples
Train Validate Test Split ratio	64:20:16
Optimizer	Adam
Rotation range	15
Zoom range	0.05
Width shift range	0.1
Height shift range	0.1
Shear range	0.05
Input size	512*512 pixels
Dropout	0.5

using Eq. 9 from the output values. As the backpropagation occurs, it counts the number of changes in the weights. The computation process begins from the last layer onwards i.e starting from the backward layer to the first layer. Forward and backward pass together contributes to one iteration. During this one iteration, a subset of the data set is passed and depicted as per batch size (BS) which is also known as one epoch and represents passing of entire data set at once.

$$\text{Cross Entropy} = -(y \log(p) + (1 - y) \log(1 - p)) \quad (9)$$

where, y denotes the true value, and p denotes the probability predicted by model.

6. Experimental results and discussion

In this work, we have performed three different experiments on three different datasets of radiology imaging. These experiments can be broadly classified into (1) Binary Image Classification on CXR of COVID-19 positive patients vs. CXR of Normal Patients (2) Binary Image Classification on CXR of COVID-19 positive patients vs. CXR of Pneumonia patients and (3) CT Scan of COVID-19 positive patients vs. CT Scan of NON-COVID-19 patients.

6.1. Experiment-1: COVID-19 vs normal

In this experiment, we have applied the proposed deep learning Algorithm 1 to classify COVID-19 infected cases from the Normal cases. For this purpose, we have used 206 CXR images of COVID-19 infected patients from the COVID-chest X-ray-dataset [18] and 364 CXR images of Normal patients from the CXR Images (Pneumonia) dataset [20,21], the count of the cases are highlighted in Fig. 8a. The primary dataset is divided into three sub-datasets i.e. training, validation, and testing sets. In train and test split, we have used 80% of images for training, and the remaining 20% for testing purposes. However, for validation purpose we have used 20% of images from the 80% of training images.

COVID-19 positive cases dataset distribution is 132,42, and 32 for training, validation, and testing respectively. Whereas, for the Normal Patients the dataset distribution is 232, 72, and 60 for training, validation, and testing purposes respectively. Once the dataset has been classified, we can apply the proposed deep learning model using Algorithm 1 on the distributed dataset.

The training accuracy, validation accuracy, training loss, and validation loss graphs are shown in the Fig. 9. As represented by a red dot on curve line of training accuracy and validation accuracy, we have obtained the best results for the proposed model on the 13th epoch. The significance of the proposed model is that it automatically avoids overfitting issue through early stopping method. Therefore, it gets stopped at 29th epoch as plotted in Fig. 9. The performance of the proposed model has been calculated by using the confusion matrix as shown in Table 2. Based on this, we have calculated the sensitivity and specificity of the proposed model. The sensitivity and specificity of the proposed model is 76.19%, and 97.22% respectively. From these results, we can infer that any patient who visits the hospital and is COVID-19 Negative (i.e., True Negatives) can be detected as Normal with very high accuracy during the tests by using the CXR and CT-Scan images. The radiologist further can apply color visualization approach using Grad-

Table 2
Confusion Matrix for the experiment-1.

		Predicted Class	
		COVID-19 (Class-1)	Normal (class 2)
Actual Class	COVID-19 (Class-1)	TP = 32	FN = 10
	Normal (class 2)	FP = 2	TN = 70

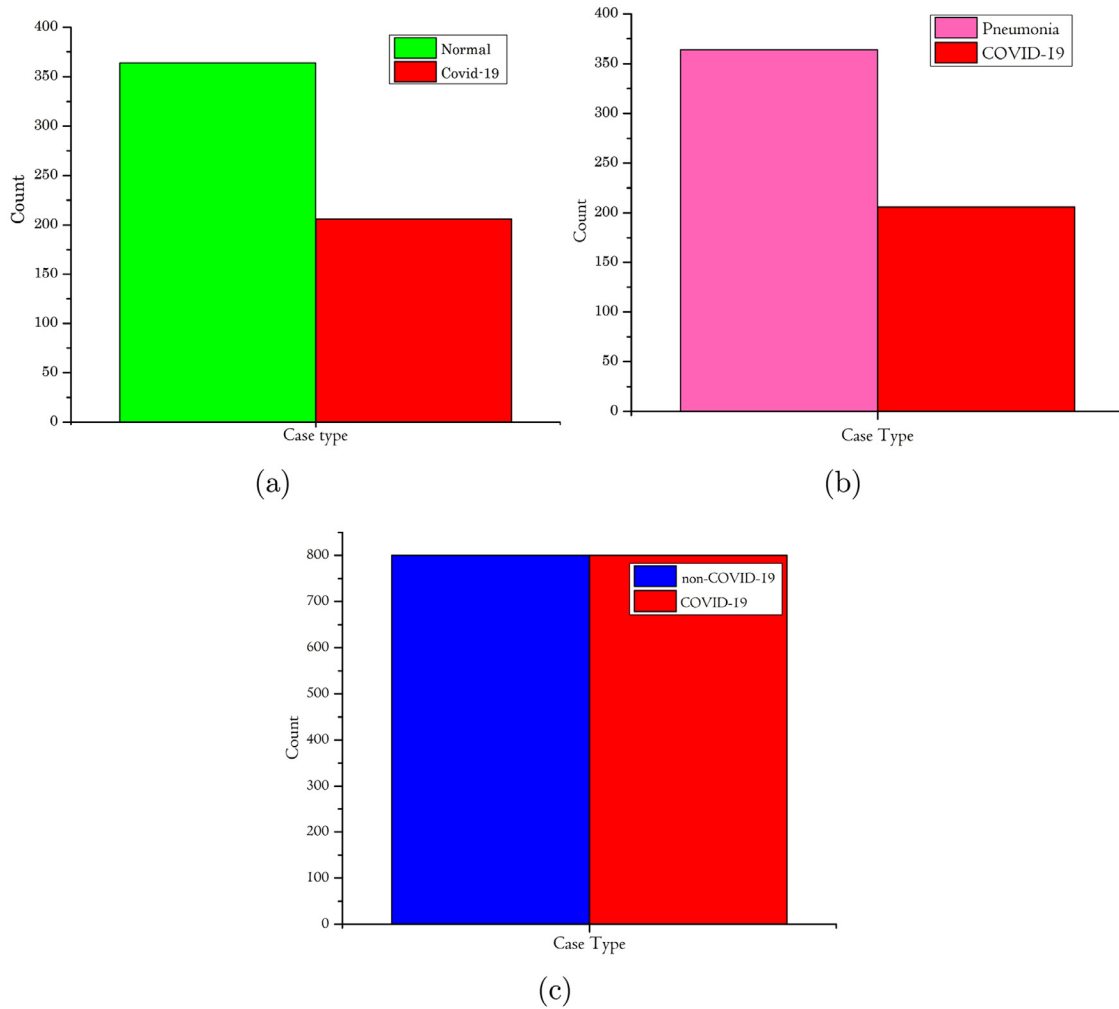


Fig. 8. Frequency of each Class in the Dataset (a) Number of images in Normal (364) and COVID-19 (206) class, (b) Number of images in COVID-19 (206) and Pneumonia (364) class, (c) Number of images in COVID-19 (800) and Non COVID-19 (800) class.

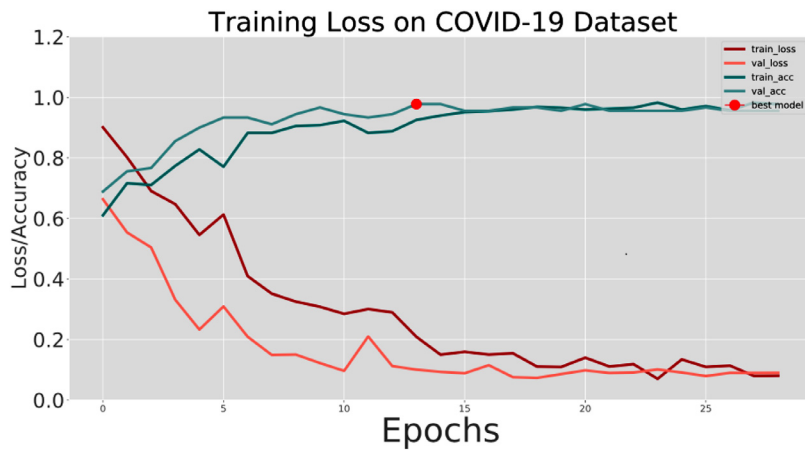


Fig. 9. Training loss, Validation loss, Training accuracy, Validation accuracy and early stopping for experiment 1.

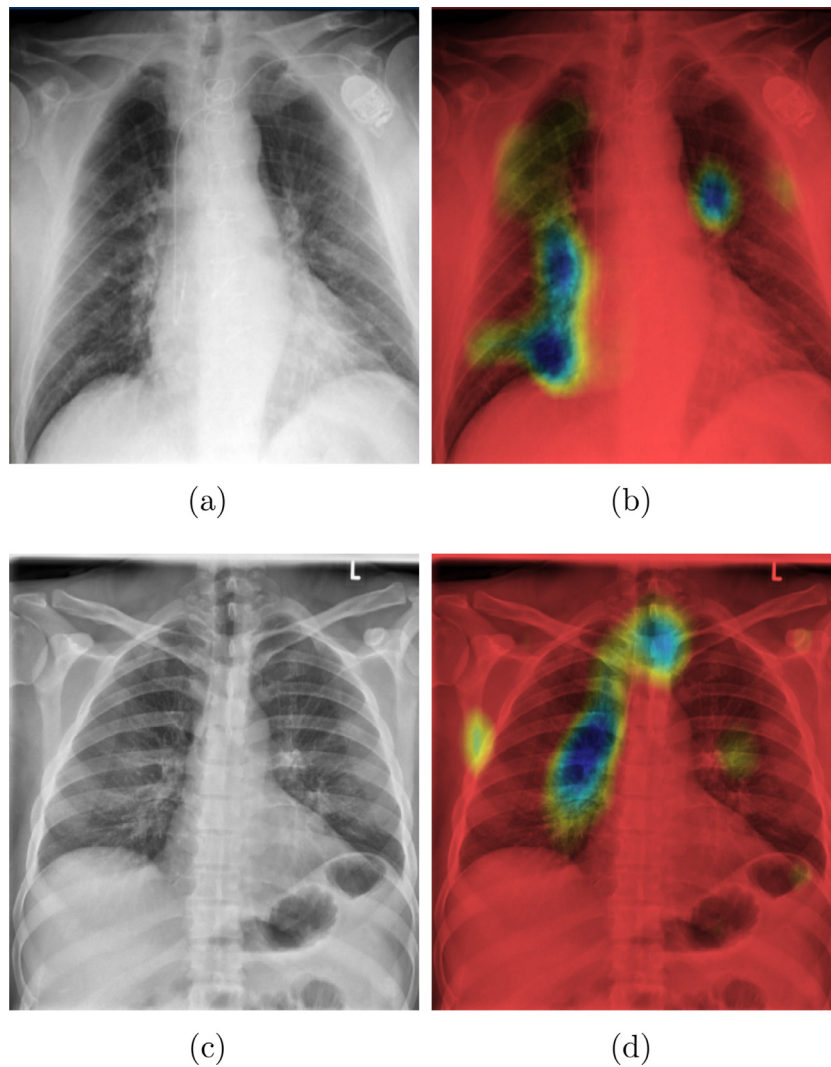


Fig. 10. Visualisation on CXR of COVID-19 infected person using Grad-CAM on the trained model. (a) Original CXR for COVID-19 vs Normal (Experiment-1), (b) Class activation map for COVID-19 vs Normal (Experiment-1), (c) Original CXR for Pneumonia vs COVID-19 (Experiment-2), (d) Class activation map for Pneumonia vs COVID-19 (Experiment-2). [Notes: The high-intensity visuals (blue and green) reflects the area of interest to our model at the time of prediction]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

CAM for making efficient and confident decision because of clear visibility of the images as shown in Fig. 10a and b. The recall, precision, and F1-score are also mentioned in the Table 5. From Table 5, we can find that proposed model has achieved an overall accuracy of 89.47% along with better understanding of the predictions of the deep learning model, by implementing the Grad-CAM technique.

6.2. Experiment-2: Pneumonia vs COVID-19

The count of images of Pneumonia and COVID-19 are highlighted in Fig. 8b. The objective of this experiment is to explore the relationship between COVID-19 positive and Pneumonia cases. In case of pneumonia, we have considered the CXR Images of Pneumonia [20,21] which has been compiled around 2–3 years ago i.e., much before the outbreak of COVID-19. Whereas, for the COVID-19 positive patients, we have considered the same data as provided in Experiment-1. The dataset split is performed in the same way as it has been done for Experiment-1, and the final distribution is 231,85, and 48 for training, testing, and validation purposes respectively for Pneumonia patients, and 133, 29, and 44 for training, testing, and validation purposes respectively for COVID-19 positive

patients. Algorithm 1 is further applied to train the dataset on the proposed deep learning model.

Here, values obtained after Experiment-2 for training accuracy, validating accuracy, training loss and validation loss are shown in the Fig. 11. This indicates the training accuracy $\approx 97\%$ after the first epoch only. However, the best model with 100% training accuracy is achieved on the 6th epoch and the model gets stopped early on the 21st epoch. to avoid overfitting.

From Table 3, we have calculated the performance parameters. Here, the obtained sensitivity is 96.55%, and the specificity is 95.29% for the positive cases of COVID-19. From the obtained results, we can infer that proposed model can detect COVID-19 patients (i.e. true positive) with 96.55% of accuracy. Further, the recall, precision and F-1 Score has been evaluated from the confusion Matrix as shown in Table 3. These calculated values are shown in Table 5. The overall accuracy of proposed model is 96.55% while detecting the COVID-19 cases correctly. For better understanding and presentation of finding the patches on the lungs, we have also implemented the color visualization approach on images by using Grad-CAM technique. These results are shown in Fig. 10c and d. Here, we can find the clear patches in the chest CXR and CT-Scan images of COVID-19 positive cases.

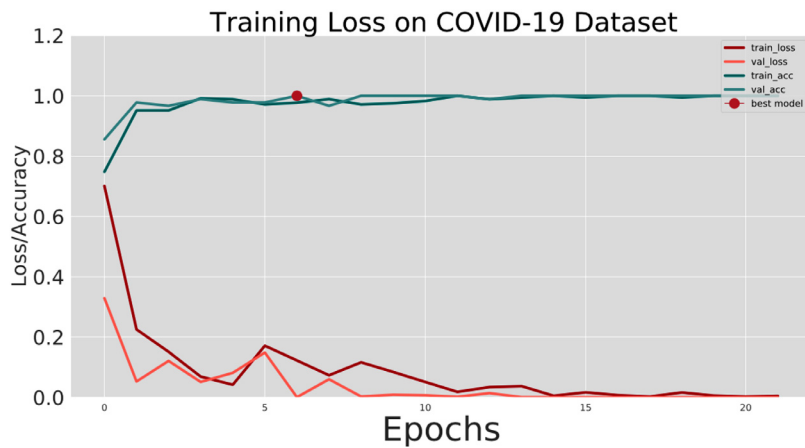


Fig. 11. Training loss, validation loss, training accuracy, validation accuracy and early stopping for experiment 2.

Table 3
Confusion Matrix for the experiment 2.

		Predicted Class	
		COVID-19(Class 1)	Pneumonia(class 2)
Actual Class	COVID-19(Class 1)	28	1
	Pneumonia(class 2)	4	81

Table 4
Confusion Matrix for the experiment 3.

		Predicted Class	
		COVID-19(Class 1)	Non-COVID-19(class 2)
Acutal Class	COVID-19(Class 1)	142	9
	Non-COVID-19(class 2)	7	162

Table 5
Evaluation of Binary Class Image Classification.

Exp	Class-1			Class-2			Overall Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
Exp-1	0.94	0.76	0.84	0.88	0.97	0.92	89.47%
Exp-2	0.88	0.97	0.92	0.99	0.95	0.97	95.61%
Exp-3	0.95	0.94	0.95	0.95	0.96	0.95	95%

6.3. Experiment-3: COVID-vs non-COVID

In this experiment, we have compared the results as obtained by CXR and CT-Scan images for COVID-19 vs. Non-COVID-19 cases. For this, CT-scan dataset of SARS-COV-2 is trained on the model for both COVID-19 and NON-COVID-19 cases. Both the cases have equal number of images i.e., 800 as highlighted in Fig. 8c. The epochs vs loss/accuracy graph is shown in Fig. 12. This indicates the best model has been obtained on the 33rd epoch. However, it gets stopped early at 47th epoch to avoid any overfitting scenario.

Through the confusion matrix presented in Table 4, sensitivity, and specificity values have been calculated, which are 94.04% and 95.86% respectively. From these results, we can claim that a COVID-19 patient can be tested accurately along with 94.04% accuracy. We have also observed that CT Scans are relatively more reliable to use in training our model as the CT Scans images provide a better and detailed description to the radiologist.

The proposed model as trained in experiment 3, also provided distinguished results when applied color visualization approach using Grad-CAM technique and displayed the affected regions of lungs. These obtained results are shown in Fig. 13a and b. Once,

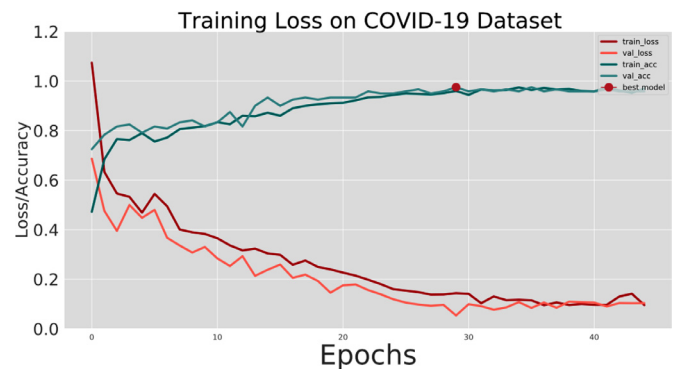


Fig. 12. Training loss, validation loss, training accuracy, validation accuracy and early stopping for experiment 3.

the proposed model is trained on CT-Scan images, the same can detect the COVID-19 patients successfully on random CXR images as shown in Fig. 13c and d. SARS-COV-2 CT Scan dataset is one of the most current dataset that has maximum number of COVID-19 and NON-COVID-19 radiology images [19].

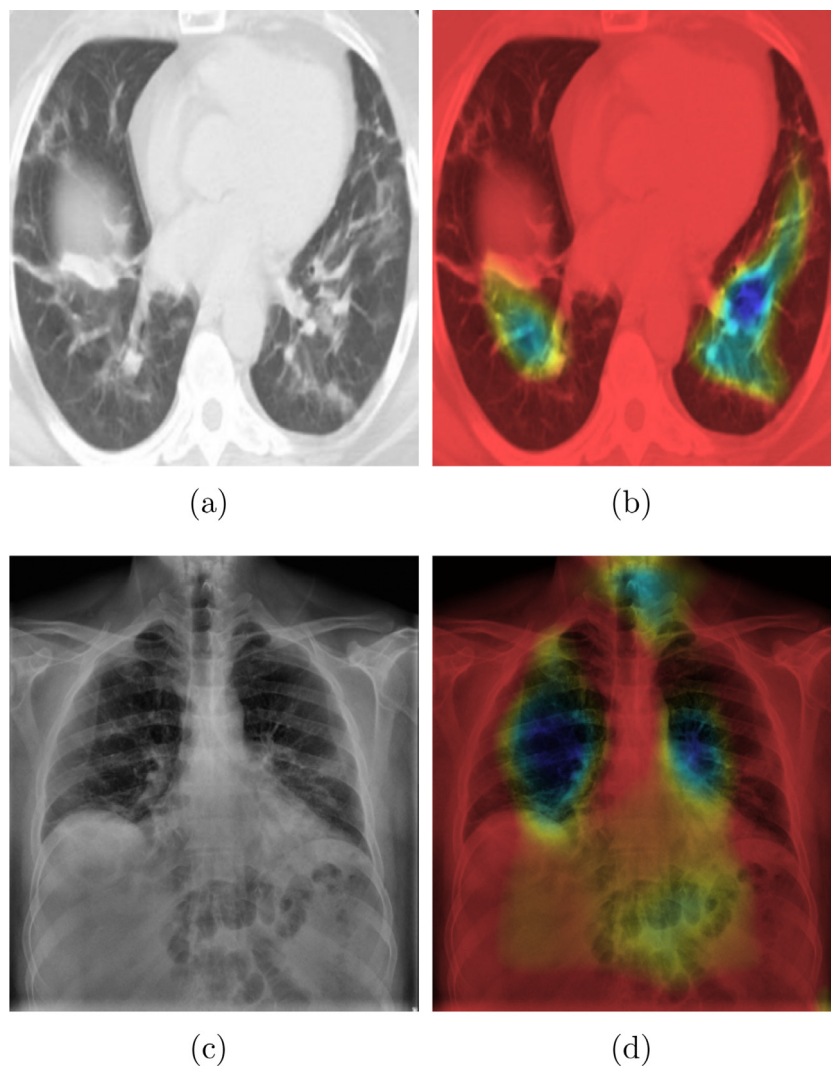


Fig. 13. Visualisations of Experiment-3 for COVID-19 vs. Non-COVID-19 infected person using Grad-CAM on the trained model. (a) Original CT-Scan image, (b) Class activation map of original CT-Scan image, (c) Original CXR image, (d) Class activation map of original CXR image. [Notes: The high-intensity visuals (blue and green) reflects the area of interest to our model at the time of prediction]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

7. Conclusion

In this work, we have performed experiments on binary image classification for the detection of COVID-19 and Non-COVID-19 positive patients. Further, from the analysis, it is revealed that non-COVID-19 positive patients may have Pneumonia or other pulmonary diseases. In various experiments for detecting the COVID-19 cases, we have considered the CXR and CT-Scan images of the chest. The proposed model provides an accuracy of 95.61% while detecting the COVID-19 cases which is much faster than the traditional RT-PCR testing approach. The weights obtained from the training of the proposed model during the processing of CT Scan images also provide a significant response to CXR images. In our experiments, we have also applied a color visualization approach by using the Grad-CAM technique to make the proposed deep learning model more interpretable and explainable. The obtained results reveal that the patient diagnosed with Pneumonia has more chances to get tested as a False Positive by the proposed algorithm. Therefore, to detect the COVID-19 cases accurately with higher recall, it is suggested to train the model on radiology images of patients with Pneumonia symptoms as well. This will help us to detect pneumonia patients as True Negative (just for clarification here, COVID-19 cases are True Positive) which were previously de-

tected as false positive. This results in an unbiased detection of COVID-19 cases in a real-time scenario.

Declaration of Competing Interest

None.

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