COVID-19 Detection on Chest X-Ray and CT Scan Images Using Multi-image Augmented Deep Learning Model

Kiran Purohit, Abhishek Kesarwani, Dakshina Ranjan Kisku, and Mamata Dalui

Abstract COVID-19 is a deadly and highly infectious pneumonia type disease. RT-PCR is a proven testing methodology for the detection of coronavirus infection in spite of having a lengthy testing time. Sometimes, it gives false-positive results more than the desired rates. To support the conventional RT-PCR methodology or testing independently without RC-PCR methodology for correct clinical diagnosis, COVID-19 testing can be acquired with images of X-Ray and CT Scan of a person. This image-based analysis will make a radical change in the detection of coronavirus in the human body with negligible false-negative and false-positive results. For the detection of COVID-19 in CT Scan and X-Ray images of coronavirus suspected individuals, this paper uses a multi-image augmented Convolutional Neural Network (CNN). For training the CNN model, multi-image augmentation utilizes discontinuity information acquired from the edged images to increase the meaningful examples. With this method, the proposed model exhibits a higher classification accuracy of around 98.97% for X-Ray and 95.38% for CT Scan images. Using multi-image augmentation, X-Ray images achieve a specificity of 98.88% and a sensitivity of 99.07% whereas a specificity of 95.98% and sensitivity of 94.78% are achieved in CT Scan images. The experimental results are also compared with VGG-16 and ResNet-50 models. The evaluation has been performed on publicly available databases comprising chest images of both X-Ray and CT Scan.

Keywords Coronavirus · CNN · Image augmentation · X-Ray · CT Scan

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D. Giri et al. (eds.), *Proceedings of the Seventh International Conference on Mathematics and Computing*, Advances in Intelligent Systems and Computing 1412,
https://doi.org/10.1007/978-981-16-6890-6_30

1 Introduction

COVID-19 or Coronavirus is a deadly disease which so far has infected millions of people and deaths are increasing day by day. Due to the deadly infectious nature of coronavirus, it is spreading rapidly among people who are exposed to COVID-19 infected individuals.

Due to unknown causes of pneumonia type infection and the ability to generate new strain by mutation, it is almost impossible to have a cure in the form of vaccine or medicine for COVID-19 affected individuals. In the affected countries, a standard diagnostic method called (RT-PCR) reverse transcription polymerase chain reaction is adopted for detection of viral nucleic acid as coronavirus infection in COVID-19 suspected individuals. The test takes four to six hours or even a whole day to give the results. The time for the generation of the result is more compared to the time of the spread of coronavirus and sometimes, it gives false-negative and false-positive results. The false-negative rate for SARS-CoV-2 RT-PCR testing is profoundly factor: most noteworthy in the initial 5 days after exposure (up to 67%), and least on day 8 after exposure (21%). In view of this investigation, SARS-CoV-2 RT-PCR false-negative rate is very high, even at its least on day 8 post-exposure, or 3 days after symptoms. One out of five individuals tested is COVID-19 negative. RT-PCR tests showed 5% false-positive rates. Therefore, for testing COVID-19 rapidly and in a more efficient way, chest images of COVID-19 suspected individuals of CT Scan and X-Ray could be an answer. Moreover, time taken by RT-PCR test, shortage of test kits, and false-positive errors make it inefficient.

In contrast, CT Scan and X-Ray images are widely accepted traditional forms of diagnosing individuals for a number of diseases which is a common practice adopted by radiologists and medics in healthcare. The CT Scan and X-Ray technologies are used for several decades since their inception in medical diagnosis. In many highly affected areas or regions, it is difficult to provide a sufficient number of RT-PCR test kits for testing COVID-19 infection for thousands of corona suspected people. Therefore, to address this issue, COVID detection can be made from chest CT Scan and X-Ray images of corona suspected individuals who are suffering from COVID-19 symptoms.

The previous investigations uncover that contaminated individuals display different visual qualities in Chest X-Ray pictures, as appeared in Fig. 1. In non-ICU patients, these qualities regularly incorporate multifocal, inconsistent reticular opacities and reciprocal ground glass opacities, while thick aspiratory unions in ICU patients. Nonetheless, the manual investigation of these visual attributes on Chest X-Ray pictures requires domain expertise and is challenging. Also, the exponential increment in the quantity of contaminated patients makes it hard to finish the finding in time, prompting high bleakness and mortality.

For CT SCAN, imaging discoveries have mostly included single or numerous injuries, sketchy or segmental GGOs, and reticular markings that essentially followed peribronchovascular and subpleural disseminations. Interlobular septal thickening

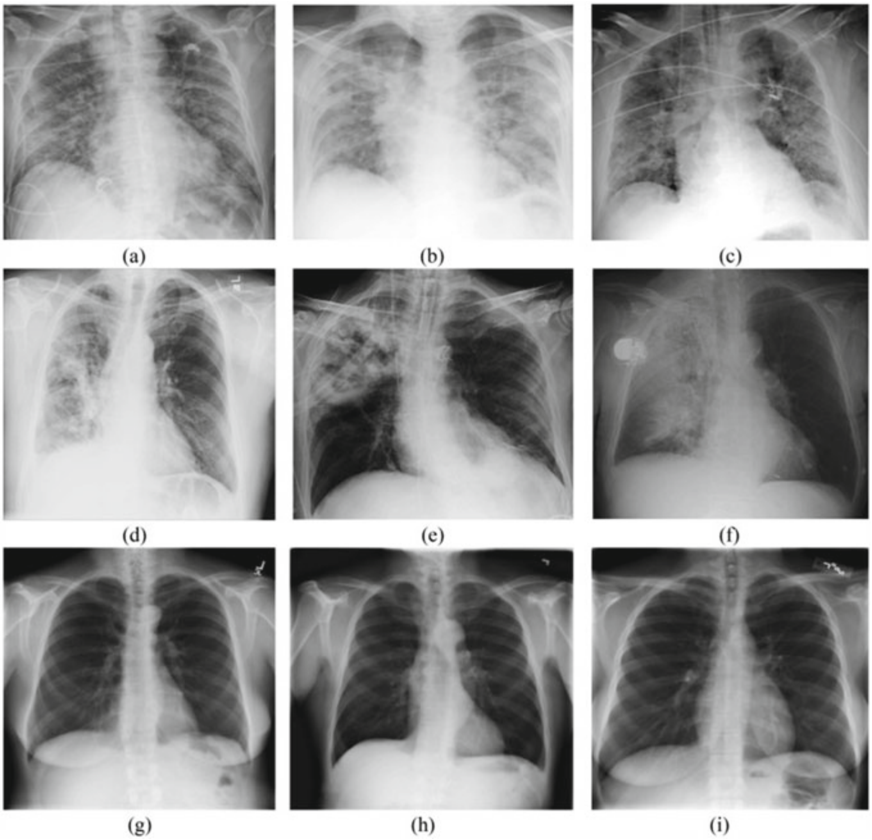


Fig. 1 **a**–**c** Chest X-Ray images infected by COVID-19, **d**–**f** Chest X-Ray images infected by Pneumonia, and **g**–**i** X-Ray images of normal persons [3]

may be available, and pleural emission and extended mediastinal lymph hubs were infrequently observed.

To deal with the issues related to the RT-PCR testing kit, we have come up with a solution by developing an AI-based multi-image augmentation method for the detection of COVID-19 infection in corona suspected persons. With this integrated framework, both chest CT Scan and X-Ray images could be tested for virus detection. This application makes use of multiple representations having sharp discontinuity information of same images of CT Scan and X-Ray, produced through first- and second-order derivative operators, which are mixed up with visible band images of X-Ray and CT Scan for training the deep model. This deep model can learn the underlying pattern of COVID-19 infected images of CT Scan and X-Ray in a more effective way from representative images as well as original images of the same person used for training. Moreover, with a simple configuration of the CNN model, this work performs well for a range of COVID-19 infected chest images of CT Scan and X-Ray.

The main objective of using the deep learning model [21] is to achieve higher accuracy of classification with chest images of CT Scan and X-Ray by separating the COVID-19 cases from non-COVID-19 cases. It is well known that someone needs a huge number of example images of both COVID-19 and non-COVID-19 individuals to train a deep model and to make the model learn about the patterns more effectively. To achieve this target, a number of representative images are generated using sharpening filters technique driven by first- and second-order derivative operators [9] and then these discontinuity information of the images are mixed up with the original CT Scan and X-Ray images separately, and further, these large number of multi-image augmentation are used for training the CNN-based deep model. The databases of images of CT Scan [26] and X-Ray [5] are publicly available in GitHub repository for experimental purpose. Both these datasets contain chest images of COVID-19 and non-COVID-19 individuals. The X-Ray database contains 67 COVID examples and the same number of non-COVID examples whereas the CT Scan database contains 345 COVID examples and the same number of non-COVID examples. To conduct the experiment, images are downsampled to 50×50 dimension from their original size. The random subsampling or holdout method is adopted for testing the model efficacy. In the holdout method, the whole dataset containing COVID positive and negative samples is divided into a number of ratios. It has been observed that when the number of training examples is increased, the model exhibits higher accuracy. Moreover, this result exhibits more consistency while layers are being changed in CNN-based deep model. To evaluate the framework in a robust and effective way, a number of metrics used are classification accuracy, F1-score, recall, precision, confusion matrix, loss, and area under curve (AUC). The values of these metrics have been determined on different ratios of training and test samples considering a number of layers in the deep model. The model correctly classifies the chest CT Scan and X-Ray images of COVID-19 cases from non-COVID-19 cases. Contributions are summarized as follows:

- Hybrid edge detection operator (novel operator) is used with other edge detectors to obtain the augmented images of CT Scan and X-Ray.
- The experiment used both images of CT Scan and X-Ray to evaluate the performance of the proposed methodology in a more exhaustive way.
- A fair comparison of the proposed methodology with the existing methods is presented to prove the efficacy for detecting COVID-19.
- The proposed methodology is evaluated with two powerful deep networks such as ResNet-50 and VGG-16 on the same set of databases of CT Scan and X-Ray.

The paper is organized as follows. Section 2 proposes the methodology to detect COVID-19 infections in chest images of CT Scan and X-Ray. Experimental results, analysis, and comparison among various deep learning models are presented in Sect. 3. In the last section, concluding remarks are made.

2 Proposed Work

For COVID-19 detection in chest images of CT Scan and X-Ray, the proposed methodology uses a number of sharpening filters such as Roberts, Prewitt, Sobel, Laplacian, Canny, Scharr, and a novel filter Hybrid.

2.1 Hybrid Filter Generation

For strengthening the process of detection of sharp discontinuity on images of CT Scan and X-Ray, a novel edge detector is used, which is called Hybrid filter [12]. It uses both Canny [9] and Sobel [9] detector to normalize the noise content as well as provides the high-frequency spatial information. This combination makes the filter helpful for image segmentation and edge detection. The image texture properties are also increased. Here, texton image [10] is used for unique texture which is generated from derivative of Gaussian [25]. Then the texton gradient image is determined by the paired disk masks. The paired disk masks are the pair of half-disk binary images. To get the texton gradient image, the pair of mask is convolved with the texton image, and the distance is calculated between two convolved images with the use of Chi-square metric [13]. The output is obtained by the combination of Sobel and Canny edge detection operator and texton gradient image as shown in Eq. 1.

$$O = Tg \times (w1 \times Canny\_edged\_image + w2 \times Sobel\_edged\_image) \quad (1)$$

where O is the image output, Tg is the image of texton gradient, and $w1$ and $w2$ are the weights ($w1 + w2 = 1$). The design process of the Hybrid filter is shown in Fig. 2.

2.2 Multi-image Representation

Sharpening of an image [9] expands the contrast between dark and bright areas to draw out the features. The sharpening method uses a high-pass kernel to an image. Sharpening is only inverse to blurring. We decrease the edge content in case of blurring, and in sharpening, we increment the edge content. For noisy images, firstly smoothing is done and then a sharpening filter is applied.

The majority of the information about the shape of an image is enclosed in the edges. Firstly, edges are distinguished in an image by the use of first- and second-order derivative operators [9], and afterward by enhancing those edges, image sharpness will increment and the image will become more clear. Consequently, COVID-19

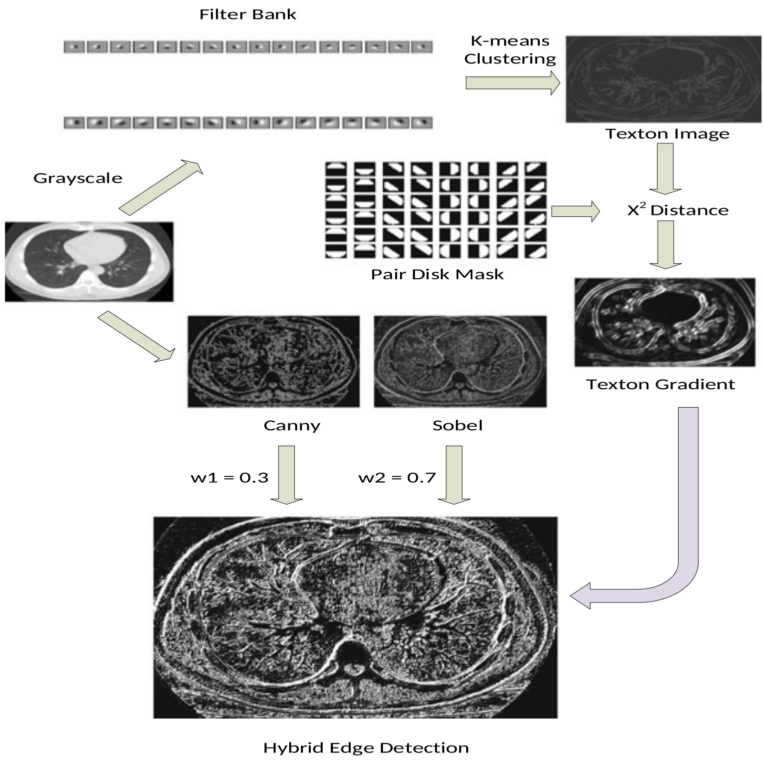
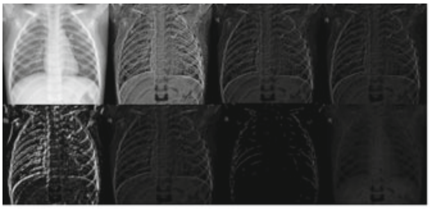


Fig. 2 Flow chart of Hybrid Edge Detector

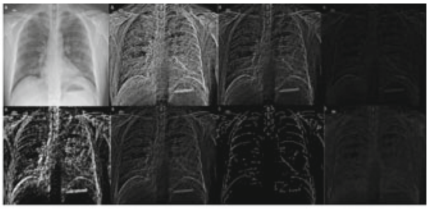
detection on chest images of CT Scan and X-Ray will be more precise and accurate if we detect on the edged image.

The CT Scan [26] and X-Ray [5] databases contain a smaller number of images which may not be useful for training the CNN model. Moreover, with a small number of examples, desired classification accuracy may not be achieved. So, to resolve this issue, we apply multi-image augmentation by increasing the number of examples as well as the diversity of available characteristics with images of CT Scan and X-Ray. For multi-image augmentation, the input is converted into a grayscale image and then histogram equalization is done to correct the contrast of the input grayscale image. To achieve better image representation with discontinuity information, a number of first- and second-order edge detectors such as Roberts, Prewitt, Laplacian, Sobel, Canny, Scharr, and newly developed Hybrid are applied. Then, the results of the edge detection operator are appended to our dataset.

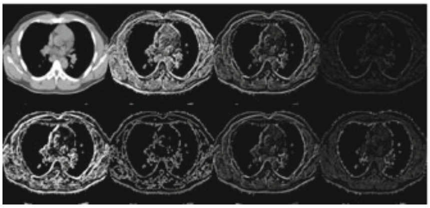
Edge detection operators perform a crucial job in separating low-level features or discovering information of the lungs. A sharp discontinuity change over the boundaries of the gray levels is called an edge. In chest images of CT Scan and X-Ray, edges represent lung boundaries, which occurs due to the change in the gray levels



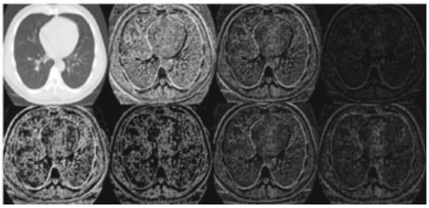
(a) Chest image of X Ray and its Multiple Representations of a COVID-19 Non-Infected Individual.



(b) Chest image of X Ray and its Multiple Representations of a COVID-19 Infected Individual.



(c) Chest CT scan and its Multiple Representations of a COVID-19 Non-Infected Individual.



(d) Chest CT scan and its Multiple Representations of a COVID-19 Infected Individual.

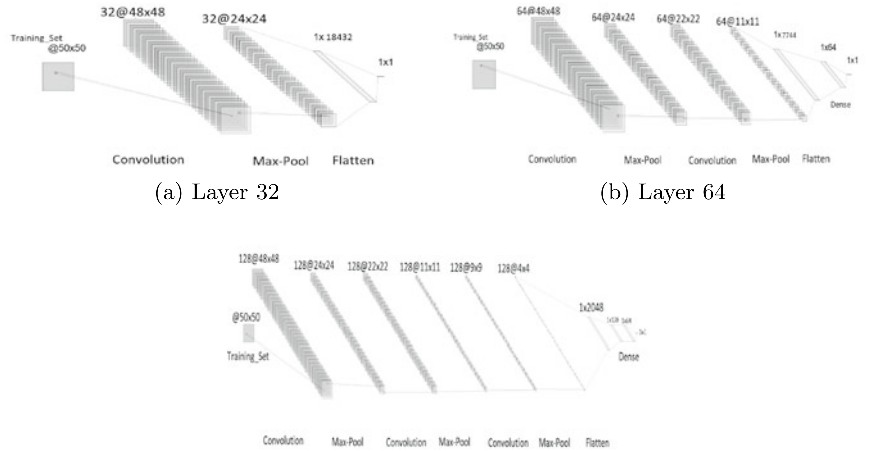
Fig. 3 Multiple representations of chest images of X-Ray and CT Scan

at these lung boundaries. Edges are detected to remove basic and smaller details, increasing the speed and reducing the complexity without losing useful data. Here, significant data is retained and non-essential data is separated out. We get more exact and accurate outcomes if the processing is performed on these edged images. Thus, COVID-19 detection on chest images of CT Scan and X-Ray is found to be more precise if detected on the edged image.

Figure 3a shows a chest X-Ray (top left) and its multiple representations obtained by applying sharpening filters, of a person not infected by COVID-19 whereas Fig. 3b shows a chest X-Ray and its multiple representations obtained by applying sharpening filters, of COVID-19 infected person. Figure 3c shows a chest CT Scan image and its multiple representations obtained by applying sharpening filters, of a person not infected by COVID-19 whereas Fig. 3d shows a chest CT Scan image and its multiple representations obtained by applying sharpening filters, of COVID-19 infected person.

2.3 Training and Classification of CNN-Based Deep Learning Model

To perform training and classification with a multi-image augmented CNN model, the basic architecture of LeNet [6] model is exploited. It is used to predict COVID



(a) Layer 32

(b) Layer 64

(c) Layer 128

Fig. 4 Convolution neural network of layer size 32, 64, and 128

and non-COVID examples from images of X-Ray and CT Scan. The deep CNN model uses three layers such as convolutional, pooling, and fully connected layers. Two activation functions viz. RELU and sigmoid are used. RELU is used after the convolutional layer and the sigmoid function is used for the classification of test images into COVID and non-COVID classes. Figure 4 shows the deep model with a number of parameters. In the training stage, a binary cross entropy-based loss function and the standard Stochastic Gradient Descent (SGD) optimizer with 32 as batch size are used. The learning rate is set as 0.01, which is linearly decayed and the maximum epoch is set to 30. To conduct the experiment, images are downsampled to 50×50 dimension from their original size. The random subsampling or holdout method is adopted to test model efficacy. In the holdout method, the whole dataset containing COVID positive and negative samples is divided into a number of ratios like 90:10, 80:20, 70:30, and 60:40 as training and testing samples. In order to alleviate the overfitting of the model, multi-image augmentation is used for training the model using sharpening filters. This augmentation generates a large number of representative images carrying discontinuity information.

Steps for detection of coronavirus infection in the images of CT Scan and X-Ray of suspected individuals:

Step 1: Accept the colored input images from the dataset.
Step 2: Convert the image into grayscale.
Step 3: Downsample the images to 50×50 dimension from their original size.
Step 4: In CNN-based deep learning model, we choose $layer\_sizes = [32, 64, 128]$, $dense\_layers = [0, 1, 2]$, and $conv\_layers = [1, 2, 3]$.
Step 5: Convolution with a 3×3 filter size is applied.
Step 6: Activation function RELU is used after convolutional layer.

Step 7: Then Max Pooling is applied with 2×2 filter size.
Step 8: Go to Step 5 if $conv\_layer - 1 > 0$.
Step 9: Flatten the matrix.
Step 10: Activation function Sigmoid is used for classification of test image into COVID and non-COVID classes.
Step 11: In training stage, the standard binary cross entropy loss, first-order SGD optimizer with 32 as batch size, and maximum epochs 30 are used.
Step 12: The random subsampling or holdout method is adopted. Whole dataset is divided in ratios like 90:10, 80:20, 70:30, and 60:40 as training and testing samples.
Step 13: Various metrics are evaluated such as F1 Score, recall, precision, accuracy, confusion matrix, loss, and area under ROC curve (AUC).
Step 14: Once the model is trained, one can easily predict whether the individual is affected by Coronavirus infection or not.

3 Evaluation

3.1 Experimental Protocol and Metrics

The proposed augmented deep model, VGG-16 and ResNet-50, uses Python and Keras package with TensorFlow [7] with Nvidia Geforce GTX 1050 GPU, 16 GB RAM, and Intel i5 Processor. To evaluate the framework in a robust and effective way, a number of metrics such as the area under curve (AUC), precision, F1-score, recall, classification accuracy, confusion matrix, and loss have been used. The values of these metrics have been determined on different ratios of training and test samples considering a number of layers in the deep model. The model correctly classifies the chest images CT Scan and X-Ray of COVID-19 cases from non-COVID-19 cases. The evaluation protocol makes use of the holdout method where the whole dataset containing COVID positive and negative samples are divided into a number of ratios. During testing, the layers are changed in the augmented-based deep model to realize the consistency of the model.

3.2 Experimental Results

It has been observed that when there is an increase in training examples, the model exhibits higher classification accuracy. For the traditional train and test ratio of 70:30, the classification accuracy is obtained around 98.97 and 95.38% for images of X-Ray and CT Scan, respectively. Examples are randomly split into training and testing sets for evaluation. The experiment is conducted twice for every split and it is noted that the accuracy of the model comes similar on both evaluations. F1 scores remain slightly similar and model loss (%) changes as the layer size is increased while setting the layer size to different values. For less training samples, a smaller layer size gives good results whereas if the training samples are increased, then more layers are required for better accuracy. The proposed deep augmented model is also compared with VGG-16 [19] and ResNet-50 [1] architecture.

Visual Geometry Group (VGG), a research group from Oxford University in the United Kingdom, proposed VGG networks. There are two commonly used networks, i.e., VGG-19 and VGG-16, here "19" represents 19 deep layers consisting of 3 Fully Connected (FC) layers and 16 Convolutional Layers (CL) whereas the "16" means 3 FC layers and 13 CL. The size of the input image in this network is $224 \times 224 \times 3$. VGG network uses an ImageNet pre-trained model which cannot improve the accuracy of COVID-19 screening as it contains a new set of images with labels. "Residual Network" also called ResNet, contains the width and depth of the neural network. These two core factors decide the complexity of the neural network. As the depth of the neural network increases, the training error increases. So, the residual network is used to solve this problem and increase the network performance (precision and accuracy) as compared to the traditional neural model. The commonly used residual networks are ResNet 18, 34 (two deep layers) and ResNet-50, 101, 152 (three deep layers). ResNet does not perform well in our case due to less amount of training examples.

The proposed deep augmented method achieves the sensitivity of 99.07% when the ratio of train and test samples is 70:30 and specificity of 98.88% when the ratio of train and test samples is 70:30 and layer size is 32 on the X-Ray dataset that contains 536 COVID-19 images and 536 non-COVID-19 images including augmented images. CT Scan dataset contains 2760 COVID-19 images and 2760 non-COVID-19 images individuals including augmented images. The sensitivity of 94.78% and specificity of 95.98% are achieved when the ratio of train and test samples is 70:30 and layer size is 64. Tables 1 and 2 show the result for original and augmented images, respectively.

The model is correctly able to classify chest images of X-Ray and CT Scan of COVID-19 examples from non-COVID-19 examples. The confusion matrix is shown in Fig. 5 for the standard ratio of train and test samples i.e., 70:30 for images of CT Scan and X-Ray with multi-image augmentation and without multi-image augmentation on three different architectures as proposed. ROC curves for images of CT Scan and X-Ray exhibiting higher accuracy when the ratio of train and test is 70:30 are shown in Fig. 7.

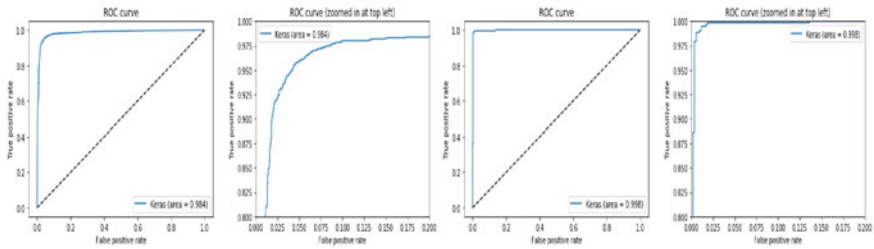
The ROC curve determined on X-Ray images with 64 layers is not shown because it seems like an overfitting having AUC as 1. Table 3 shows COVID-19 screening performance of models having higher accuracy with different train-test values. Figure 6 shows the optimal accuracy comparison between original and augmented techniques on both datasets of CT Scan and X-Ray. It is found that in the X-Ray dataset, the accuracy slightly differs in both original and augmented techniques due to less number of examples. Whereas, in the CT Scan dataset, the augmented technique performed with a number of representative images is found better than the non-augmented technique with original images. Proposed and existing models classification accuracies are shown in Table 4. The existing models either used CT Scan images or X-Ray

Table 1 COVID-19 screening performance in original images with CT scan and X-Ray datasets

	CT Scan images					X-Ray images				
	Proposed			ResNet	VGG	Proposed			ResNet	VGG
Train-Test	Layers					Layers				
60–40%	**32**	**64**	**128**	**50**	**16**	**32**	**64**	**128**	**50**	**16**
Accuracy (%)	88.7	90.87	87.68	88.7	78.7	98.51	99.25	98.51	50	98.51
Loss (%)	31.45	36.13	65.75	70.9	45.73	6.49	2.59	13.16	23.89	6.25
AUC (%)	94.5	95.2	93.5	88.7	78.7	99.9	100	98.5	50	98.5
Precision	0.86	0.9	0.89	0.91	0.72	0.97	1	0.97	0.5	0.97
Sensitivity (%)	92.17	92.17	85.51	85.5	93.62	100	98.51	100	1	100
Specificity (%)	85.22	89.57	89.86	91.88	63.76	97.01	100	97.01	0	97.01
F1 Score	0.89	0.91	0.87	0.88	0.81	0.99	0.99	0.99	0.67	0.99
70–30%	**32**	**64**	**128**	**50**	**16**	**32**	**64**	**128**	**50**	**16**
Accuracy (%)	89.57	92.03	90.29	78.84	77.54	99.25	97.1	100	50	98.51
Loss (%)	29.79	26.81	50.84	15.6	45	5.21	12.09	2.22	55.6	6.19
AUC (%)	94.8	95.9	95.7	78.8	77.5	100	99.8	100	50	98.5
Precision	0.91	0.93	0.87	0.71	0.76	0.99	1	1	0.5	0.97
Sensitivity (%)	87.25	91.01	95.07	97.39	81.15	100	94.03	100	88.05	100
Specificity (%)	91.88	93.04	85.51	60.28	73.91	98.51	100	100	11.94	97.01
F1 Score	0.89	0.92	0.91	0.82	0.78	0.99	0.97	1	0.64	0.99
80–20%	**32**	**64**	**128**	**50**	**16**	**32**	**64**	**128**	**50**	**16**
Accuracy (%)	94.06	95.22	94.35	93.48	78.7	99.25	97.01	99.25	51.49	98.51
Loss (%)	18.93	17.16	41.09	28.3	42.97	3.84	6.27	12.05	10.57	5.02
AUC (%)	98.1	98	96.8	93.5	78.7	100	100	98.6	51.5	98.5
Precision	0.93	0.95	0.94	0.93	0.72	0.99	1	0.99	1	0.97
Sensitivity (%)	95.07	95.65	94.78	94.49	93.04	100	94.03	100	2.98	100
Specificity (%)	93.04	94.78	93.91	92.46	64.34	98.51	100	98.51	1	97.01
F1 Score	0.94	0.95	0.94	0.94	0.81	0.99	0.97	0.99	0.06	0.99
90–10%	**32**	**64**	**128**	**50**	**16**	**32**	**64**	**128**	**50**	**16**
Accuracy (%)	94.93	**98.26**	98.26	94.49	83.33	99.25	**100**	99.25	50	99.25
Loss (%)	20.65	**9.47**	11.68	31.83	40.26	3.21	**1.08**	2.2	68.33	3.95
AUC (%)	98.4	**99.5**	99	0.91	83.3	100	**100**	100	50	99.3
Precision	0.97	0.97	**0.98**	0.91	0.79	0.99	**1**	0.99	0.5	0.99
Sensitivity (%)	92.46	**99.42**	98.55	98.26	91.01	100	**100**	100	1	100
Specificity (%)	97.39	97.1	**97.97**	90.72	75.65	98.51	**100**	98.51	0	98.5
F1 Score	0.95	**0.98**	0.98	0.95	0.85	0.99	**1**	0.99	0.67	0.99

Table 2 COVID-19 screening performance in augmented images with CT scan and X-Ray datasets

	CT scan images					X-Ray images				
	Proposed			ResNet	VGG	Proposed			ResNet	VGG
Train-Test	Layers					Layers				
60–40%	**32**	**64**	**128**	**50**	**16**	**32**	**64**	**128**	**50**	**16**
Accuracy (%)	93.46	92.54	91.59	85.53	85.07	98.88	98.79	98.04	93.66	90.39
Loss (%)	22.82	48.46	65.33	59.9	37.15	8.92	10.38	12.12	21.54	21.54
AUC (%)	97.2	96.5	96	85.5	92	99.7	99.4	99.4	93.7	90.4
Precision	0.92	0.93	0.91	0.86	0.88	0.99	0.99	0.98	0.95	0.99
Sensitivity (%)	94.67	91.99	91.74	84.31	81.15	99.06	98.7	97.95	91.97	81.52
Specificity (%)	92.25	93.08	91.45	86.75	88.99	98.7	98.88	98.13	95.33	99.25
F1 Score	0.93	0.93	0.92	0.85	0.84	0.99	0.99	0.98	0.94	0.89
70–30%	**32**	**64**	**128**	**50**	**16**	**32**	**64**	**128**	**50**	**16**
Accuracy (%)	95.05	95.38	92.46	89.02	88.99	98.97	99.44	98.69	90.76	92.26
Loss (%)	19.44	26.97	37.33	52.16	35.49	7.4	**1.91**	8.05	48.19	17.81
AUC (%)	97.8	98.4	97.2	89	93.4	99.7	100	99.6	90.8	92.3
Precision	0.96	0.96	0.95	0.9	0.9	0.99	1	0.99	0.99	0.99
Sensitivity (%)	93.64	94.78	89.38	87.71	87.83	99.07	99.07	98.33	82.27	85.82
Specificity (%)	96.48	95.98	95.54	90.32	90.14	98.88	99.81	99.06	99.25	98.69
F1 Score	0.95	0.95	0.92	0.89	0.89	0.99	0.99	0.99	0.9	0.92
80–20%	**32**	**64**	**128**	**50**	**16**	**32**	**64**	**128**	**50**	**16**
Accuracy (%)	96.47	96.99	95.45	92.75	91.16	99.07	98.88	99.16	96.18	93.1
Loss (%)	13.79	16.39	21.58	31.42	26.25	7.63	5.18	4.87	20.58	17.35
AUC (%)	98.6	99	98.2	92.7	97.1	99.5	99.7	99.8	96.2	93.1
Precision	0.96	0.97	0.95	0.94	0.96	0.99	0.99	0.99	0.99	0.97
Sensitivity (%)	96.73	97.39	95.83	90.83	86.38	99.25	99.25	99.44	92.91	88.99
Specificity (%)	96.2	96.6	95.07	94.65	95.94	98.88	98.52	98.89	99.44	97.2
F1 Score	0.96	0.97	0.95	0.93	0.91	0.99	0.99	0.99	0.96	0.93
90–10%	**32**	**64**	**128**	**50**	**16**	**32**	**64**	**128**	**50**	**16**
Accuracy (%)	98.5	**98.41**	96.9	96.09	92.61	**100**	99.63	99.63	93.38	93.84
Loss (%)	**7.27**	8.75	13.84	14.8	22.28	3.66	2.57	2.5	24.7	16.41
AUC (%)	99.4	**99.6**	99	96.1	97.8	**100**	99.9	100	93.4	93.8
Precision	0.98	**0.98**	0.96	0.95	0.9	**1**	1	1	0.89	0.98
Sensitivity (%)	**98.69**	98.37	97.5	96.88	96.23	**100**	99.63	99.44	99.44	89.92
Specificity (%)	98.29	**98.44**	96.3	95.3	88.99	**100**	99.63	99.81	87.31	97.76
F1 Score	**0.98**	0.97	0.97	0.96	0.93	**1**	1	1	0.94	0.94



(a) CT Scan images with multi-image augmentation having 64 layers when train and test ratio is 70:30 (accuracy=95.38%)

(b) X-Ray images with multi-image augmentation having 32 layers when train and test ratio is 70:30 (accuracy=98.97%)

Fig. 5 ROC curves

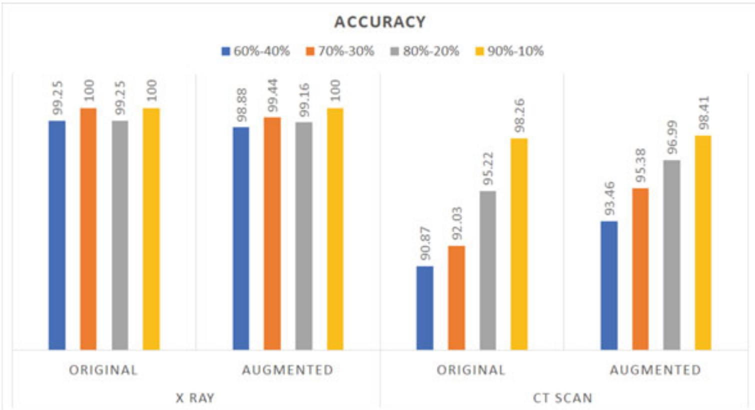


Fig. 6 COVID-19 screening accuracy

images for evaluation. Whereas, the proposed augmented deep model has used both images of CT Scan and X-Ray with a quite large number of samples.

3.3 Comparison

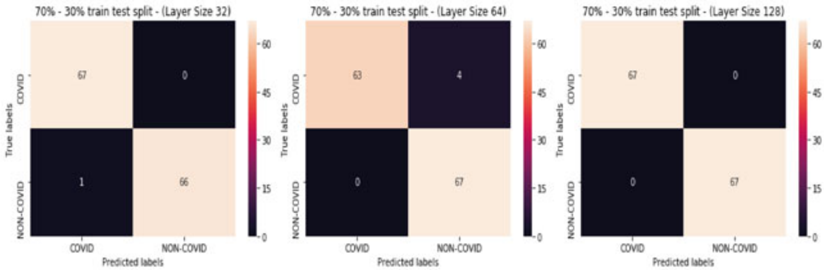
Authors in [11] made a COVIDX-Net for detection of COVID-19 in images of X-Ray. An accuracy of 90% is obtained with 25 COVID-19 (+ve) and 25 normal examples. Authors in [22] developed COVID-Net using deep network to detect COVID-19. It achieved 92.4% accuracy determined on 53 COVID-19 (+ve) and 8066 normal X-Ray examples. Ghoshal et al. [8] used the CNN model on 25 COVID-19 (+ve) examples and obtained an accuracy of 92.9%. Authors in [2] used transfer learning on 224 COVID-19, 700 pneumonia, and 504 normal examples. It obtained 98.75% accuracy in two-class problem and 93.48% accuracy in the three-class problem. Murugan and

Table 3 COVID-19 screening performance of outperforming model with respect to accuracy having different train and test values

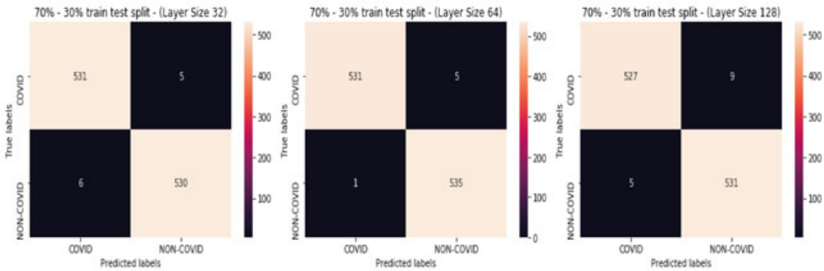
	Original		Augmented		Original		Augmented	
	CT scan	X-Ray	CT scan	X-Ray	CT scan	X-Ray	CT scan	X-Ray
Train-Test	**60–40%**				**70–30%**			
Layers	**64**	**64**	**32**	**32**	**64**	**128**	**64**	**64**
Accuracy (%)	90.87	99.25	93.46	98.88	92.03	100	95.38	99.44
Loss (%)	36.13	2.59	22.82	8.92	26.81	2.22	26.97	1.91
AUC (%)	95.2	100	97.2	99.7	95.9	100	98.4	100
Precision	0.9	1	0.92	0.99	0.93	1	0.96	1
Sensitivity (%)	92.17	98.51	94.67	99.06	91.01	100	94.78	99.07
Specificity (%)	89.57	100	92.25	98.7	93.04	100	95.98	99.81
F1 Score	0.91	0.99	0.93	0.99	0.92	1	0.95	0.99
	Original		Augmented		Original		Augmented	
	CT Scan	**X-Ray**	**CT Scan**	**X-Ray**	**CT Scan**	**X-Ray**	**CT Scan**	**X-Ray**
Train-Test	**80–20%**				**90–10%**			
Layers	**64**	**32**	**64**	**128**	**64**	**64**	**64**	**32**
Accuracy (%)	95.22	99.25	96.99	99.16	98.26	100	98.41	100
Loss (%)	17.16	3.84	16.39	4.87	9.47	1.08	8.75	3.66
AUC (%)	98	100	99	99.8	99.5	100	99.6	100
Precision	0.95	0.99	0.97	0.99	0.97	1	0.98	1
Sensitivity (%)	95.65	100	97.39	99.44	99.42	100	98.37	100
Specificity (%)	94.78	98.51	96.6	98.89	97.1	100	98.44	100
F1 Score	0.95	0.99	0.97	0.99	0.98	1	0.97	1

Goel [14] used the E-DiCoNet model on three different classes and achieved an accuracy of 94.07%. Authors in [18] made use of CNN to obtain the features of the image and classified it using Support Vector Machine (SVM). They attained an accuracy of 95.38% using SVM and ResNet-50. Authors in [15] applied three different deep models which are Inception-ResNetV2, InceptionV3, and ResNet-50. They achieved 98% accuracy using 50 COVID-19 positive images of X-Ray and 50 normal examples. Tulin et al. [16] applied DarkCovidNet, a deep model to detect COVID-19. They used 1125 images which include 125 COVID-19 positive, 500 (pneumonia), and 500 without any findings to train the model and achieved accuracies of 98.08% for two classes and 87.02% for three classes.

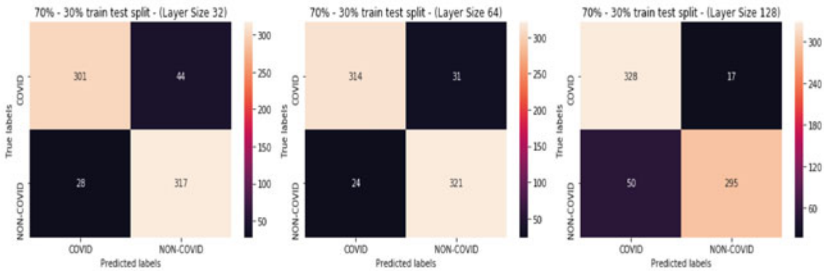
Wang et al. [23] achieved 82.9% accuracy by applying a deep model called modified Inception using CT Scan images of 195 COVID-19 (+ve) and 258 normal examples. Ying et al. [20] obtained 86% accuracy using 777 COVID-19 (+ve) and 708 normal CT Scan examples using DRE-Net, a deep pre-trained ResNet-50 model. Authors in [24] obtained 86.7% accuracy for detection of COVID-19 by applying ResNet coupled with 175 Healthy, 219 COVID-19 positive, and 224 pneumonia CT



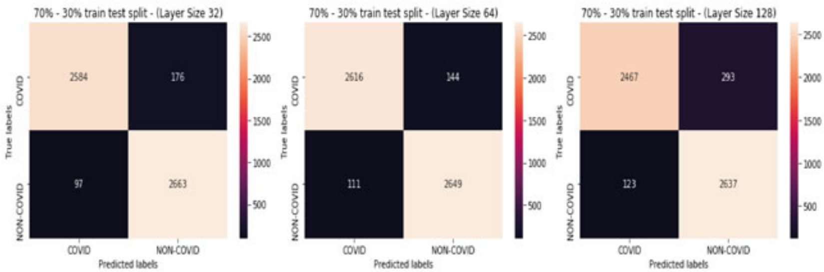
(a) X-Ray images without multi-image augmentation



(b) X-Ray images with multi-image augmentation



(c) CT Scan images without multi-image augmentation



(d) CT Scan images with multi-image augmentation

Fig. 7 Confusion Matrix of our model when train and test ratio is 70:30

Table 4 Comparison among various COVID-19 techniques based on deep learning

Study	Images	Subjects	Methodology	Accuracy (%)
Hemdan et al. [11]	X-Ray	Covid 19(+ve) – 25 Normal(25)	CovidX Network	90
Wang and Wong [22]	X-Ray	Covid 19(+ve) – 53 Healthy(8066) Covid 19(-ve) – 5526	Covid Network	92.4
Ghoshal et al. [8]	X-Ray	Covid 19(+ve) – 25 Others - #Not available	CNN	92.9
Ioannis et al. [2]	X-Ray	Covid 19(+ve) – 224 Healthy(504) Pneumonia(700)	VGG-19 Network	93.48
Murugan & Goel [14]	X-Ray	Covid 19(+ve) – 900 Healthy(900) Pneumonia(900)	E-DiCoNet	94.07
Sethy et al. [18]	X-Ray	Covid 19(+ve) – 25 Covid 19(-ve) – 25	ResNet-50 and SVM	95.38
Narin et al. [15]	X-Ray	Covid 19(+ve) – 50 Covid 19(-ve) – 50	ResNet-50 and Deep CNN	98
Tulin et al. [16]	X-Ray	No Findings – 500 Covid 19(+ve) – 125 Pneumonia(500)	DarkCovidNet	98.08
Wang et al. [23]	CT Scan	Covid 19(+ve) – 195 Covid 19(-ve) – 258	M-Inception	82.9
Ying et al. [20]	CT Scan	Healthy(708) Covid 19(+ve) – 777	DRE-Net	86
Xu et al. [24]	CT Scan	Healthy(175) Covid 19(+ve) – 219 Viral pneumonia(224)	Location Attention + ResNet	86.7

(continued)

Table 4 (continued)

Study	Images	Subjects	Methodology	Accuracy (%)
Zheng et al. [27]	CT Scan	Covid 19(+ve) – 313	3D Deep Network + UNet	90.8
		Covid 19(-ve) – 229		
Pathak et al. [17]	CT Scan	Covid 19(+ve) – 413	Fine-tuned ResNet32	93.01
		Normal(439)		
Chen et al. [4]	CT Scan	Covid 19(+ve) – 51	UNet++ Network	95.2
		Others(55)		
Proposed method	X-ray	Covid 19(+ve) – 536	Multi-image augmentation + CNN	99.44
		Covid 19(-ve) – 536		
	CT Scan	Covid 19(+ve) – 2760		95.38
		Covid 19(-ve) – 2760		

Scan images. Authors in [27] introduced a 3D deep CNN for COVID-19 prediction and obtained 90.8% accuracy using 313 COVID-19 positive and 229 COVID-19 negative CT Scan examples. Authors in [17] made use of fine-tuned ResNet32 on CT Scan images having two classes and achieved an accuracy of 93.01%. Chen et al. [4] introduced a UNet++ Network for COVID-19 detection and achieved 95.2% accuracy using 51 COVID-19 (+ve) and 55 COVID-19 (-ve) CT Scan examples.

Due to less number of X-Ray or CT Scan, examples that are used to train the deep learning models often exhibit the classification accuracies not up to the mark. Whereas, the proposed augmented deep model uses a large number of images of CT Scan and X-Ray for training. This multi-image augmentation has driven the CNN to exhibit higher classification accuracies while a basic deep learning architecture is used. Moreover, the proposed model is compared with VGG-16 and ResNet-50 on the same set of images of CT Scan and X-Ray. The proposed augmented model outperforms ResNet-50 and VGG-16 as well as the existing models too.

4 Conclusion and Future Work

This paper has proposed an augmented CNN to detect COVID-19 on chest images of CT Scan and X-Ray and classify from non-COVID-19 cases. The proposed model need not require to extract the feature manually, it is automated with end-to-end structure. Most of these previous studies have fewer examples for training the deep models. In contrast, the proposed model has used a multi-image augmentation technique driven by first- and second-order derivative edge operators and this augmentation generates a number of representative edged images. This augmentation technique provides a sufficient number of examples for training the model, making it robust. While CNN is trained with these augmented images, the classification accuracies of 99.44% for X-Ray images and 95.38% for CT Scan images are obtained. The experimental results are found to be highly convincing and emerged as a useful application for COVID-19 testing on chest images of CT Scan and X-Ray of corona suspected individuals. The subtle responses of various abnormalities like tuberculosis, pneumonia, influenza, and so forth confound the classifier, restricting the performance of the system. Future works may include the detection of multiple conditions such as pneumonia, bronchitis, and tuberculosis along with COVID-19 of suspected individuals having the respiratory illness.

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