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LiteCovidNet: A lightweight deep neural network model for detection of COVID-19 using X-ray images

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Abstract

The syndrome called COVID-19 which was firstly spread in Wuhan, China has already been declared a globally "Pandemic." To stymie the further spread of the virus at an early stage, detection needs to be done. Artificial Intelligence-based deep learning models have gained much popularity in the detection of many diseases within the confines of biomedical sciences. In this paper, a deep neural network-based "LiteCovidNet" model is proposed that detects COVID-19 cases as the binary class (COVID-19, Normal) and the multi-class (COVID-19, Normal, Pneumonia) bifurcated based on chest X-ray images of the infected persons. An accuracy of 100% and 98.82% is achieved for binary and multi-class classification respectively which is competitive performance as compared to the other recent related studies. Hence, our methodology can be used by health professionals to validate the detection of COVID-19 infected patients at an early stage with convenient cost and better accuracy.

KEYWORDS

chest X-ray, classification, COVID-19, deep neural network, LiteCovidNet

1 | INTRODUCTION

Coronavirus, also titled Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV-2), is the most disastrous virus in the history of the pandemic that had been discovered in late December 2019.[1] It is considered a syndrome of the respiratory system, the outbreak in Wuhan, Hubei Province, China.[2] This virus lately called Coronavirus Disease (COVID-19), recognized world-widely as Global Communal Health Extremity by World Health Organization (WHO) in January 2020, also acquired the status of "Pandemic" on March 11, 2020.[3–9] Till August 13, 2021, there are approximately 206 million confirmed cases across the world and 4.3 million deaths reported from more than 200 different countries and territories. The worst-hit countries were the USA, India, and Brazil.[10] This virus is spreading through human-to-human transmission via either respiratory droplets or contact routes.

Coronaviruses are among the largest groups of viruses that belong to the Nidovirales order including Roniviridae, Mesoniviridae, Arteriviridae, and Coronaviridae families. All viruses in the Nidovirales order are enveloped in non-segmented positive-sense ribonucleic acid (RNA) viruses. All of them contain very large genomes for RNA viruses. Coronaviruses contain a non-segmented, positive-sense RNA genome of 30 kilobases (kb). Coronaviridae and Nidovirales spread promptly in humans as well as mammals.[11–13] The COVID-19 virus causes different kinds of illnesses which range from symptomatic to asymptomatic infections. The main symptoms of COVID-19 are cold, dry cough, fever, sore throat, weakness, tiredness, etc. There are two major modes of transmission of the COVID-19 virus, that is, respiratory or droplets and contact. Respiratory droplets are generated when an infected person coughs or sneezes. Any person who is in close contact with someone who has respiratory symptoms (sneezing, coughing) is at risk of being exposed to potentially infective respiratory droplets.[14,15] Thus, symptomatic persons are assumed to play a vital role in the transmission of the virus. Different kinds of protocols are being followed by different countries to manage the spread of the virus. Mobile-based applications for regular tracking of the spread such as Arogya Setu (India), HaMagen (Israel), DataSpende (Germany), HomeQuarantine (Poland), ENS (Austria, Belgium), etc. are also playing a crucial role in the COVID-19 era.[3]

Early detection of the virus is explicit in today's time.[16] The standard test used for detecting a confirmed case is Real-Time Reverse Transmission-Polymerase Chain Reaction (RT-PCR) test.[17] Respiratory samples are required for conducting this test which is time-consuming and expensive as well. The approximate cost for conducting this test is more than $500 in the USA while in India it costs range from INR 600 to 6500 approximately.[18] This test has a lower rate of detection and requires multiple test confirmations. A rapid test is required for winning the battle against the COVID-19. Chest X-ray images and CT scan images can also be used for detecting the traces of COVID-19. Literature showcases that COVID-19 causes abnormalities in the lungs which can be visualized in the chest X-ray images. Hence, these images can be used for detecting COVID-19 in the person whereas X-ray images require an expert to recognize the abnormalities. The two most recent studies related to the COVID-19 are discussed in References 19 and 20 for the detection of COVID-19 using CT scan images by the convolutional neural network (CNN) model and the Generalized susceptible-infected-removed (SIR) epidemic model.

In this paper, we have developed a deep learning-based model called "LiteCovidNet" which can detect the COVID-19 in the person efficiently as well as economically and also with a lower rate of misclassification. The model makes use of a deep learning-based CNN to extract the unique features from the X-ray images of COVID-19. This CNN is a combination of multiple layers. The model called "LiteCovidNet" is firstly trained and then tested to categorize X-ray images as COVID-19 infected, Pneumonia, and non-COVID-19 or Normal cases. The results achieved by our deep learning-based method prove that X-ray images can be used for detecting COVID-19 in real-world scenarios.

The major contributions are discussed below:

1. We have proposed a deep learning-based "LiteCovidNet" model, which is capable of classifying the person either to be COVID-19 positive or not, based on their Chest X-ray images.
2. LiteCovidNet is a better and fast method than other state-of-art techniques.
3. The method can help health professionals to detect the COVID-19 rapidly and efficiently.

The rest of the paper is organized as follows: Section 2 discusses the literature survey; Section 3 presents materials and methods which include datasets description and methodology. Section 4 discusses experimental studies. While Section 5 and Section 6 include discussion, conclusion, and future scope of the research.

2 | RELATED WORK

Artificial intelligence has surmounted since it achieved popularity ranging from basic digit recognition[21] to recognize human actions.[22] Artificial intelligence-based deep learning is currently being used in violence detection, biometric systems, handwriting recognition, text analysis system,[23] etc. In the last few years, it has also shown great improvement in the field of medical science.[18,24] In medical imaging, it has been used in the detection of brain tumors, kidney diseases, cardiovascular illnesses, etc., and recently it is being used for the detection of COVID-19.

The detection of COVID-19 using these deep learning-based models may facilitate the health professionals with an early and effective tracing of the virus in the infected person. Following the lead, the study has been conducted on various traditional and machine learning-based diagnosis models. These models are lacking in extracting the important features and preprocessing the image. These limitations can thus be handled by using deep learning-based methods. Recently, the detection of medical images is done by dint of deep learning-based models. Deducting from the same, we have categorized our literature on COVID-19 detection based on the modality of the images, which are X-ray images and CT scan images.[25–27]

2.1 | Modality as X-ray images

X-ray images are being used primarily for COVID-19 detection. Many researchers have given precise results using these X-ray images. Table 1 summarizes the existing work reported by different authors.

Ucar and Korkmaz[34] has used SqueezeNet with the Bayesian optimization model. They have used learning rate and momentum parameters. The authors have used 5949 Chest X-ray images which include 1583 Normal, 4290 Pneumonia and 76 COVID-19 confirmed samples,

TABLE 1 Literature survey for COVID-19 detection using X-ray images

References	Year	Technique(s)	Dataset(s)	Performance (in %)
28	2020	Truncated convolutional neural network (CNN) network	DI-162 COVID-19 positive cases and 340 TB negative cases from China	Accuracy = 99.50
			D2-162 COVID-19 positive cases and 80 TB healthy cases from the USA	Accuracy = 94.04
			D3-162 COVID-19 positive cases and 1583 Pneumonia healthy cases	Accuracy = 100
			D4-162 COVID-19 positive cases and 1583 Pneumonia healthy cases, 340 TB healthy cases, and 80 healthy cases from the USA	Accuracy = 99.87
			D5-162 COVID-19 positive cases and 4280 positive and 1583 healthy Pneumonia cases	Accuracy = 99.96
			D6-162 COVID-19 positive cases and 4280 positive and 1583 healthy Pneumonia cases, 342 positive and 340 healthy cases of TB from China, and 58 positives and 80 healthy cases from the USA	Accuracy = 99.92
29	2020	Transfer learning with generative adversarial networks	5863 X-ray images with normal and Pneumonia cases	Accuracy = 98.97
30	2020	CNN using ResNet18, SqeezeNet, ResNet50 and DenseNet121	COVID-19 X-ray 5k dataset with 2084 training and 3100 test images, ChexPert dataset with 250 X-ray images	Sensitivity = 97.5 Specificity = 90
31	2020	Deep learning-based model	100 chest images of COVID-19 confirmed cases, 1431 cases of Pneumonia	Sensitivity = 96.00 Specificity = 70.65
32	2020	Deep learning-based ResNet50, InceptionV3, Inception-ResNet combined	50 images of confirmed cases and 50 Normal cases	Accuracy = 98 (ResNet) Accuracy = 97 (InceptionV3) Accuracy = 87 (InceptionV3 combined with ResNet)
33	2020	Combined version of Xception and Resnet50V2	180 COVID-19 cases, 6054 Pneumonia cases and 8851 Normal cases	Accuracy = 99.50 Average Accuracy = 91.4
18	2020	Pre-trained model ResNet101, Xception, InceptionV3, MobileNet and NASNet	Dataset1-219 COVID-19 cases, 1345 Pneumonia cases and 1341 Normal cases	Accuracy = 99.53 (binary class)
			Dataset2-142 COVID-19 Chest X-ray images	Accuracy = 93.08 (multi-class)

and achieved exactness of 100% on COVID-19 and 96.73% with Pneumonia and 98.04% on Normal cases.

Khan et al.[35] have used transfer learning on a pre-trained Xception convolutional neural network to categorize the sample into four classes such as COVID-19, pneumonia bacteria, pneumonia viral and non-COVID cases and achieved 89.6% in four classes and 95% in three classes.

Pandit et al.[36] proposed a deep convolutional-based neural network method for fast COVID-19 identification using the patients' chest X-ray images. The authors have used more than 150 images of patients collected from

Kaggle for evaluation and also achieved 93% accuracy for COVID-19 detection.

Li et al.[37] proposed a discriminative cost-sensitive learning method for COVID-19 detection using chest X-ray images. The authors have also collected a huge dataset of 2239 chest X-ray images which includes 239 confirmed COVID-19, 1000 confirmed pneumonia (bacterial/viral), and 1000 healthy images. The method achieved 97.01% accuracy, 97% precision, 97.09% sensitivity, and 96.98% F1 score.

2.2 | Modality as CT images

Recently Chest CT patterns have attracted researchers to detect the COVID-19 cases. From the extensive related

TABLE 2 Literature survey for COVID-19 detection using CT scan images

References	Year	Technique(s)	Dataset(s)	Performance (in %)
38	2020	Transfer learning with stationary wavelet, Phase 1-image augmentation, Phase 2-detection using convolutional neural network (CNN), Phase 3-abnormality localisation in CT images	349 COVID-19 CT images and 397 Normal images	Accuracy = 99.4 Sensitivity = 100 Specificity = 98.6
39	2020	CNN based residual network	219 COVID-19 images and 224 Pneumonia and 175 Normal images	Accuracy = 99.6 Sensitivity = 98.2 Specificity = 92.2
40	2020	CNN to classify the case as COVID-19 positive or negative, CNN equipped with multi-objective differential evolution	Chest CT images	The model increases accuracy, sensitivity, and specificity by 1.9789%, 1.8262%, and 1.6827% as compared to the previous
41	2020	COVID-19 diagnosis using joint classification with segmentation	144 167 images of 400 COVID-19 patients, 3855 CT images of 200 patients, and 350 unidentified cases	Dice score = 78.3 Sensitivity = 95 Specificity = 93
42	2020	Deep learning-Based 2D and 3D models	157 international patient data from Chine and USA	Accuracy = 99.6 Sensitivity = 98.2 Specificity = 92.2
43	2020	Data augmentation techniques with conditional generative adversarial network (GANs)	742 Total images (345 COVID-19 positive and 397 COVID-19 negative cases)	Accuracy = 82.91 Sensitivity = 77.66 Specificity = 87.62
44	2020	Harmony search optimization and Otsu thresholding	90 slices of coronal view and 20 of axial lung view	Efficient in extracting the COVID-19 section
45	2020	DenseNet model equipped with transfer learning	25 COVID-19 positive and 195 COVID-19 negative CT scan images	Accuracy = 84.7
46	2021	Stochastic pooling neural network (SPNN) PatchShuffle Stochastic Pooling Neural Network (PSSPNN)	Four types of CCT were used: (i) COVID-19-positive patients, (ii) community-acquired pneumonia (CAP), (iii) second pulmonary tuberculosis (SPT), and (iv) healthy control (HC)	SPNN: MA F1-score = 95.02% PSSPNN: MA F1-score = 95.79%
47	2021	FGCNet with deep feature fusion from graph convolutional network and convolutional neural network	320 COVID-19 images and 320 healthy control images.	Sensitivity = 97.71% ± 1.46 Specificity = 96.56% ± 1.48 Precision = 96.61% ± 1.43 Accuracy = 97.14% ± 1.26 F1-score = 97.15% ± 1.25 Matthews correlation coefficient (MCC) = 94.29% ± 2.52

study, it has been analyzed that CT images of the Chest can be used for early COVID-19 classification. Therefore, in Table 2, we have given a summary of methods where the researchers have used CT images for COVID-19 detection.

Fang et al.[48] studied the RT-PCR and chest CTs sensitivity for COVID-19 detection. From the study, the authors found that CT images of the chest have high sensitivity than RT-PCR.

Gozes et al.[42] proposed an artificial intelligence-based CT tool for the analysis of detection and quantification of COVID-19. The proposed module is capable of extracting the slices from the lungs automatically. The model has achieved 98.2% sensitivity and 92.2% specificity on the datasets.

Huang et al.[49] proposed a method called FaNet based on deep learning which is capable of detecting COVID-19 and severity using the 3D CT images and other clinical parameters. A dataset of 416 patients has been used in which 207 are Normal and the other 209 are COVID-19 positive cases. The proposed method has achieved 98.28% and 94.83% accuracy for the detection of COVID-19 and severity respectively.

3 | MATERIALS AND METHODS

3.1 | Datasets

Datasets play an important role in the detection of COVID-19 using computer vision-based deep learning methods. In this section, we will discuss the dataset that is being used for experimental work. For the tracing of COVID-19, we use X-ray image datasets obtained from two different sources as discussed below. The dataset used for the current work is gathered from two different sources as shown in Table 3 and then we merged them. The dataset contains image samples of COVID-19 confirmed cases, Normal and Pneumonia cases. The total number of images are 4236 of which 1281 are COVID-19 confirmed cases, 1475 are Normal and 1480 are Pneumonia cases. The respective links for both datasets are given in Table 3.

3.1.1 | Dataset 1

The first dataset that has been used is X-ray images developed by Tawsifur Rahman and his team. The X-ray images for this dataset are taken from various sources including the Italian Society of Medical and Interventional Radiology COVID-19 dataset, a novel coronavirus dataset developed by Cohen et al.,[50] and images collected

TABLE 3 Datasets information

Class	Number of images	Dataset reference
COVID-19	1281	Dataset 1: [https://www.kaggle.com/tawsifurrahman/covid19-radiography-database] Dataset 2: [https://github.com/AshuMaths1729/COVID-19_XRay_Classifier]
Normal	1475	
Pneumonia	1480	
Total X-ray images	4236	

from 43 different publications. This dataset contains 1200 COVID-19 images, 1341 Normal images, and 1345 Pneumonia images. The dataset is also available at https://www.kaggle.com/tawsifurrahman/covid19-radiography-database.

3.1.2 | Dataset 2

The second dataset is developed by Cohen et al.[50] and Kermany et al.[51] and the images were collected from different open access sources. The dataset is updated constantly using the shared resource from different researchers. A complete set of 125 persons were considered including 43 female and 82 male samples that were found to be confirmed. The dataset does not provide the metadata of every patient. Only the age of 26 confirmed patients is given and the average age was found to be 55 years. The dataset is available on GitHub with the link https://github.com/AshuMaths1729/COVID-19_XRay_Classifier.

3.2 | Methodology

In this section, a detailed discussion of the classification framework and the proposed "LiteCovidNet" architecture is laid out.

3.2.1 | Classification framework

A host of academic writing as well as plenty of research articles already exists for detecting COVID-19 and Pneumonia. The classification techniques of the machine and deep learning are employed while diagnosing the CT scan and chest X-ray images to detect an infected person and their results are quite fair in terms of accuracy. To design a classification model, several steps are to be followed. The X-ray images taken from two data sources are not preprocessed and are even not of equal size. For this, foremost all the images are resized and then converted to red, green, and blue (RGB) channel. In the next step, the dataset is split into training and testing parts, and with this training data, the structure of the proposed model is formed. In the end, the evaluation of the model which is performed by testing the model using test data is carried out. Based on the results obtained by evaluating the model, images are classified into binary class (COVID-19, Normal) and multi-class (COVID-19, Normal, and Pneumonia). The overall workflow of the classification framework is shown in Figure 1.

3.2.2 | Proposed LiteCovidNet architecture

The field of Artificial Intelligence has revolutionized after the immense growth in the field of deep learning. In "Deep Learning," the word "Deep" is used as a measure of the depth of the network. The depth of the network is dependent on the number of layers. The presence of these layers makes the model strengthened.

A lightweight deep learning model is defined to be a network with a total number of parameters less than 5 million. Its main advantage is the low memory requirement, which makes it suitable to be executed on any platform including mobile phones and computers. Typically, a lightweight deep learning model is fabricated on a compact architecture.[52–54] Our proposed LiteCovidNet model is designed in such a form to support a lightweight architecture without using any pre-trained model or transfer learning. It can deal with a limited amount of data available. The proposed model is suitable for fast screening purposes so that superior-targeted diagnoses can be performed to optimize the cost and test time. The salient characteristic of the lightweight architecture is that it can allow the model to be deployed on various platforms such as android phones, Apple iPhones, tablets, and computers without being bothered about the RAM and storage capacity. And hence, so far so that, naming this model as LiteCovidNet indicates a lightweight deep learning model for the detection of COVID-19. Here, the word "Lite" signifies lightweight or lite architecture which is suitable to run on low memory devices just like the lite version of an application that is run on mobile phones having limited RAM.

The proposed LiteCovidNet model consists of three convolutional layers with variable filter sizes (32 and 64) and a fixed kernel size of 3 × 3 followed by the ReLU activation function and max-pooling after each convolutional layer. There is one flattening layer and five dense layers of size 512, 256, 128, and 64 followed by dropout and a final dense layer with a softmax activation function. The model comprises just 2.8 million total

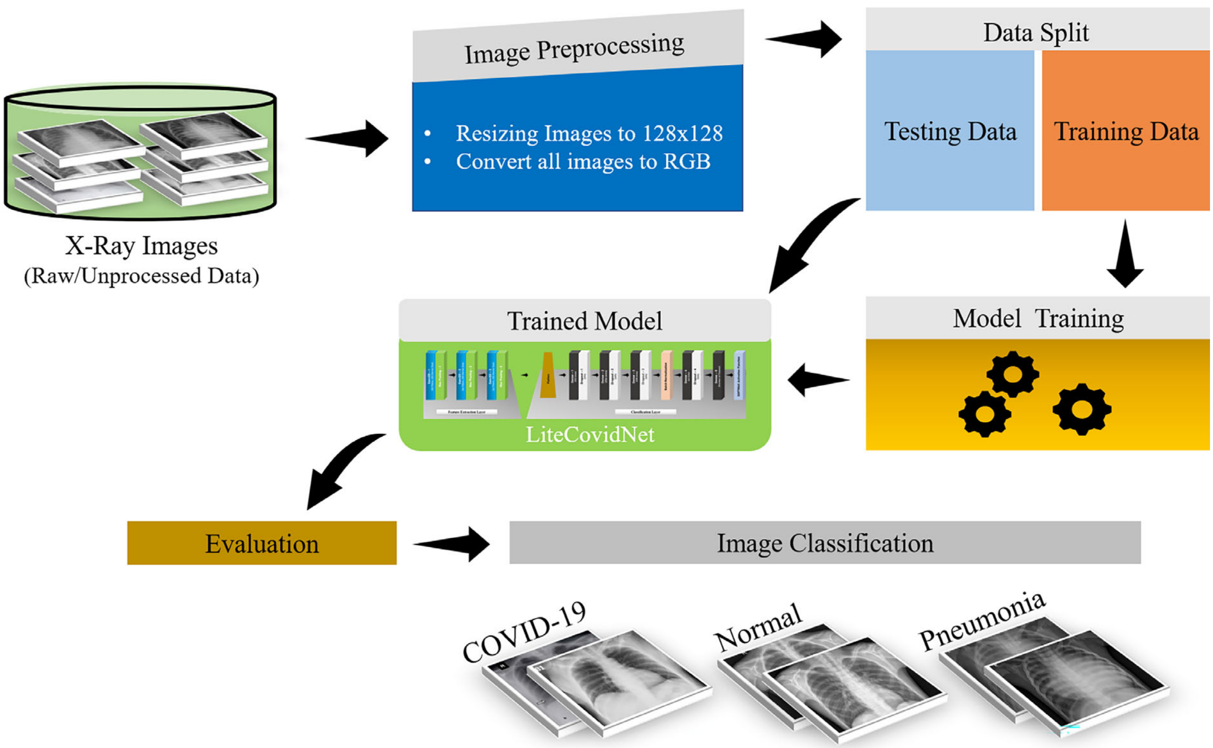


FIGURE 1 Workflow representation of classification framework

parameters. The layer-wise description of the proposed architecture is shown in Table 4.

Input layer

In this layer, the input is provided to the network. The images in the datasets are not of the same resolution. Hence, images are firstly scaled to a fixed size of 128 × 128 × 3 representing height, width, and the size of the channel. A quite similar instance of such an image is shown in Figure 2. The size of the channel is kept at 3 for a colored image and for grayscale images, it is kept at 1.

Convolutional layer

This layer is the building block of the whole network.[55] The parameters of this layer are filter size or neurons, kernel size, and padding. Neurons are responsible for several filters being used for extracting the features. The kernel is the spatial size of the output volume.

ReLU layer

Different activation functions are used for the network. Here, CNN layers are activated by the Rectified Linear Unit (ReLU). ReLU has different versions also such as Leaky ReLU, exponential linear unit (ELU), parametric rectified linear unit (PReLU), etc.

MaxPooling

MaxPooling layer in the convolutional neural network is used to downsample the output achieved from the last layer. This layer reduces the number of parameters and is also used to avoid the overfitting of the model. Moreover, this layer is responsible for minimizing the computational cost of the model.

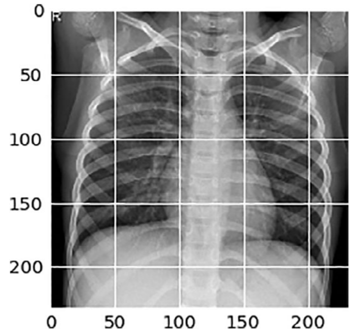


FIGURE 2 Resized X-ray image sample (128 × 128)

TABLE 4 Details of LiteCovidNet architecture

Layer type	Number of filters	Kernel size	Pool size, stride	Output shape	Number of trainable parameters
conv2d_1 (Conv2D)	32	(3 × 3)	-	126 × 126 × 32	896
max_pooling2d_1 (MaxPooling2D)	-	-	(2 × 2), 0	63 × 63 × 32	0
conv2d_2 (Conv2D)	64	(3 × 3)	-	61 × 61 × 64	18 496
max_pooling2d_2 (MaxPooling2D)	-	-	(3 × 3), 0	20 × 20 × 64	0
conv2d_3 (Conv2D)	64	(3 × 3)	-	18 × 18 × 64	36 928
max_pooling2d_3 (MaxPooling2D)	-	-	(2 × 2), 0	9 × 9 × 64	0
flatten (Flatten)	-	-	-	5184	0
dense_1 (Dense)	-	-	-	512	2 654 720
dropout_1 (Dropout)	-	-	-	512	0
dense_2 (Dense)	-	-	-	256	131 328
dropout_2 (Dropout)	-	-	-	256	0
dense_3 (Dense)	-	-	-	128	32 896
dropout_3 (Dropout)	-	-	-	128	0
batch_normalization (BatchNo)	-	-	-	128	512
dense_4 (Dense)	-	-	-	64	8256
dropout_4 (Dropout)	-	-	-	64	0
dense_5 (Dense)	-	-	-	3	195

Fully connected layer

Fully connected layers or FC layers are also called dense layers. The output feature maps of the final convolution and pooling layer are transformed into a one-dimensional array of vectors and connected to one or more dense layers in which every input is connected to every output by a learnable weight.[56] The size of the last dense layer is kept equal to the total number of target classes.

The overall description of the layers is given in Table 4 and the proposed architecture is presented in Figure 3. The proposed LiteCovidNet algorithm is illustrated in Algorithm 1.

The first layer of the network is a 2D convolutional layer that has 32 filters responsible for extracting the features from the image. The kernel size of the layer is 3×3. A total number of 896 features are learned in this layer. The max-pooling layer that follows the first convolutional layer has a pool size of 2×2.

The second convolutional layer is consisting of 64 filters and the kernel size is 3×3. The number of parameters extracted is 18 496 and the max-pooling layer following this layer has a pool size of 3×3.

The third convolutional layer includes 64 filters and the kernel size is 3×3. The total number of learnable parameters in this layer is 36 928. The max-pool layer is of 2×2 pool size.

The model is then followed by flattening, five dense layers followed by the dropout to drop the features that are not useful, and finally, batch normalization is performed.

Each convolutional layer was compiled utilizing the Adam optimization method and, dropout layers of various units are applied which means that 50% of neurons will randomly set to zero during each training epoch thus avoiding overfitting on the training dataset.

4 | EXPERIMENTAL STUDIES

We have detected COVID-19 from a binary set of images which constitutes COVID-19 confirmed and Normal samples and, multiple sets of images where we have taken COVID-19 confirmed images, Pneumonia cases, and Normal cases. The ratio of the images for binary and multi-class is shown in Figure 4.

4.1 | Experiment setup

The whole experimental work was carried out on a Jupyter Notebook provided by Google's Collaboratory environment which can be freely used since it is provided by Google for research purposes using an NVIDIA Tesla K80 GPU of 12 GB. We have used Python 3 version in the experiment for implementing our proposed algorithm and the main open-source libraries used are:

- *TensorFlow*[57]
- *Keras*[58]
- *Matplotlib*[59]
- *Numpy*[60]
- *Scikit*[61]
- *Pandas*[62]

4.2 | Parameters tuning

Each convolutional layer is shared and fixed to a common hyper-parameter. All the experimental results were also tested according to these hyper-parameters. The parameter tuning details are elucidated acutely in the below section.

A total of 200 epochs were performed while training the model to avoid the problem of overfitting with a batch size of 25. To refrain from overfitting problems, an early stopping technique is also used that ends the learning process. The early stopping process ceases the model training when no further improvement could be brought by the validation score. For early stoppage, a total of 15 epochs were used. To compile a deep learning model, an optimizer is required. Optimizers are algorithms that are used to change the attributes such as learning rate and weight to reduce the losses with much less effort. It helps in getting faster results. The proposed model is compiled with the adam optimizer for 1e−3, and 0.8 as the initial learning rate, and momentum respectively.

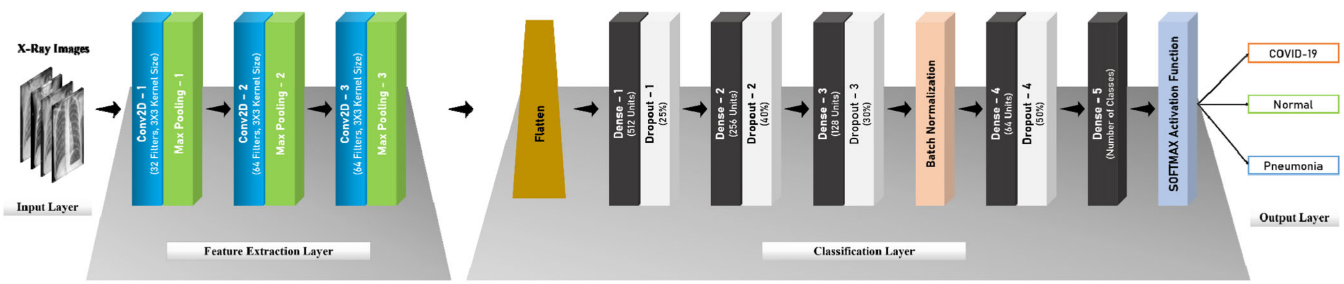
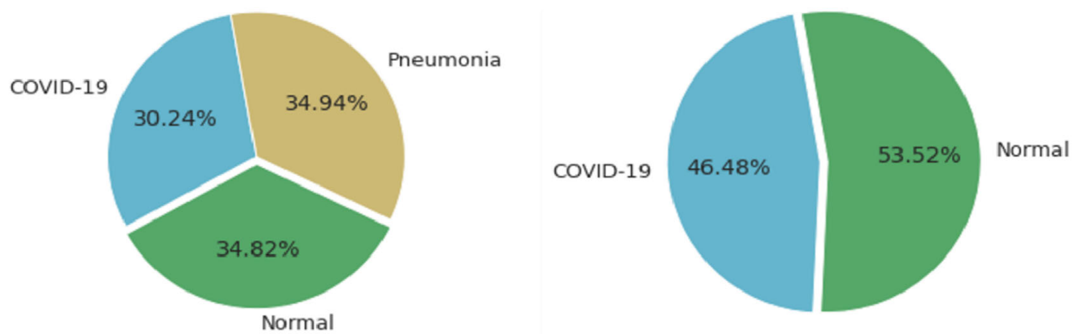


FIGURE 3 Proposed LiteCovidNet architecture

ALGORITHM 1 LiteCovidNet algorithm

Input: Raw chest X-ray images data.
Output: Image classification {Binary class: COVID-19, Normal} or {Multi-class: COVID-19, Normal, Pneumonia}

1. Apply image preprocessing: *Resizing images to 128 × 128*, *Convert to RGB*, *Shuffling images*
2. Data splitting: *Training (80%)* and *Testing (20%)* *// LiteCovidNet model building using training data*
3. Pass images into the convolutional layer to create a feature map
4. Feed feature map to max-pooling layer to extract features
5. **Repeat** *step 3* and *step 4* **for** $i = 1$ to 3
6. Apply flatten layer on output attained from last max-pooling layer to get a one-dimensional array of features *// 1-D array of features will pass to next layer, that is, dense layer*
7. Dense layer (j): Feed all output from the previous layer to all its neurons to change dimensions
8. Pass output of Dense layer (j) to dropout layer to reduce the number of neurons
9. **Repeat** *step 7* and *step 8* **for** $j = 1$ to 3
10. Apply batch normalization to speed up training by standardizing and normalizing the input data
11. Feed output of *step 10* to Dense layer
12. Again pass the output of the Dense layer to the dropout layer to reduce the number of neurons
13. Input the reduced number of neurons into the Dense layer
14. Apply softmax activation function
15. **Output:** Obtain output {for binary class: COVID-19, Normal} or {for multi-class: COVID-19, Normal, Pneumonia}



(A) Binary class data distribution (B) Multi-class data distribution

FIGURE 4 Data distribution chart

Adam stands for adaptive moment estimation. It is an adaptive learning rate optimization algorithm used for compiling a deep learning model. The main motive for using adam optimizer is that it requires little memory and is computationally quite efficient. Whereas the learning rate determines the rate of learning of deep or machine learning model that decides the number of moves required to minimize the value of loss function, and the momentum is used to improve both model training speed and accuracy. The output of a node (like yes or no), is determined by a distinct function called the activation function. An activation function is added to help the deep neural network to learn complex patterns of X-ray image data. ReLU activation function is extensively used and is the default choice as it gives better results.

The dataset used was randomly split into 80% and 20% for training and testing. The number of images in the training and test data is shown in Table 5.

4.3 | Performance metrics

Different parameters are used to evaluate the performance of the model.[23,63] For the detection of COVID-19 different

TABLE 5 Number of X-ray images in train and test data

Number of X-ray images		
	Binary class	**Multi-class**
Training data	2205	3389
Testing data	551	847
Total images	2756	4236

TABLE 6 Confusion matrix

	Predicted C1	**Predicted C2**
Actual C1	True Positive	False Negative
Actual C2	False Positive	True Negative

authors have used different parameters. Some of them are Accuracy, Specificity, Sensitivity, Precision, and F1-Score. These parameters are defined using the confusion matrix labels which are shown in Table 6, that is, True Positive, True Negative, False Positive, and False Negative.

True Positive is the number of correctly identified images of a class whereas True Negative is the samples that are not detected of a class from which they do not belong. False positives are the number of wrongly identified samples and false negatives are the number of samples of a class that are detected from another class. Positioning the concept on these matrices, the major parameters are defined as:

Accuracy

It is defined as the number of correctly identified COVID-19 samples to the total number of COVID-19 samples. This is shown in Equation (1). Accuracy for all classes is the number of correctly identified samples of any particular case to the number of all the samples and other classes as well. Accuracy for all classes is represented in Equation (2).

$$\text{Accuracy (for each class)} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FP}+\text{FN}+\text{TN}} \tag{1}$$

$$\text{Accuracy (for all classes)} = \frac{\text{Number of correct classified samples}}{\text{Number of all samples}} \tag{2}$$

Specificity

It is defined as the number of True Negative samples to the Number of True negative samples and False Positive samples. It is shown in Equation (3).

$$\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}} \tag{3}$$

Sensitivity

It is defined as the number of True Positive samples to the number of True Positive samples and False Negative samples. It is shown in Equation (4).

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{4}$$

Precision

Precision is defined as the number of True Positive samples to the Number of True Positive samples and False Positive samples. It is shown in Equation (5).

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}} \tag{5}$$

Recall

Recall for any class is defined as the number of correctly predicted positive values out of the total positive values that are true in that particular sample of the class.[64,65] It is shown in Equation (6).

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{6}$$

F1-Score

It is defined as the harmonic mean of the Precision and Recall. It is shown in Equation (7).

$$\text{F1}-\text{Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision}+\text{Recall}} \tag{7}$$

4.4 | Experimental results

This section deals with the testing results of the model. We have performed experiments to detect and categorize the COVID-19 confirmed cases using the chest X-ray images. The effectiveness of the model has been evaluated using the performance parameters. We have evaluated the model for two categories, that is, binary and multi-class datasets. Model accuracy and model loss for the binary class are shown in Figure 5 and for multi-class are shown in Figure 6.

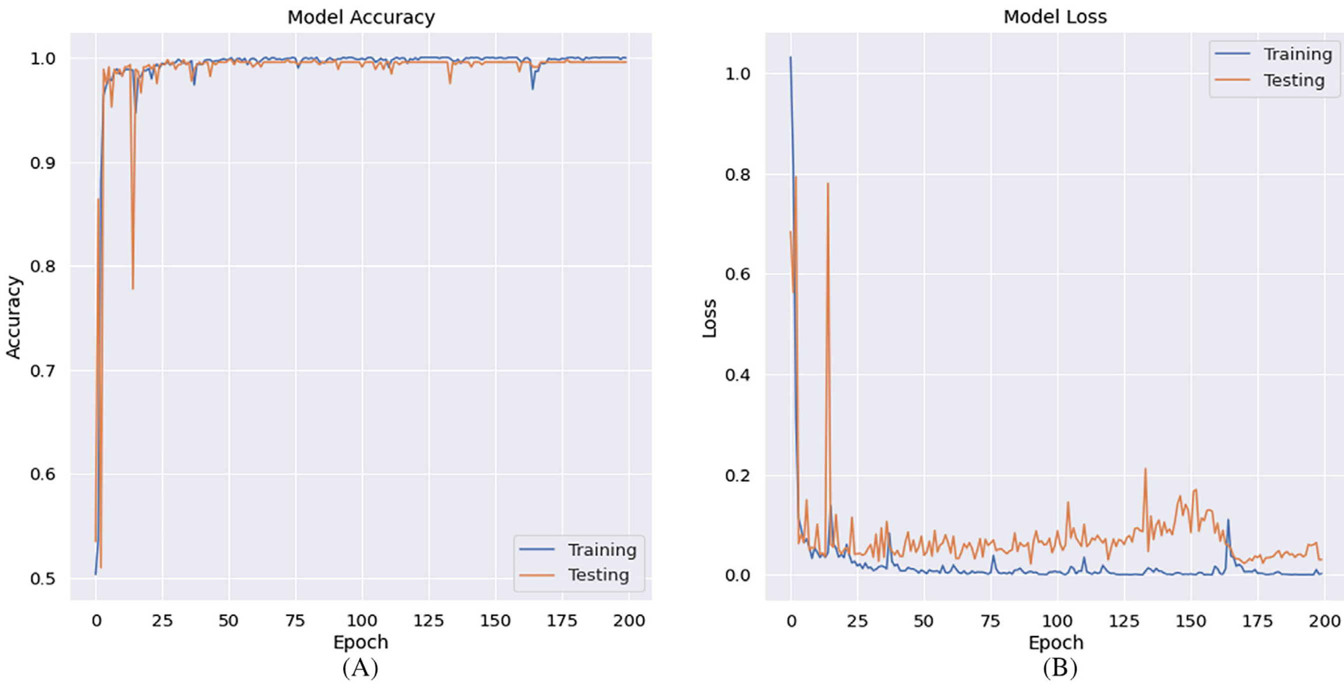


FIGURE 5 Model accuracy (A) and loss (B) for binary class

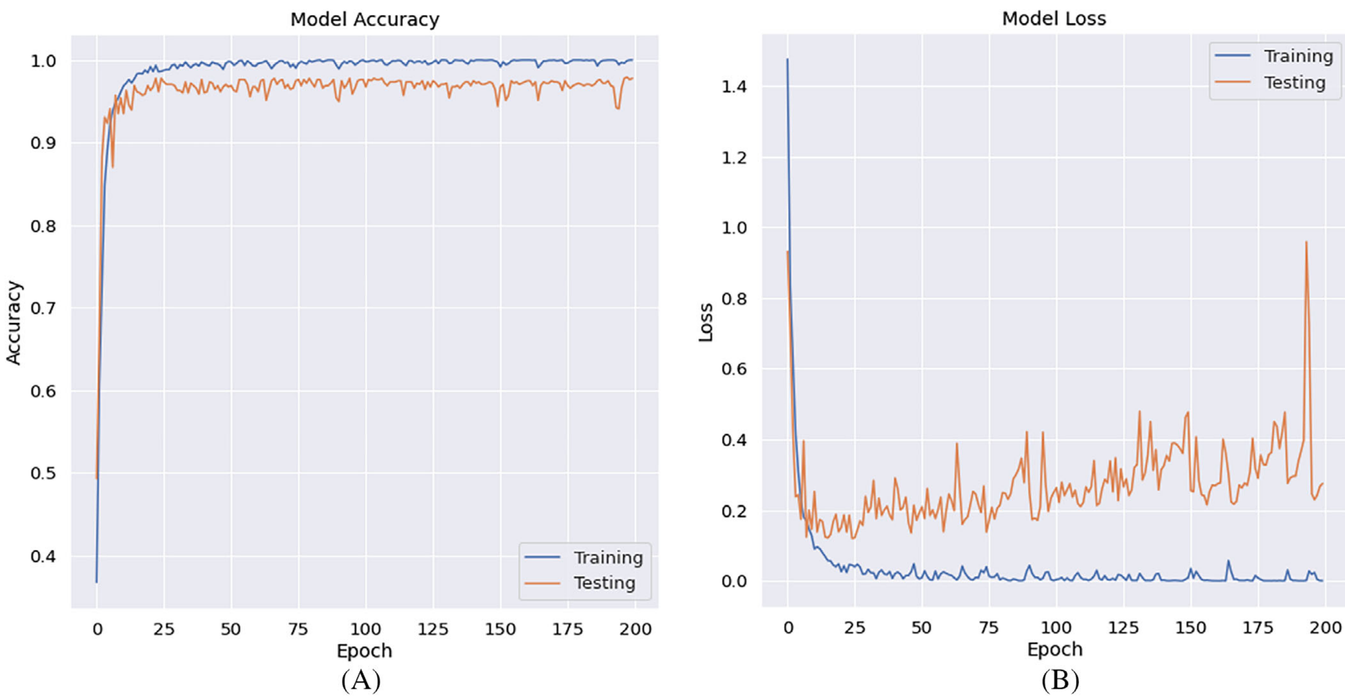


FIGURE 6 Model accuracy (A) and loss (B) for multi-class

A comparative study of the existing techniques for COVID-19 detection is represented in Table 7. Table 8 represents the results for the proposed "LiteCovidNet" for both the binary and multi-class experiments. From the table, we can conclude the effectiveness of the model. For the binary class experiment, the model achieved 100% accuracy and for the multi-class experiment, the model achieves 98.82% overall accuracy.

TABLE 7 Comparative study for COVID-19 detection (modality as chest X-ray images)

References	Technique(s)	Classification type	Precision	Sensitivity	Specificity	F1-score	Accuracy
12	VGG-16 based faster regions with convolutional neural network (CNN)	Binary class (COVID-19, non-COVID-19)	99.29%	97.65%	95.48%	98.46	97.36%
34	Deep Bayes-SqueezeNet (COVIDiagnosis-Net)	Multi-class (COVID, Normal, Pneumonia)	N/A	N/A	99.10%	98.30%	98.26%
37	Discriminative cost-sensitive learning (DCSL)	Multi-class (Normal, COVID-19, Pneumonia)	97%	97.09%	N/A	96.98%	97.01
66	DarkCovidNet	Binary class (COVID, no-findings)	98.03%	95.13%	95.30%	96.51%	98.08%
		Multi-class (COVID, no findings, Pneumonia)	89.96%	85.35%	92.18%	87.37%	87.02%
67	ResNet50 and VGG-16 based deep learning method	Binary class (COVID-19, Pneumonia)	N/A	N/A	N/A	N/A	89.20%
68	VGG-19	Multi-class (COVID, Pneumonia, Normal)	N/A	98.66%	96.46%	N/A	96.78%
69	Support vector machine (SVM)	Binary class (COVID-19, healthy)	N/A	N/A	N/A	N/A	94.12%
70	VGG-CapsNet	Binary class (COVID-19, non-COVID-19)	N/A	N/A	N/A	N/A	97%
		Multi-class (COVID-19, Normal, Pneumonia)	N/A	N/A	N/A	N/A	92%
71	CNN model "COVID-ScreenNet"	Multi-class (non-infected, COVID-19, Pneumonia)	N/A	N/A	N/A	N/A	97.71%
72	CVDNet	Multi-class (COVID-19, Normal, Pneumonia)	96.72%	N/A	N/A	96.68%	96.69%
73	cGAN	Binary class (COVID-19, Normal)	N/A	100%	98.30%	N/A	98.70%
		Multi-class (COVID-19, Normal, Pneumonia)	N/A	99.30%	98.10%	N/A	98.30%
Proposed LiteCovidNet		Binary class (COVID-19, Normal)	100%	100%	100%	100%	100%
		Multi-class (COVID-19, Normal, Pneumonia)	98.33%	100%	100%	98.33%	98.82%

Note: N/A: Authors did not perform the specified classification.

The confusion matrix for binary class (CMB) and multi-class (CMM) is shown in Figure 7. It shows that only one Normal case has been detected as Pneumonia and two Pneumonia cases are detected as Normal.

5 | DISCUSSION

So far, the size of available COVID-19 datasets is small and is insufficient for training purposes. Thus, two

TABLE 8 Binary and multi-class results for proposed "LiteCovidNet"

Experiment type	Label	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	Overall accuracy (%)
Binary class	COVID-19	100	100	100	100	100
	Normal	100	100	100	100	
	Average	100	100	100	100	
Multi class	COVID-19	100	100	100	100	98.82
	Normal	97.00	100	100	98.00	
	Pneumonia	98.00	100	100	97.00	
	Average	98.33	100	100	98.33	

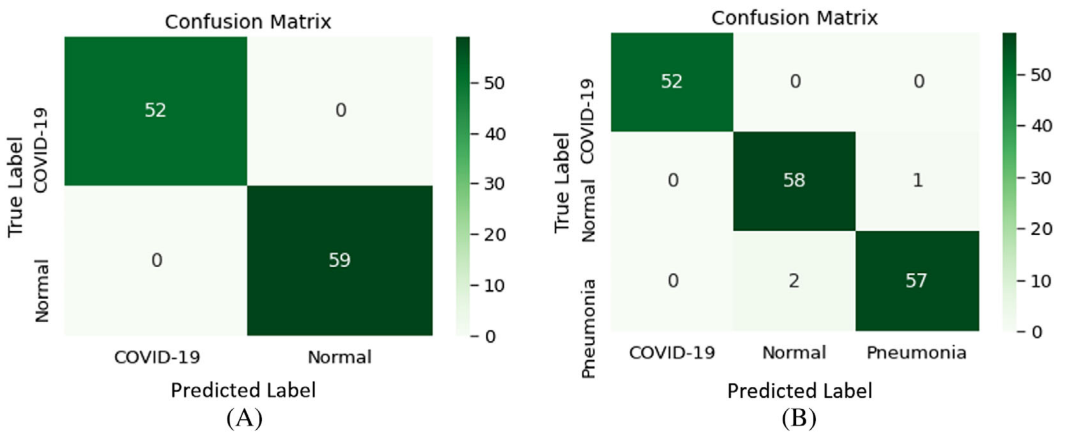


FIGURE 7 Confusion matrix for (A) CMB (B) CMM

different open-source datasets are selected for the purpose and merged into a single dataset to enlarge its length and to avoid issues related to class imbalance. These two datasets were also composed of various datasets as discussed in Sections 3.1.1 and 3.1.2.

To show the accuracies and significance of our research work, we compared our proposed LiteCovidNet model illustrated in Figure 3 and Table 4 with other recently developed models with the extensive literature on COVID-19 detection using chest X-ray images. Different research articles were studied and their performance matrices like accuracy along with precision, sensitivity, specificity, and F1-measure values are compared as shown in Table 7. Additionally, a comparison of performance was drawn out between our proposed model and six more lightweight deep-learning models such as SqueezeNet, ShuffleNet-v1, MobileNet-v1, MobileNet-v2, MobileNet-v3, and DarkCOVID-Net. It becomes evident from the analysis of results (comparative study and 6 lightweight models) that the LiteCovidNet model has achieved higher accuracies for both classification experiments (binary and multi-class) than all other related classification work. For the binary class experiment, the LiteCovidNet model has achieved 100% accuracy which is a benchmark and higher than all other related work. Moreover, for the multi-class experiment LiteCovidNet model has provided 98.82% accuracy which is also higher than the other related model discussed in the literature. These results are discussed in Table 8 and also presented in Figure 7 in terms of the confusion matrix. The graph is plotted between model accuracy and loss of training and testing phase for both binary class and multi-class experiments as shown in Figures 5 and 6 respectively.

The WHO recommended RT-PCR as a confirmatory and laboratory test for COVID-19. But, the test is confined to a limited number of laboratories. The low accuracy of the RT-PCR test inspires health experts and researchers to find alternative techniques of diagnosis. The radiological scrutiny for diagnosing infectious diseases such as Alzheimer's, appendicitis, tuberculosis, osteoporosis, arthritis, pneumonia, etc. over many decades. But the manual reading of X-ray images is a slow-moving task. It is difficult for health experts to guarantee a speedy response in the present situation of the global pandemic. No doubt, the RT-PCR test method to detect COVID-19 is still important. However, its drawbacks have also been highlighted for it is time-consuming (delay in response time), default methodology, the possibility of collecting the specimens in mistaken localizations, etc. Furthermore, it is risky for front-line experts to take a sample of COVID-19 affected patients.

The main objective of this research work is to construct a clinical decision classification framework that can identify COVID-19 cases at an early stage. COVID-19 detection using chest X-ray images is a time-saving technique where the tools are trained using a dataset, collected from different sources and these trained tools may prove practical for radiologists in the early detection of COVID-19 cases. Our proposed model can identify COVID-19 affected persons and even pneumonia persons without any human interference at an economical cost with apex accuracy. Therefore, we believe this proposed model might be of assistance to health professionals in the early diagnosis of COVID-19. The encouraging results of deep learning models in the detection of COVID-19 from chest X-ray images indicate that deep learning plays a crucial role to fight this pandemic.

6 | CONCLUSION AND FUTURE SCOPE

Early detection of COVID-19 affected people is important to prevent the widespread of this disease. In this paper, we have developed a LiteCovidNet model based on deep learning that analyses the chest X-ray images of the patient to confirm if he is COVID-19 infected. The model is capable of detecting the COVID-19 case from binary and multi-class classification without human intervention. Two publicly available datasets have been used which contain the chest X-ray images of COVID-19 infected patients, Pneumonia, and Normal cases. A total of 4236 images are used of which 1281 are COVID-19 confirmed, 1475 are Normal and 1480 are Pneumonia cases. We have achieved overall 100% accuracy in detecting binary class and 98.82% accuracy when we performed multi-class detection for COVID-19.

The proposed network outperforms other state-of-the-art models in the COVID-19 detection. Also, our method incorporates a few parameters which makes it computationally efficient. On analyzing the performance score of the proposed "LiteCovidNet" network, it can be used as a milestone in the COVID-19 screening. Such methods can be beneficial for locations where enough test kits are not available. The proposed methodology may be used as a supplementary tool for the health professionals to detect the COVID-19 from Chest X-ray images.

We hope that for future work, larger datasets of COVID-19 patients will be made available and by using those datasets, the method can be made more robust. Current work can be extended by designing automated tools based on a multi-modality deep learning model using a large number of digital CT scans and X-ray images that must be evaluated by radiologists. Moreover, the gamut of the paper is laid out for researchers to use deep learning models to identify COVID-19 in a noisier environment. The work also motivates the researchers to work for cross datasets as training and testing of the network.

AUTHOR CONTRIBUTIONS

Sourabh Shastri and Vibhakar Mansotra contributed to the study's conception and design. Sachin Kumar contributed to designing, implementing, and evaluating the deep neural network model. Shilpa Mahajan contributed to the initial draft of the manuscript. Sourabh Shastri and Sachin Kumar contributed to collating the datasets. Kuljeet Singh, Surbhi Gupta, Rajneesh Rani, and Neeraj Mohan contributed to the data preparation and revision of the manuscript.

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This research work is dedicated to COVID-19 frontline workers.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available on Kaggle at https://www.kaggle.com/datasets/sachinkumar413/covid-pneumonia-normal-chest-xray-images.

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