Automated Detection of COVID-19 using Chest X-Ray Images and CT Scans through Multilayer-Spatial Convolutional Neural Networks

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Abstract

The novel coronavirus-2019 (Covid-19), a contagious disease became a pandemic and has caused overwhelming effects on the human lives and world economy. The detection of the contagious disease is vital to avert further spread and to promptly treat the infected people. The need of automated scientific assisting diagnostic methods to identify Covid-19 in the infected people has increased since less accurate automated diagnostic methods are available. Recent studies based on the radiology imaging suggested that the imaging patterns on X-ray images and Computed Tomography (CT) scans contain leading information about Covid-19 and is considered as a potential automated diagnosis method. Machine learning and deep learning techniques combined with radiology imaging can be helpful for accurate detection of the disease. A deep learning approach based on the multilayer-Spatial Convolutional Neural Network for automatic detection of Covid-19 using chest X-ray images and CT scans is proposed in this paper. The proposed model, named as the Multilayer Spatial Covid Convolutional Neural Network (MSCovCNN), provides an automated accurate diagnostics for Covid-19 detection. The proposed model showed 93.63% detection accuracy and 97.88% AUC (Area Under Curve) for chest x-ray images and 91.44% detection accuracy and 95.92% AUC for chest CT scans, respectively. We have used 5-tiered 2D-CNN frameworks followed by the Artificial Neural Network (ANN) and softmax classifier. In the CNN each convolution layer is followed by an activation function and a Maxpooling layer. The proposed model can be used to assist the radiologists in detecting the Covid-19 and confirming their initial screening.

Keywords

COVID-19, Machine Learning, Convolutional Neural Network, X-rays Images, CT Scans.

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I. Introduction

The corona virus infection flared-up in Wuhan, the capital city of Hubei Province, China in December 2019 [1]–[3]. It killed over hundreds and infected more than thousands of people within early few days of the novel corona virus pestilence. The scientists in China named it 2019 novel Corona virus (2019-nCov) [4]. The International Committee of Viruses named it as Severe Acute Respiratory Syndrome Corona Virus-2 (SARS-CoV-2) whereas the infection is named as the Corona virus disease-2019 (Covid-19) [5]-[7]. The subcategories of the corona viruses are alpha-CoV (α), beta-CoV (β), gamma-CoV (γ) and delta-CoV (δ). SARS-CoV-2 is declared a member of the beta-CoV (β) subgroup. People of Kwantung were infected in 2003 by corona virus resulting in Severe Acute Respiratory Syndrome (SARS-CoV). SARS-CoV was also declared to be part of beta-CoV (β) subgroup [8]. SARS-CoV, in 26 countries of Globe, infected over 8000 people with a 9% death rate. Similarly, SARS-CoV-2 infected over 6,728,537 people with a 4% death rate across 202 countries of the World. The infection rate of the SARS-CoV-2 is higher compared to SARS-CoV. The reason for the high infection rate is the regrouping of S Protein in RBD area [9]. Beta-corona viruses infected those people that have close contact with bats [10]-[11]. SARS-CoV-1 and MERS-CoV were transmitted to humans from the cats and Arabian camels. The discovery of the pangolin offspring corona virus and its proximity to SARS-CoV-2 suggested that pangolins can be the possible hosts of the novel 2019 corona viruses [12]. The World Health Organization (WHO) and Centers for Diseases of the US have announced corona virus infection with evidence of human-to-human transfer from five different cases outside China, (Italy [13], US [14], Nepal [15], Germany [16], and Vietnam [17]). On 5 June 2020, SARS-CoV-2 confirmed more than 6,728,537 cases, 3,271,261 recovered cases, and 393,667 death cases. In [18] the statistics about SARS-CoV-2 are shown. Geographical statistics

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about confirmed Covid-19 cases till June 6, 2020 are obtained from 202 countries (according to the World Health Organization (WHO)). National/International travelling and close contacts with the infected people have been identified as the main reasons of worldwide spread. Huge efforts are being put into developing the vaccines and curing drugs to treat the deadly infection [19]-[20].

Thoracic radiology evaluation is used to diagnose suspected Covid-19 patients. But, scientific methods to identify the virus inside human bodies through machine learning and deep learning using chest x-ray images and computed tomography (CT) scans are potential methods. Timely finding the infection is important in the effort to guarantee the well-timed cure. Machine learning-based studies showed that imaging pattern on the chest x-ray images and CT scans of the patients diagnosed with Covid-19 is a potential analysis tool. The motivation behind the presented study is to detect the Covid-19 using CNN networks. We intend to provide a simple solution with better results. The target of the proposed work is to detect Covid 19 in x-ray images and CT scans efficiently. From the literature it is obvious that performance of relatively simple model VGG 16 is better as compared to the modern GoogleNet and ResNet. Therefore, we are focused on trying a simple version of 2D-CNN inspired from VGG-11. Our CNN network is a subset of VGG-11 which consists of 5 convolution layers each is followed by an activation, and pooling layer. Also, in our network single dense layer with 512 neurons is used instead of multiple dense layers with large number of neurons. This helped in reducing the system complexity in terms of system parameters. The main contributions of this study are given as:

i) A Multilayer-Spatial Convolutional Neural Network with low complexity (few parameters) is proposed that is able to accurately detect the Covid-19 disease, achieving significant detection accuracy and AUC.
ii) The previous studies are based on either X-ray images or CT scans for Covid-19 detection. But, we have used both chest X-ray images and CT scans in this study to effectively train the proposed network for Covid-19 detection.
iii) We have developed two diverse databases for X-ray images and CT scans. The first database contains 723 chest X-ray images whereas the second database contains 3228 chest CT scans. Both databases are freely available for further studies.

The remaining paper is organized as follows. The literature review is given in Section II. The proposed deep learning method for Covid-19 detection is discussed in Section III. Materials and methods are presented in Section IV. Results and discussions are presented in Section V. Finally, the conclusions are presented in Section VI.

II. Literature Review

From the public health viewpoint, quick isolation of patients is vital for controlling this contagious disease [1]-[3] and the best possible use of on hand resources that rapidly befall insufficient and plagued by an exponentially increasing number of patients and protracted times of the treatment. Researchers and scientists of the different disciplines are working along with public health officials to comprehend Covid-19 pathogenesis. Jointly they are working with the policymakers to urgently develop strategies, vaccines and curing drugs to treat the deadly novel disease. Thoracic radiology evaluation is used to diagnose suspected patients of Covid-19 [21]. But, scientific methods to identify the virus inside human bodies through Machine Learning and Deep Learning using chest X-ray images and Computed Tomography (CT) scans are potential methods. Timely detection and diagnosis of the disease is important in the efforts to guarantee timely treatment. Recent studies demonstrated imaging patterns on the chest X-Ray images and CT scans of the patients diagnosed with Covid-19 as potential analysis tool. The analysis revealed bilateral lung opacities on 98% chest X-ray images and CT scans in the infected people in Wuhan city and uttered lobular and subsegmental regions of consolidation as the most usual findings [22].

Other studies demonstrated high rates of ground-glass opacities and consolidation, with a rounded morphology and peripheral lung distribution [23]. Recently, many conventional image processing and machine/deep learning methods are used to diagnose the diseases by classifying the digitized chest X-ray images [24]-[25]. Class decomposition of the Covid-19 as Covid and non-Covid with X-ray images is considered as one of the significant methods for diagnosing this contagious disease [26]-[28]. Quick detection of the Covid-19 can help controlling the transmission of disease and to monitor the chain of infections. Chest CT scans are more helpful to diagnose Covid-19 as compared to the Reverse-Transcription Polymerase Chain Reaction (RT-PCR) which is collected from the swab samples of the patients and showed 97.3% accuracy to classify Covid-19 [29]. Convolution Neural Networks (CNNs) are the most accepted methods which have revealed a great ability and high precision to construe Covid-19 classification with medical imaging (X-ray images or CT scans). A Covid-19 classification method for the pathogen-confirmed Covid-19 is proposed [30] by using CNNs which are based on the Inception Net. The network achieved 82.9% classification accuracy by using 453 CT scans of pathogen-confirmed Covid-19. A multi-class classification method is proposed [31] to detect Covid-19 by using a pre-trained ResNet-50 (DRE-Net). For the classification, 86 CT scans of non- Covid-19, 100 CT scans of bacterial pneumonia and 88 CT scans of Covid-19 are used and showed 86% classification accuracy for Covid-19. Chest X-ray images are used to detect the Covid-19 in [32]. In the proposed method, deep features have been extracted using CNN which are based on pre-trained ImageNET. In the last layer Support Vector Machine, SVMs, are used for classification. A multi-class classification method is proposed [27] using deep CNN, called COVID-Net. Chest radiography images are used to classify Covid-19 and non- Covid-19.

Several other studies have been carried out to highlight recent contributions to Covid-19 detection [33]-[36]. In [37] a deep CNN, called DeTraC is adapted and validated for Covid-19 chest X-ray images classification. The proposed method traced irregularities in the chest X-ray images and examined class boundaries by using class decomposition method. The proposed method showed 95.12% classification accuracy (97.91% sensitivity and 91.87% specificity) for Covid-19. A deep learning-based classification method is proposed in [38] to extract deep features applying ResNet152 to classify chest x-ray images of Pneumonia and Covid-19 patients. SMOTE has been applied to balance the imbalance data points of normal and Covid-19. The proposed method showed 97.31% classification accuracy on Random Forest and 97.7% using XGBoost predictive classifiers. Various models including Alexnet, Googlenet, and Restnet18 have been analyzed to detect the Covid-19 in [33]. A novel method for detecting Covid-19 is proposed using chest X-ray images. A binary classification is used to detect the Covid-19 and non- Covid-19 whereas multi-class classification is used to detect Covid-19, non-Covid-19 and Pneumonia. The DarkNet was applied as a classifier for You Only Look Once (YOLO) real-time object detection system with 17 Convolutional layers using different filtering on each layer. The method showed 98.08% classification accuracy for binary classes and 87.02% for multi-class. An intelligent computer vision method called Residual Exemplar Local Binary Pattern (ResExLBP) has been proposed in [39] to detect Covid-19 which is based on preprocessing, feature extraction and feature selection, respectively. During the preprocessing, image-resizing and grayscale-conversion has been used whereas an

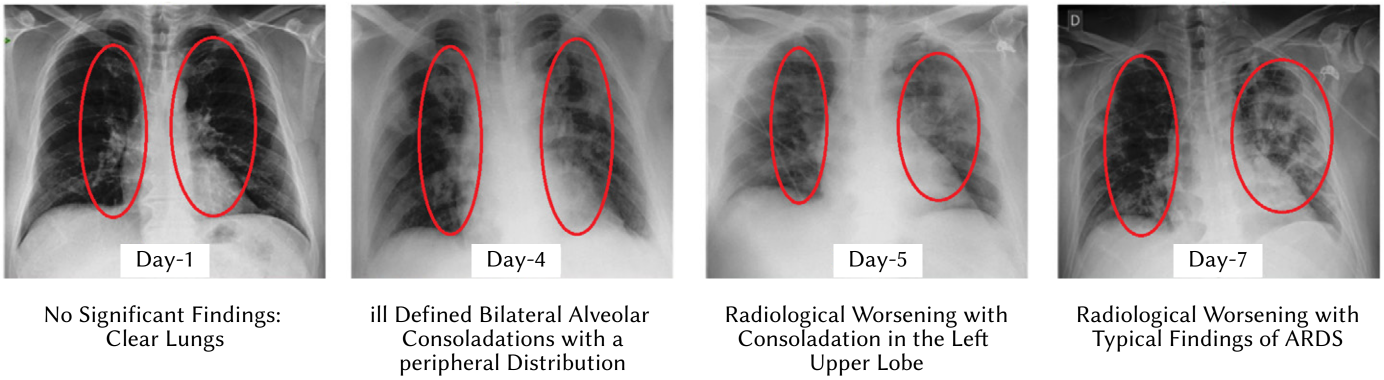

Fig. 1. Chest X-ray images of a 50-year-old COVID-19 patient over a week.

TABLE I. Comparative Analysis of Various Methods for Covid-19 Detection with Datasets and Evaluating Metrics

S. No	Reference	Database Nature	Model Evolution Metrics	Network for Detection
1	[26]	**X-Ray Images**: Covid-19, Normal, Viral Pneumonia and Bacterial Pneumonia	AUC, Precision, NPV, F1-Score and Sensitivity	ResNet-50 with 50 Layers
2	[27]	**X-Ray Images**: Covid-19, Normal, and Viral Pneumonia	AUC, Precision, and Sensitivity	COVID-Net CNN
3	[30]	**CT Scans**: Covid-19 and Normal	AUC, Precision, NPV, F1-Score and Youden Index.	Fully connected CNN with Multiple Classifiers.
4	[31]	**CT Scans**: Covid-19, Normal, and Bacterial Pneumonia	AUC, and Recall (Sensitivity)	Details Relation Extraction neural network (DRE-Net)
5	[32]	**X-Ray Images**: Covid-19, Normal, and Viral Pneumonia	Accuracy, Sensitivity and Specificity	Deep CNN Architecture
6	[33]	**X-Ray Images**: Covid-19, Normal, Viral Pneumonia and Bacterial Pneumonia	Accuracy, Specificity, Recall, F1-score and Precision	Deep Transfer Learning CNN
7	[34]	**X-Ray Images**: Covid-19, and Viral Pneumonia	Accuracy, Specificity, Sensibility	Single Shot Multibox Detector (SSD)
8	[35]	**CT Scans**: Covid-19	Diagnosis based detection	CNN and Management of Patients
9	[36]	**CT Scans**: Covid-19, Normal, and Viral Pneumonia	Accuracy, Sensitivity and Specificity	Multiple CNN with Classifiers
10	[37]	**X-Ray Images**: Covid-19, Normal, and SARS	Accuracy, Sensitivity and Specificity	Deep Transfer Learning CNN

iterative ReliefF (IRF)-based feature selection is used. Decision Tree, Linear Discriminant (LD), Support Vector Machine (SVM), K-Nearest Neighborhood (KNN) and Subspace Discriminant (SD) approaches have been selected as classifiers during the classification phase. Zhao et al. [40] not only found ground-glass opacities (GGO) or mixed GGO in most of the patients, but they also observed a consolidation, and vascular dilation in the lesion. Li and Xia [35] reported GGO and consolidation, interlobular septal thickening and air bronchogram sign, with or without vascular expansion, as common CT features of Covid-19 patients. Peripheral focal or multifocal GGO affecting both lungs in 50%– 75% of patients are another observation [41]. Similarly, Zu et al. [42] and Chung et al. [43] discovered that 33% of chest CT scans can have rounded lung opacities. Fig. 1 shows chest X-ray images at days 1, 4, 5 and 7 for a 50-year-old Covid-19 patient.

In this paper, a deep learning model is proposed which is based on the 2D-Spatial Convolutional Neural Network for automatic detection of Covid-19 using chest X-ray images and CT scans. The proposed model is trained with 723 x-ray images and 3228 CT scans of both genders and various age groups. The x-ray images and CT scans are associated to Covid-19 and non-Covid-19 diagnosed patients. The proposed model provided an improved automated accurate detection of Covid-19 disease. Table I presents various deep learning methods with network types, database type and evaluation metrics used to assess the detection capabilities. It is clear from the Table I that most of the networks are complex and operate with more variables which make them complex as compared to the proposed method which has a relatively small number of parameters. Moreover, none of them has used both x-ray images and scans for detection. On the other hand, the proposed model has used x-ray images and scans for Covid-19 detection with less complexity.

III. Proposed Deep Learning Method for Covid-19 Detection

CNN is as an effective machine learning method which provides up to date results by considering various layers of features. Recently 2D-CNN gained popularity in the area of image characterization [44], object detection and localization [45]-[47], face recognition [48], activity recognition [49]-[50]. Inspired by the performance of the 2D-CNN in the area of computer vision, we have used this network for automated detection of novel corona virus. In this study, a multilayer spatial CNN (2D-CNN) has been introduced to learn the prominent features needed for effective detection of Novel Covid-19 from X-ray images/CT Scan. CNN is a multilayer network architecture inspired from the neurobiology of the visual cortex. It contains an input layer, hidden layers, and an output layer. The hidden layer comprises of combination of the convolution layer, activation layers, pooling layers, normalization layers and fully connected layers. The

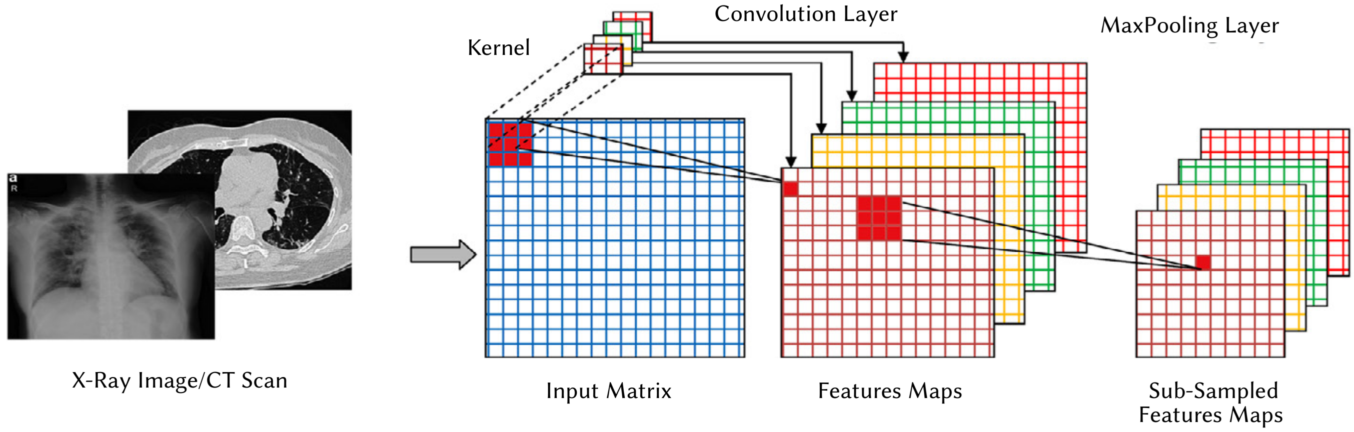

Fig. 2. Schematic presentation of Convolution and Max-Pooling layers.

convolution layers are used for extracting prominent features needed for classification of input data into desired classes. The convolution layer is the main building block of a CNN architecture. The prominent features are obtained through filters in the convolution layer. The filter coefficients convolved over height and width of the input data results in a 2D activation map of the filter. CNN has the capability to learn those filter coefficients, which activate when a particular feature at some spatial position is observed. The convolution layer is followed by an activation layer which is used to transform the input signal to an output signal. The output signal will be used as an input signal to the following layer. The activation layer normally uses a nonlinear function like sigmoid, tanh, ReLU, Leaky ReLU, etc. To speed up the learning process and avert the overfitting problem pooling layers are introduced in the CNN. The main task of this layer is to down sample the input data which reduces the spatial information to be processed. Among various pooling techniques average pooling and max pooling are the most prominent ones. The fully connected layer is similar to the conventional ANN. Its task is to set a path for the effective detection/classification.

A schematic presentation for the flow of input data from the convolution layer (C) and Max-pooling (M) layer, respectively, is given in Fig. 2. Inspired by the performance of CNN, a spatial CNN model has been proposed for auto mated detection of the COVID-19. The proposed model is composed of 5 Convolutional layers (with different number of filters, sizes, and strides), 5 maxpooling layers, a fully connected layer with 512 neurons, and a softmax classifier. An activation function has been used after each convolution layer and fully connected layer. For the activation function two different settings i.e. ReLU and Leaky ReLU activation functions are separately analyzed. The orientation of various layers used in the proposed model is depicted in Fig. 3. The first Convolutional layer contains 64 filters, each with size of (3, 3), and stride (1, 1). Similarly, the 2nd and 3rd Convolutional layer contain 128 filters each with size of (3, 3), and stride (1, 1). Furthermore, 4th and 5th Convolutional layer contain 256 filters each of size (3, 3), and stride (1, 1). All pooling layers use maxpooling strategy with the pooling window of size (2, 2), and strides (2, 2). The output of the last maxpooling layer is converted from 2D to 1D using a flatten layer. Then the output of the flatten layer is fed to the fully connected (Dense) layer with 512 neurons using sigmoid as an activation function. The fully connected layer is an actually conventional ANN architecture. At the output layer a softmax classifier is used to assign detection probabilities to each output. We have used SGD optimizer for learning weights. We have used a learning rate of 0.001, momentum = 0.9, and binary cross entropy loss function. The layer details and layer parameters of the model are given in Table II. First, the images are resized and preprocessed to fit in the model. The features are extracted from the input images which are needed for the classification of the input data into desired classes. The features are obtained using filters in the convolution layer. The filter

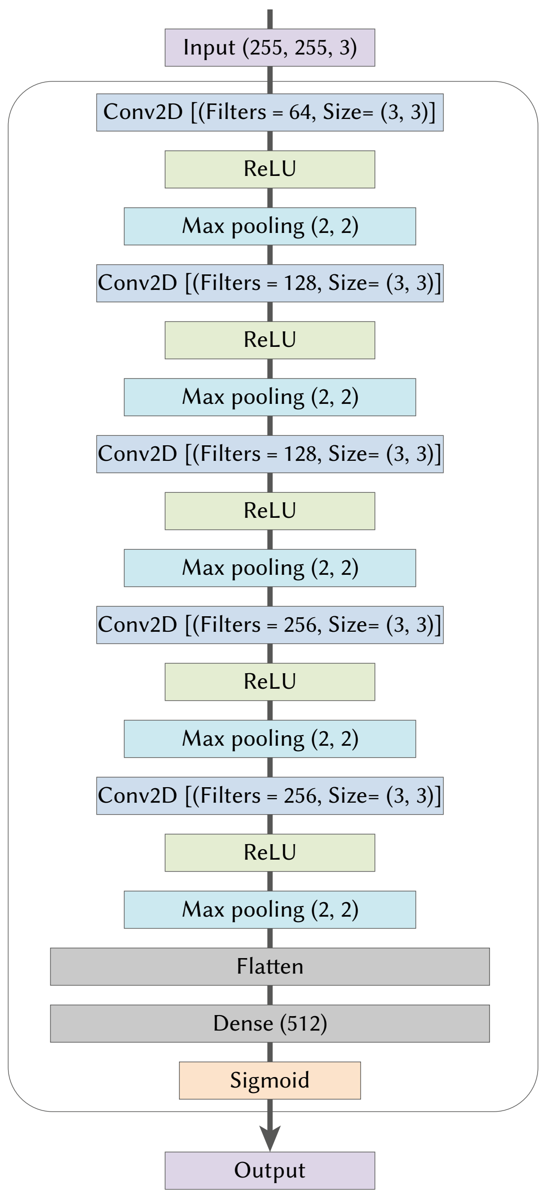

Fig. 3. The orientation of various layers used in the proposed model.

coefficients convolved over height and width of the input data results in a 2D activation map of the filter. The convolution layer is followed by the activation layer which is used to transform the input signal to an output signal. The output signal is used as an input to next layer. The activation layer used nonlinear functions ReLU and Leaky ReLU. To boost the learning process and prevent the overfitting problem, the max pooling layers are used in the CNN. The task of this layer is to down sample the input data that minimizes the spatial information need to be processed.

TABLE II. The Layers and Parameters of the Proposed Model

Layer Type	Output Shape	Parameters
Input Layer	[254 254 3]	0
Conv2D	[254 254 64]	1792
Maxpooling2	[127 127 64]	0
Conv2D	[127 127 128]	73856
Maxpooling2	[64 64 128]	0
Conv2D	[64 64 128]	147584
Maxpooling2	[32 32 128]	0
Conv2D	[32 32 256]	295168
Maxpooling2	[16 16 256]	0
Conv2D	[16 16 256]	590080
Maxpooling2	[8 8 256]	0
Flatten	[16384]	0
Dense	[512]	8389120
Dropout	[512]	0
Dense	[2]	1026
Activation	[2]	0

The main target of the proposed work is the efficient detection of Covid-19 in x ray images and CT scans. It is concluded from the literature that the performance of a relatively simple model such as VGG-16 [58] is better than the state of the art ResNet [26] and GoogleNet [57]. Therefore, this shows that the detection problem can be done with a relatively simple method. In this study, we focused on trying to efficiently detect the Covid-19 with a simple version of 2D-CNN inspired from VGG-11. Our network is a subset of VGG-11 which consists of 5-convolution layers, each is followed by ReLU/Leaky ReLU activation function and max-pooling layer. Moreover, in our network, we have used a single dense layer that consists of 512 neurons instead of three dense layers with large number of neurons in each. Such network architecture arrangements helped us in reducing the system complexity in terms of system parameters and provided better results compared to the other networks. It is observed and verified that the proposed network outperformed the existing state of the art by considerable margins. So, our main and important contribution is to select a simple combination of different layers for achieving an efficient model in terms of system parameters and performance.

IV. Experimental Setup

In the experimental setup, we discuss the database of x-ray images and scans to detect covid-19 in the patients. We have used several evaluation metrics to assess the effectiveness of the 2D-CNN-based learning method for covid-19 detection.

A. X-ray Images and CT Scans Databases

To detect COVID-19 infection, we have used X-ray images from two different sources. For simplicity, we will use images instead of X-ray images afterward. The databases are developed by using images from various open access sources [51]-[53]. The first database contains a total of 625 images in which 125 images belong to Covid-19 diagnosed patients and 500 are normal images. Similarly, the second database contains a total of 98 images in which 70 images belong to Covid-19 diagnosed patients and 28 are normal images. In our study, we have combined both databases and generated a new diverse database with 723 images of both genders and various age groups in which 195 images belong to Covid-19 diagnosed patients and 528 are non-Covid-19 images. We also have used Computed Tomography (CT) scans from two different sources to detect Covid-19. For simplicity, we will use the term scans instead of CT scans afterward. The databases are developed using scans from the Tongji Hospital, Wuhan, China [54] and Sao Paulo, Brazil [55]. The first dataset from Tongji Hospital, Wuhan contains a total of 746 scans where 349 scans are associated to Covid-19 patients whereas 397 are non-Covid-19 scans. Similarly, the second database from Sao Paulo, Brazil contains a total of 2482 scans in which 1252 scans belong to Covid-19 patients and 1230 are non-Covid-19 scans. We have combined both databases and generated a new diverse database with a total of 3228 scans of both genders and various age groups. The new database contains 1601 scans which belong to Covid-19 patients whereas 1627 are non-Covid-19 scans. Fig. 4 demonstrates samples images and scans of Covid-19 and non-Covid-19 cases selected from the new databases.

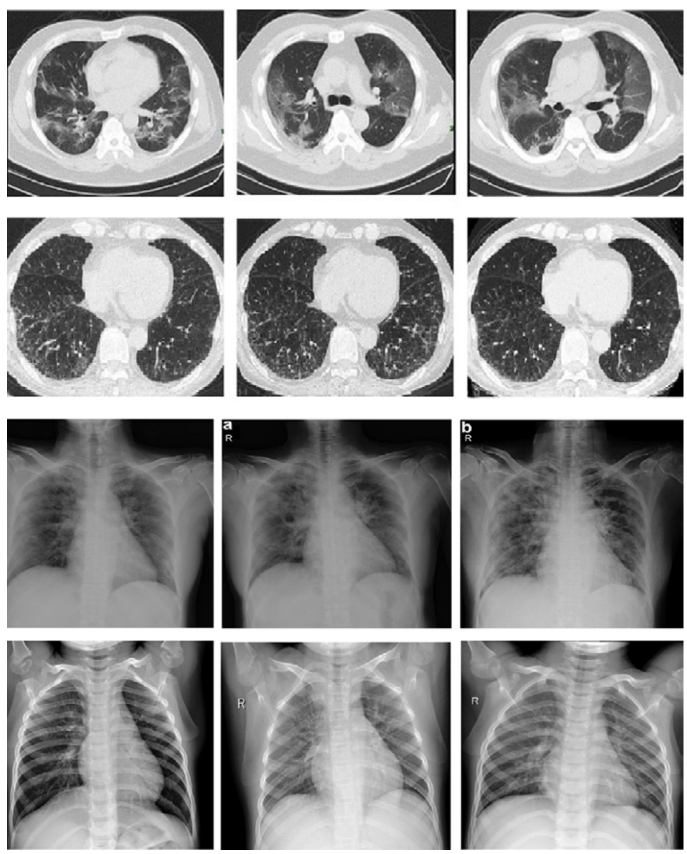

Fig. 4. Samples images and scans of COVID-19 and non-COVID-19 cases in the new databases.

B. Evaluation Criteria

To examine the effectiveness of the proposed model, the confusion matrix along with the Receiver operating characteristics (ROC) and Area under Curve (AUC) [56] are calculated, which determines the potentials of the proposed model for Covid-19 detection. The usefulness and productivity of the proposed model are also measured using the conventional evaluation metrics including accuracy, precision, sensitivity, and F1 score, which are represented in terms of the confusion matrix. The evaluation metrics are given by the following equations as:

$$\text{Accuracy}: \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Sensitivity}: \frac{TP}{TP+FN} \tag{2}$$

$$\text{Precision}: TP/(TP+FP) \tag{3}$$

$$\text{F1-Score}: \frac{2*TP}{2*TP+FP+FN} \tag{4}$$

Where, *TP*, *TN*, *FP*, and *FN* denote True Positive, True Negative, False Positive, and False Negative, respectively.

V. Results and Discussions

We performed a number of intense experiments to detect Covid-19 using the two new diverse databases containing CT scans and X-ray images. We have trained the MS*Cov*CNN deep learning model to classify CT scans and X-ray images into Covid-19 and non-Covid-19 cases. The performance of the proposed model is examined using random validation procedure for the binary classification problem. We have performed experiments by splitting the training data in two splits: 80:20 and 50:50, that is, 80% of CT scans and X-ray images are used for training and 20% for validation. Similarly, 50% of CT scans and X-ray images are used for training and 50% for validation. In the experiments, we have used two activation functions: ReLU and Leaky ReLU and repeated the experiments for both split separately. Table III shows the experimental results in terms of the Accuracy and AUC for the two splits using ReLU and Leaky ReLU activations. It can be observed from Table III that a high average network accuracy and AUC for CT scans and X-ray images are achieved when leaky ReLU is used in the proposed model. The average accuracy of the network is improved by 1.16% and 1.06% for X-ray images and CT scans, respectively. Similarly, the average AUC of the network is improved by 2.01% for the X-ray images and 0.47% for CT scans. Consequently, the leaky ReLU is selected as potential activation function for the proposed model. At the start of training procedure, we observed a significant increase in the values of loss function which has largely been decreased at the end of the training procedure. When the proposed deep learning model examined all X-ray images and CT scans over and over again for all epochs during the training, the rapid ups and downs are slowly reduced in the later part of the training.

TABLE III. Accuracy and AUC of the Proposed Model for Chest X-ray Images and CT Scans Using ReLU and Leaky ReLU Activations

Database: Chest X-Ray Images				
Data Split	ReLU		Leaky ReLU	
	Accuracy	AUC	Accuracy	AUC
80:20	90.76%	96.42%	91.53%	97.11%
50:50	93.59%	95.33%	95.72%	98.65%
Average	92.18%	95.87%	93.34%	97.88%

Database: Chest CT Scans				
Data Split	ReLU		Leaky ReLU	
	Accuracy	AUC	Accuracy	AUC
80:20	91.95%	95.79%	92.64%	96.31%
50:50	88.82%	94.52%	90.25%	95.52%
Average	90.38%	95.15%	91.44%	95.92%

Tables IV-V indicate the performance of the proposed deep learning model for two splits using chest X-ray images and CT scans. The proposed model achieved significant results in terms of the Covid-19 detection and achieved improved accuracy percentage along with other important metrics. It can be observed from Tables IV-V that the proposed model achieved better results for chest X-ray images as compared to CT scans. The proposed model achieved 91.53% network accuracy for 80:20 split whereas achieved 95.72% network accuracy for 50:50 split. A high accuracy is reported for 50:50 split setting. The AUC, an important evaluation parameter indicates that the proposed model achieved better results. An average of 97.88% AUC is achieved with the proposed model. Moreover, 50:50 split achieved better AUC percentage as compared to the 80:20 split for chest X-ray images. Similarly, 91.44% average network accuracy and 95.92% AUC for CT scans are achieved with the proposed model. We secondly examined the results of the proposed model by using Confusion Matrixes and ROC for the binary classification problem in order to detect the novel Covid-19. The Confusion Matrixes and ROC are drawn for 80:20 and 50:50 splits of X-ray images and CT scans for both ReLU and Leaky ReLU activation functions. The vertical axis of confusion matrix shows the true labels whereas horizontal axis indicates the predicted labels of Covid-19 and non-Covid-19, respectively. For example, consider the confusion matrix obtained from the 80:20 split of X-ray images for ReLU activation function, see Fig. 5(A). The element in first-row first-column indicates true negatives which means that 98% of negative samples are classified correctly (non-Covid-19). Similarly, the element of first-row second-column indicates false positive which means that 2% of negative samples are confused with the positive labels. The element of second-row first-column represents false negative which means that 19% of positive labels are identified as negative labels. Finally, the element of second -row and second-column shows true

TABLE IV. Performance Evaluation of the Proposed Model: S*Cov*CNN Using Accuracy, Sensitivity and AUC

Database: X-Ray Images							
Split	TP	TN	FP	FN	Accuracy	Sensitivity	AUC
80:20	32	87	3	8	91.53%	80%	97.11%
50:50	65	204	3	9	95.72%	87.83%	98.65%
Avg	48.5	145.5	3	8.5	93.63%	84%	97.88%

Database: CT Scans							
Split	TP	TN	FP	FN	Accuracy	Sensitivity	AUC
80:20	282	259	35	8	92.63%	97.24%	96.31%
50:50	541	597	48	75	90.24%	87.82%	95.52%
Avg	411.5	428	41.5	41.5	91.44%	92.53%	95.92%

TABLE V. Performance Evaluation of the Proposed Model: S*Cov*CNN Using Precision and F1-score

Database: X-Ray Images						
Split	TP	TN	FP	FN	Precision	F1 Score
80:20	32	87	3	8	91.42%	85.33%
50:50	65	204	3	9	95.58%	91.54%
Avg.	48.5	145.5	3	8.5	93.50%	88.44%

Database: CT Scans						
Split	TP	TN	FP	FN	Precision	F1 score
80:20	282	259	35	8	88.95%	92.91%
50:50	541	597	48	75	91.85%	89.79%
Avg.	411.5	428	41.5	41.5	90.40%	91.35%

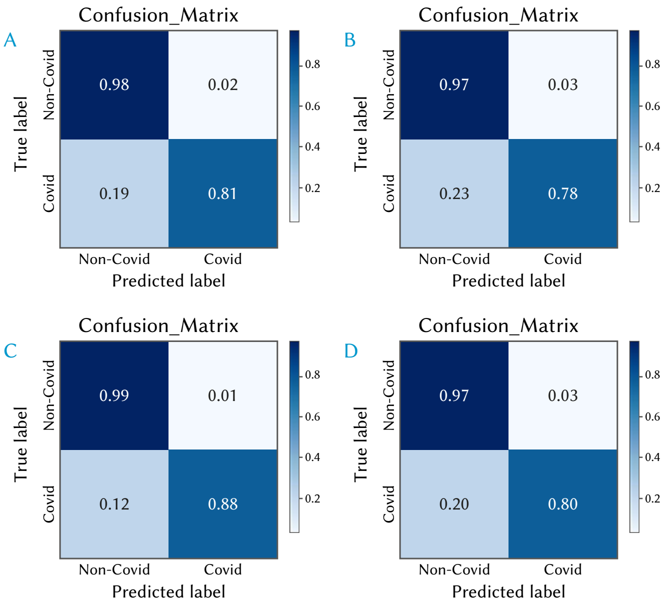

Fig. 5. Confusion Matrices for Chest X-ray images. (A) 80:20 split with ReLU activation function, (B) 80:20 split with Leaky ReLU activation function, (C) 50:50 split with ReLU activation function, (D) 50:50 split with Leaky ReLU activation function.

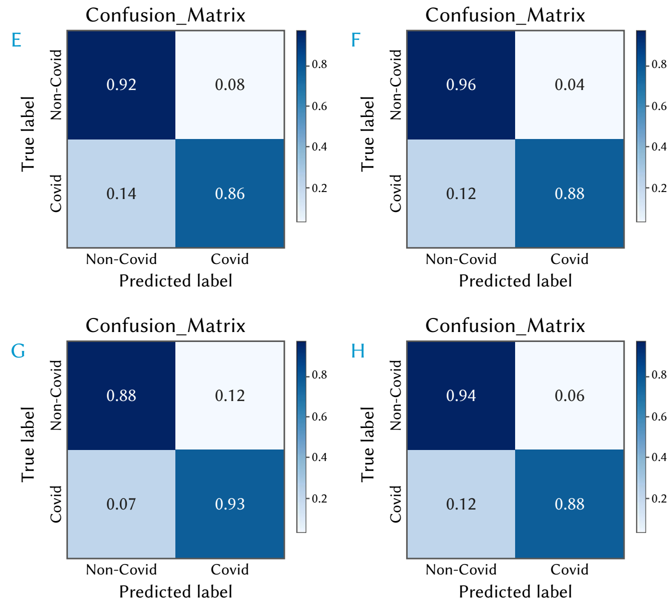

Fig. 6. Confusion Matrices for Chest CT scans. (E) 80:20 split with ReLU activation function, (F) 80:20 split with Leaky ReLU activation function, (G) 50:50 split with ReLU activation function, (H) 50:50 split with Leaky ReLU activation function.

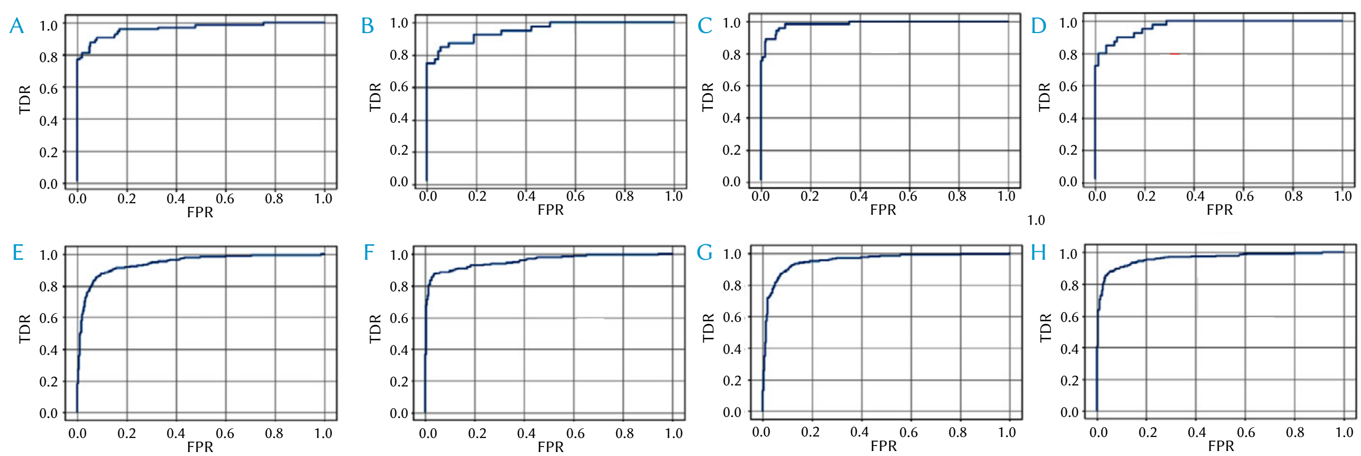

Fig. 7. ROC analysis for Chest X-ray images and CT scans. (A) 80:20 split with ReLU activation function, (B) 80:20 split with Leaky ReLU activation function, (C) 50:50 split with ReLU activation function, (D) 50:50 split with Leaky ReLU activation function, (E) 80:20 split with ReLU activation function, (F) 80:20 split with Leaky ReLU activation function, (G) 50:50 split with ReLU activation function, (H) 50:50 split with Leaky ReLU activation function.

positive which means that 81% of the positive samples are correctly classified as Covid-19. Consider the confusion matrix obtained from the 50:50 split of CT scans for leaky ReLU activation function, see Fig. 6(H). The element in first-row first-column indicates true negatives which means that 94% of negative samples are classified correctly (non-Covid-19). Similarly, the element of first-row second-column indicates false positive which means that 6% of negative samples are confused with the positive labels. The element of second-row first-column represents false negative which means that 12% of positive labels are identified as negative labels. Finally, the element of second-row and second-column shows true positive which means that 88% of positive samples are correctly classified as Covid-19. The confusion matrix for chest X-ray images and CT scans are illustrated in Fig. 5-6, respectively. Non-linear filters in the initial layers of network act as preprocessing layers which helps in extracting prominent features by learning the filter coefficient. So, preprocessing in case of convolution neural network may not help in improving the results. Comparison of the complexity of state of the art networks is given in Table VI. ROC plots are depicted in Fig. 7 which indicates the true positive vs. false positive rates. ROC plots are used to show the separation of features from each other. We also provided log loss, MSE, MAE, and MLSE for evaluating the proposed method in Table VII.

TABLE VI. Network Complexity Analysis

S.No.	Technique	Parameters
1.	AlexNet	62 Million
2.	VGG 16	138.36 Million
3.	Inception V3	41.33 Million
4.	ResNet 50	25.56 Million
5.	Proposed Method	9.49 Million

TABLE VII. Comparison of Various Methods for Loss

Method	Split	MSE	Log Loss	MAE	MSLE
Leaky ReLU	50:50	0.1517	0.2719	0.1809	0.1235
Leaky ReLU	80:20	0.1369	0.1995	0.1577	0.1215
ReLU	50:50	0.1819	0.3404	0.2099	0.1544
ReLU	80:20	0.1396	0.2100	0.1606	0.12298

A. Comparison with Other Methods

In this section, we have compared the proposed deep learning model with other competing deep learning models for Covid-19 detection. For comparison purpose, we have selected xDNN [55], ResNet [26], GoogleNet [57], VGG-16 [58], AlexNet [57], Decision Tree [59], and AdaBoost [60]. All deep learning approaches for Covid-19 detection are evaluated using Accuracy, precision, sensitivity, F1-score and AUC. Table VIII shows the performance of the proposed deep learning model and the competing models. In this experiment we have combined X-rays and CT scans into a single dataset. We achieved better performance in terms of Accuracy, precision, sensitivity, F1-score and AUC compared to other competing methods for covid-19 detection in the literature. For example, accuracy of the proposed detection method is improved from 91.73%, 93.75 and 94.96% with GoogleNet, AlexNet and ResNet to 97.48% with S*Cov*CNN. Similarly, the AUC is improved from 95.19%, 79.51%, 94.96% and 97.36% with the AdaBoost, Decision Tree, VGG-16 and xDNN to 97.36% with S*Cov*CNN. Precision, sensitivity and F1 score of the proposed model is consistently higher than the competing methods. Decision Tree performed less as compared to other methods. The improvements in the evaluation metrics with respect to Decision Tree is plotted in Fig. 8. In convolutional neural networks complexity of a model is defined by the number of parameters.

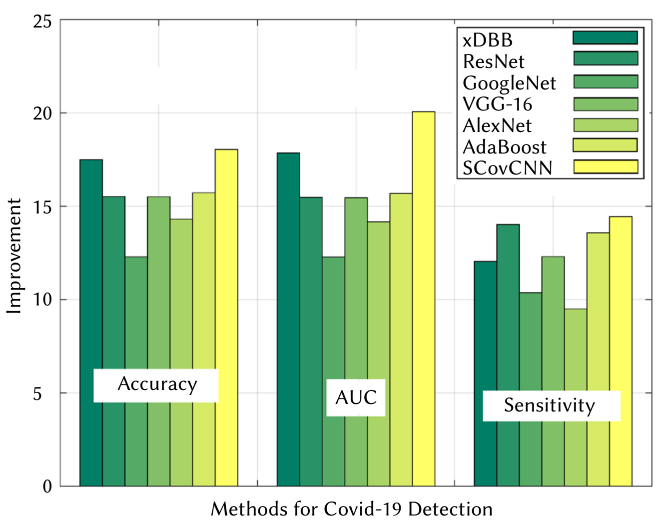

Fig. 8. Accuracy, AUC and Sensitivity improvements of various methods with reference to Decision Tree.

VI. Conclusions

In this study, we have proposed a multilayer-Spatial Convolutional Neural Network for automatic detection of Covid-19 using chest X-ray images and CT scans. The proposed model showed 98.18% detection accuracy and 99.98% AUC for chest x-ray images and 97.14% detection accuracy and 99.51% AUC for chest CT scans. The previous studies are based on either X-ray images or CT scans for Covid-19 detection. But, we have used both chest X-ray images and CT scans in this study to effectively train the proposed network for Covid-19 detection. We have developed two diverse databases for X-ray images and CT scans. First database contains 723 chest X-ray images whereas the second database contains 3228 chest CT scans. Both databases are freely available for further studies. The proposed model is evaluated using a number of metrics including confusion matrix, ROC, AUC, accuracy, precision, sensitivity, and F1 scores, respectively. We have performed experiments by splitting the training data in two splits: 80:20 and 50:50, that is, 80% of CT scans and X-ray images are used for training and 20% for validation. Similarly, 50% of CT scans and X-ray images are used for training and 50% for validation. We have drawn the following conclusions:

1. The average accuracy and AUC of the proposed model is improved by 1.16% and 1.06% for X-ray images and CT scans whereas 2.01% for X-ray images and 0.47% for CT scans. Therefore, it is concluded that the leaky ReLU is the potential activation function for the proposed model.
2. We concluded that there was a significant increase in the values of loss function which has largely been decreased at the end of training procedure. The proposed deep learning model examined all X-ray images and CT scans over and over again for all epochs during the training, hence, rapid fluctuations in loss function values are slowly reduced in the later part of the training.
3. It is concluded that the proposed model achieved significant results in terms of the Covid-19 detection and achieved higher accuracy, AUC, sensitivity and F1 scores. The proposed model achieved 91.53% network accuracy for 80:20 split whereas achieved 95.72% network accuracy for 50:50 split. A high accuracy is reported for 50:50 split setting.
4. It is concluded that the proposed model achieved better performance in terms of the accuracy, precision, sensitivity, F1-score and AUC compared to competing methods for covid-19 detection. The accuracy of the proposed detection method is improved from 91.73%, 93.75 and 94.96% with GoogleNet, AlexNet and ResNet to 97.48% with S*Cov*CNN.

In the future work, we will be devoted in attempting further improvements in the performance of the proposed model and will extend the proposed model into a more powerful model. In addition, we will systematically examine the complex networks and classifiers to find more accurate results in terms of Covid-19 detection.

TABLE VIII Comparison with Competing Methods

Database: X-Ray Images/CT Scans					
Methods	Accuracy	Precision	Sensitivity	F1 score	AUC
xDNN [55]	97.38%	91.6%	95.53%	97.31%	97.36%
ResNet [26]	94.96%	93.00%	97.15%	95.03%	94.98%
GoogleNet [57]	91.73%	90.20%	93.50%	91.82%	91.79%
VGG-16 [58]	94.96%	94.02%	95.43%	94.97%	94.96%
AlexNet [57]	93.75%	94.98%	92.28%	93.61%	93.68%
Decision Tree [59]	79.44%	76.81%	83.13%	79.84%	79.51%
AdaBoost [60]	95.16%	93.63%	96.71%	95.14%	95.19%
S*Cov*CNN	**97.48%**	**97.18%**	**97.57%**	**97.37%**	**99.57%**

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