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A CNN Approach to Identify COVID-19 Patients among Patients with Pneumonia

Kuldeep Singh*[1], Jaspreet Kaur[2]

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Abstract: Due to COVID-19 pandemic, the healthcare system has been collapsed worldwide. Keeping in view of the shortage of healthcare services during these times, the automated identification of COVID patients among other non-COVID patients suffering from pneumonia is an essential task. It will help the medical professionals for speedy diagnosis of the patients with appropriate treatments. Therefore, the present work presents an automated approach for detection of COVID patients using convolutional neural network model. This approach takes into account chest X-ray images of COVID positive patients as well as non-COVID pneumonia patients for the training of the proposed CNN model. The simulation results show that the proposed CNN model performs binary classification of COVID and non-COVID pneumonia classes with an average accuracy of 97.92%, sensitivity of 99.69% and specificity of 98.48%. Thus, the proposed CNN model is an effective technique for the accurate identification of COVID patients among other patients suffering from bacterial or viral pneumonia using X-ray images.

Keywords: *CNN, COVID, Pneumonia, X-ray images.*

1. Introduction

Coronavirus disease (COVID-19) is one of the most fatal pandemics of human age. It is an infectious disease instigated by a newly discovered virus, which is named as SARS-CoV-2 [1,2]. As per latest statistics up to the end of November 2021, approximately more than 270 million population of the world is the victim of this diseases and the number of deaths reaches to more than 53,35,000 [3]. This figure is increasing day by day.

A person infected with this disease may experience clinical symptoms, including high or mild fever, dry cough, sore throats and respiratory illness such as severe pneumonia, acute respiratory distress syndrome (ARDS) [4]. For old age people or patients suffering from cardiovascular disease, chronic respiratory disease, cancer, and diabetes etc. may suffer from life-threatening illness [2]. During these days, the reverse transcription-polymerase chain reaction (RT-PCR) test is a widely accepted technique for identifying patients with COVID [5,6]. But the lower sensitivity of this test at early stages [6], limited availability of RT-PCR kits and longer time taken by medical professionals for testing using this method of large population assists the further spread of COVID-19. Therefore, other traditional health monitoring techniques such as CT-scans or X-rays should also be incorporated for testing purposes. The chest scan of the patients with potential symptoms of COVID using these methods could facilitate the healthcare staff in their rapid isolation and diagnosis.

Generally, pneumonia is an infectious disease of lungs, which is caused by various kinds of bacteria, viruses or fungi [7]. Since the severe illness caused by coronavirus also leads to pneumonia. So, there exists an urgent need for identifying COVID patients with severe illness among non-COVID patients suffering from other types of pneumonia, so that proper diagnostic procedure could be followed for their treatment. The chest scans using X-rays could play a significant role in this task. However, the manual analysis of X-ray images by doctors or physicians is a tedious and error-prone method, which needs to be automated using machine learning. Various researchers have started working in this direction for detection of COVID patients using automated analysis of X-rays images. The recent research work carried out by a few of the researchers in this domain has been demonstrated in table III. The present work also presents a convolutional neural network model for classification of COVID patients and non-COVID patients with other pneumonia symptoms using X-ray images, so that COVID patients could be identified and diagnosed effectively. This automated technology could help in fast and accurate monitoring of patients.

2. Proposed Methodology

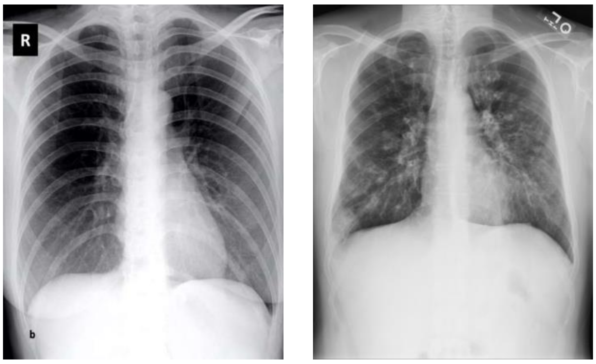
This section discusses X-rays datasets of COVID patients and other patients with pneumonia symptoms, pre-processing of X-rays images as well as the proposed CNN model for classification.

2.1. X-Ray Images Dataset

The present work takes into account X-ray images dataset of 125 COVID positive patients, which was developed by Cohen et al. 8 by collecting X-ray images from several open-access online sources. This work also employs 500 X-ray images of non-COVID patients suffering from pneumonia from ChestX-ray8 database, developed by Wang et al. 9. In this way, the present work performs a binary classification of COVID and non-COVID pneumonia X-ray images to identify the patients suffering from COVID-19 among other patients suffering from normal pneumonia using both

[1] Department of Electronics Technology, Guru Nanak Dev University Amritsar-143005, India, ORCID ID: 0000-0003-1465-6740
[2]Department of Electronics Technology, Guru Nanak Dev University Amritsar-143005, India, ORCID ID: 0000-0001-7127-5333
** Corresponding Author Email: kuldeep.ece@gndu.ac.in*

datasets. A generalized view of X-rays images taken from COVID patient and a non-COVID patient suffering from pneumonia has been illustrated in figure 1.



(a) (b)

Fig. 1. A view of X-ray Images of (a) COVID Patient and, (b) Non-COVID patient suffering from Pneumonia

2.2. Preprocessing

In this step, the X-ray images taken from different patients are grouped into two output classes labelled with COVID and pneumonia. These images are also resized to a size of 32 × 32 pixels before classification in order to maintain uniformity of images. This resizing of images also helps in reducing the computational and processing burden, which further speeds up the process of detecting COVID patients. These images are also normalized to keep its pixel values between 0 and 1.

2.3. Convolutional Neural Network based Classification

The present work proposes a convolutional neural network (CNN) model 10 for the classification of COVID and pneumonia X-ray images shown in Figure 2. The architectural details of the proposed CNN model are also mentioned in Table 1.

Table. 1. Architectural Details of the Proposed CNN Model

Layers	Functions	Output Shape	Kernels and their Size
0	Input	32 × 32 × 4	-
1	Convolution	32 × 32	64, (5 × 5)
2	Max Pooling	16 × 16	64, (2 × 2)
3	Convolution	16 × 16	32, (5 × 5)
4	Max Pooling	8 × 8	32, (2 × 2)
5	Convolution	8 × 8	16, (5 × 5)
6	Max Pooling	4 × 4	16, (2 × 2)
7	Convolution	4 × 4	8, (3 × 3)
8	Max Pooling	2 × 2	8, (2 × 2)
9	Dropout	2 × 2	8 (Drop. Probability = 0.25)
10	Flatten	32	-
11	Dense	16	-
12	Dense	2	-

This model has been fed with resized X-rays images belong to COVID patients and non-COVID pneumonia patients. It consists of a combination of convolution and max-pooling layers, which is repeated four times (see figure 2). Each convolution layer uses ‘tanh’ activation and ‘same’ padding. The number of kernels and their corresponding kernel sizes for these layers have been mentioned in table I. Apart from these layers, the present model also takes into account a dropout layer having a dropping probability of 0.25 to avoid the problem of overfitting in the proposed model. Then it consists of flatten later, which is further followed by two fully connected dense layers having 16 and 2 neurons respectively for binary classification of COVID and non-COVID pneumonia images. The last dense layer makes use of ‘sigmoid’ activation function. This model uses ‘Adam’ optimizer for training purpose with loss function of ‘categorical cross-entropy’ and 100 epochs.

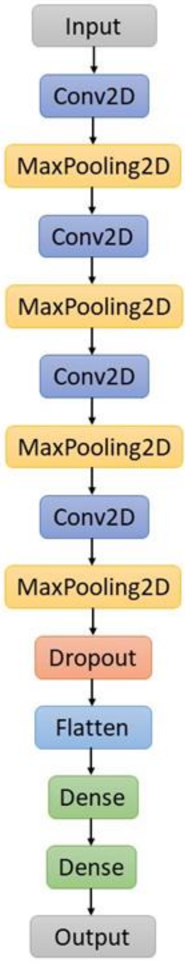


Fig. 2. Proposed Model of Convolutional Neural Network

3. Results and Discussion

In this section, the simulations results obtained from the proposed CNN model are analyzed. The proposed CNN model has been executed on a laptop having Intel i7 (8th Generation) processor, 16 GB RAM, NVIDIA GEFORCE GTX 1060 GPU of 6 GB and Windows 10 operating system. For this implementation, the total dataset of COVID and pneumonia X-ray images has been split in two sets, having 90% images for training and 10% for testing of the proposed model. Out of training dataset, 10% images are further kept for validation of the proposed model. The performance of CNN classifier has been analyzed on the basis of accuracy [11,12], sensitivity [11,12], specificity [11,12], false delivery rate (FDR) [13] and false omission rate (FOR) [13]. In order to get the stable performance of the classifier model, ten randomly selected simulation runs have been carried out and the average of these runs have been taken into consideration.

Table 2 shows the performance of the proposed CNN model in terms of above-mentioned performance metrics for 10 different simulation runs. This table and figure 3 also show its performance for an average of 10 runs. As per this figure, the proposed CNN approach provides an accuracy of 97.82%, the sensitivity of 99.69%, a specificity of 91.48% for classification of COVID and pneumonia patients. It also provides FDR and FOR values of 2.28% and 1.1% respectively for this task. These performance measures reveal the highly accurate performance of the proposed CNN algorithm for identification of COVID patients.

Table 2. Performance Analysis of the proposed CNN Model for identification of COVID Patients

Runs	Accuracy (%)	Sensitivity (%)	Specificity (%)	FDR (%)	FOR (%)
1	99.2	100	96.3	1.01	0
2	95.2	100	77.78	5.77	0
3	97.6	98.98	92.59	2.02	3.85
4	99.2	100	96.3	1.01	0
5	97.6	97.96	96.3	1.03	7.14
6	97.6	100	88.89	2.97	0
7	98.4	100	92.59	2	0
8	97.6	100	88.89	2.97	0
9	99.2	100	96.3	1.01	0
10	97.6	100	88.89	2.97	0
Avg.	**97.92**	**99.69**	**91.48**	**2.28**	**1.1**

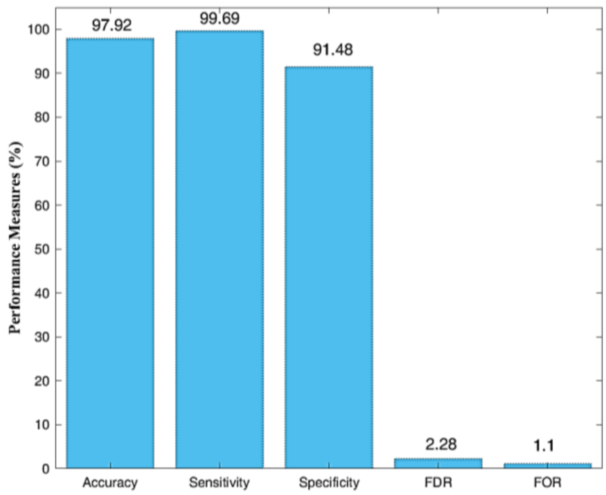
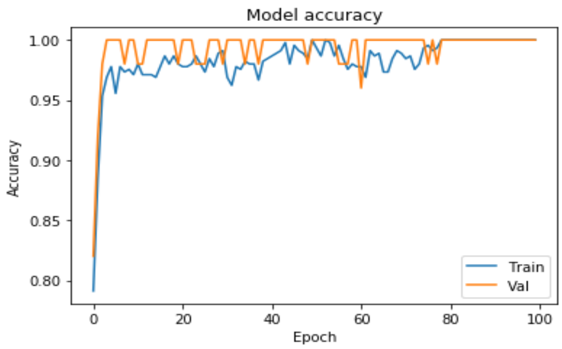
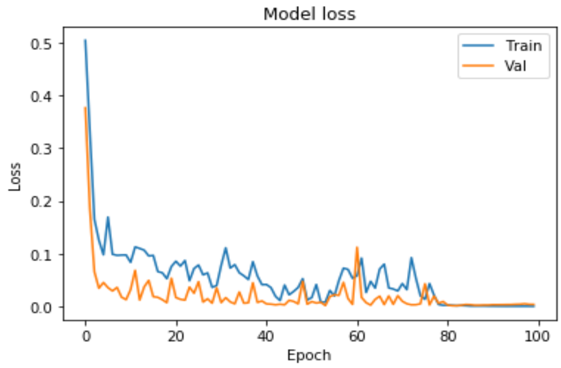


Fig. 3. Performance of CNN algorithm in terms of Averages Values of Performance Metrics

In addition, the performance of the proposed CNN model has also been examined in terms of accuracy and loss with respect to a number of epochs. As shown in figure 4(a), the accuracy curve shows an abrupt rise in its value and then attains an approximately constant level. Similarly, figure 4(b) shows an exponential decline in loss function with respect to epochs, which reaches a constant level of nearly zero value. These curves ensure the consistent and stable performance of the proposed CNN approach for identification of COVID patients.



(a)



(b)

Fig. 4. Performance of CNN Model in terms of (a) Accuracy and, (b) Loss Function

Similarly, the proposed technique has also been analyzed with few of the recently published techniques for detection of COVID patients among other cases in table 3. It is also evident from this table that the proposed model performs superior than other models for the given task. Therefore, the overall analysis of the proposed CNN model and comparison with recently published techniques firmly reveal the efficiency of the proposed CNN model for accurate detection of COVID patients among other non-COVID pneumonia patients using chest X-ray images.

Table 3. Comparison of the proposed approach with other recently published approaches

Author	X-rays Data Classes	Technique	Results
Mahmud et al. [14]	2 classes (COVID-19, Bacterial pneumonia)	CNN (CovXNet)	Accuracy = 94.7%
Ozturk et al. [15]	3 classes (COVID-19, Pneumonia, no findings)	CNN (DarkCovidNet)	Accuracy = 87.02%
Rahimzadeh et al. [16]	3 classes (Normal, COVID-19, Pneumonia)	Hybrid of Xception and ResNet50V2 CNN models	Accuracy = 91.4%
Vaid et al. [17]	2 classes (Normal, COVID-19)	CNN model	Accuracy = 96.3%
Hemdan et al. [18]	2 classes (Normal, COVID-19)	COVIDX-Net (CNN Model)	Accuracy = 90%
Proposed Approach	**2 classes (COVID-19, pneumonia)**	**Proposed CNN model**	**Accuracy = 97.92%**

4. Conclusion

The present work proposes a CNN model for classification of COVID-19 patients and other patients suffering from pneumonia. This model makes use of chest X-ray images of the respective patients for training and testing of the proposed model. The classification results reveal the suitability of this model with an average accuracy of 97.92%, which is considered to be an excellent accuracy in clinical scenarios. This model could reduce the efforts of the doctors and other healthcare workers during the diagnosis of the patients.

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