Detection and diagnosis of COVID-19 infection in lungs images using deep learning techniques

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Abstract

World’s science and technologies have been challenged by the COVID-19 pandemic. Each and every community across the globe are trying to find a real-time novel method for accurate treatment and cure of COVID-19 infected patients. The most important lead to take from this pandemic is to detect the infected patients as soon as possible and provide them an accurate treatment. At present, the worldwide methodology to detect COVID-19 is reverse transcription-polymerase chain reaction (RT-PCR). This technique is costly and time taking. For this reason, the implementation of a novel method is required. This paper includes the use of deep learning analysis to develop a system for identifying COVID-19 patients. Proposed technique is based on convolution neural network (CNN) and deep neural network (DNN). This paper proposes two models, first is designing DNN on the basis of fractal feature of the images and second is designing CNN using lungs x-ray images. To find the infected area (tissues) of the lungs image using CNN architecture, segmentation process has been used. Developed CNN architecture gave results of classification with accuracy equal to 94.6% and sensitivity equal to 90.5% which is much better than the proposed DNN method, which gave accuracy 84.11% and sensitivity 84.7%. The outcome of the presented model shows 94.6% accuracy in detecting infected regions. Using this method the growth of the infected regions can be monitored and controlled. The designed model can also be used in post-COVID-19 analysis.

KEYWORDS

classification, convolution neural network, COVID-19, deep neural network, segmentation

1 | INTRODUCTION

COVID-19 or novel coronavirus has already been declared as a pandemic worldwide in the year 2020. The city named Wuhan in China was the first to suffer due to this pandemic. Human contact was the main cause of this virus and later, most of the countries across the globe got affected by this severe virus. Employing deep learning for medical image analysis is in demand these days for better prediction or diagnosis of any disease. Image classification and object detection techniques support deep learning for this purpose.1 The most precarious step to fight this virus is the rapid screening of infected patients2 as the seasonal flu symptoms are also pretty analogous to this virus. To reduce the mortality from COVID-19, the initial step is to put a control on its spread.

Deep learning algorithms, especially convolution networks, have swiftly become a popular choice for
analyzing medical images. The whole world is struggling to find or design a novel method to identify the COVID-19 patients accurately and cure them within time. In the present time, reverse transcription-polymerase chain reaction (RT-PCR) is the reliable technique to identify patients infected by COVID-19. Detection of nasopharyngeal swab/viral nucleic acid from sputum is the main task of RT-PCR. Some specified material is to be needed for this test and this is the main demerit because the material is not easily available. The true positive rate of this test is not up to the mark hence it has low sensitivity. Time taking process of this test is also a limitation. Furthermore, patients find this testing procedure difficult and inconvenient. Thus, due to these concerns, an alternative method for diagnosis is needed that can address these problems.

Deep learning combined with x-ray, magnetic resonance imaging (MRI), and computed tomography (CT) scan imaging could yield significant biomarkers for the COVID-19 disease. By using radiography and radiology images, the prediction of the disease can be done more promptly. But some studies have shown that detection of COVID-19 infected patients is not very much effective, using chest radiograms. Throughout the globe, lung disease is very common. Some important and common lung diseases include fibrosis, asthma, pneumonia, tuberculosis, chronic obstructive pulmonary disease, etc. Coronavirus also affects the lungs primarily. Diagnosis of lung diseases is vital in early stage for timely treatment. For this, image processing along with machine learning and deep learning models can play an important role. Various types of deep learning models are applied for lung disease prediction, including convolutional neural network (CNN), vanilla neural network, and visual geometry group-based neural network (VGG) and capsule network. For extracting significant information from the dataset, deep neural network (DNN) is an important technique. In all these, the accessibility of large dataset and commanding graphical processing units are also very useful for attaining the goal. Besides it, an effective DNN design synthesis has been discovered newly. These types of designs not only are very precise in expectation, but also computationally efficient. As a result, for COVID-19, some researchers have chosen DNNs as artificial intelligence (AI) diagnosis systems. The major advantages of the technique are enhanced accessibility and good efficiency.

When the process for detection was executed on abdominal CT images, it was noticed that the nature of the viral pneumonia and COVID-19 are different in early phase. Hence, medical experts declared that the diagnosis of COVID-19 in early phase is the basic need of treatment. As compared to RT-PCR testing methodology, the radiographic patterns and CT scans show better sensitivity and specificity for automatic classification with AI models. Furthermore, in detailed review, it has been noted that in the extracting feature, RT-PCR is the main method in detecting COVID-19. Detection of COVID-19 can be easy and may be distinguishable from similar type of flu and pneumonia when using deep learning methods.

This research proposes a deep CNN architecture for the diagnosis of COVID-19 based on the classification of x-ray images. An effective and reliable CNN classification was a challenge due to the lack of a sufficient-size and high-quality x-ray picture dataset. Deep CNN-based model has been proposed that can automatically recognize patterns linked to COVID-19-related lesions from chest CT images. The image ground truth for the COVID-19 lesions scanned by the radiologist was assessed as the major criterion of the segmentation method in this context. To apply deep learning for detection of lungs diseases, three main phases are image preprocessing, training, and classification. Lung disease diagnosis entails dividing an image into healthy lungs and disease-infected lungs. Training is required to obtain the lung disease classifier, also known as a model.

In the categorization of the images, suggested model produced encouraging outcomes. As a result, the proposed system based on CNN model was created to detect COVID-19. During the application phase, the system correctly distinguished all COVID-19 cases from non-COVID-19 cases. Organization of this paper is as follows: Section 2 has three parts. In first part, feature extraction and classification technique based on fractal methods and ANN have been used. Second part involves analysis of sensitivity and accuracy based on classical CNN methods. For the separation of infected tissues in the lungs, MRI images, CNN-based segmentation method has been used in third part. This will provide help in solving detection problems. Section 3 illustrates the performance analysis and explains presented methods. Results and findings of presented paper are discussed in Section 4. Section 5 of the paper presents the state-of-the-art comparison. Section 6 concludes the presented paper.

2 | METHODS APPLIED FOR DIFFERENT MECHANISM

2.1 | Fractal techniques for feature extraction

Features extraction includes rearranging the quantity of needed resources to precisely express a huge amount of information. When execution of multifarious data
be calculated using Equation (3) and from Equation (4), we find the covariance matrix.

\[
\text{Variance} = \frac{1}{M} \sum_{i=1}^{m} Tt
\]

\[
\text{Cov} = AvA^T v,
\]

where \( Av = [\text{Variance } 1, \text{Variance } 2, ..., \text{Variance } n] \) and \( \text{Cov} = N^2 \times N^2 \) and \( Av = N^2 \times M \). Eigenvalues of covariance are achieved by using Equation (5).

\[
Ui = AvVi.
\]

Selecting eigenvector is the last step in this method. A group of properties of an in-built state function in the form of \( N \) samples in a \( d \)-dimensional space \( \{x_1, x_2, ..., x_N\} \) such that \( xi = Rd \) belongs to \( C \). The class is available from \( [Li, i = 1, 2, ..., C] \). In order to find linear transmission and mapping of \( d \)-dimensional space of the principal dimension to \( m \)-dimension such that \( m < d \) fractal algorithm is more efficient. The total covariance matrices are having the class of scattered matrices; these matrices are designed using Equations (6) and (7). New feature vector is located at \( y_i = Rm \).

\[
ST = \sum_{k=1}^{N} (xk - \mu)(xk - \mu)^T
\]

\[
W_{\text{fractal}} = \arg\max [W^TSTW] = [w1w2, ..., wf],
\]

where mean of all samples is denoted by \( \mu \) and \( \{wi, i = 1, 2, ..., f\} \) is a set of eigenvector of \( m \)-dimension of \( S_T \) that is associated with the largest eigenvalue \( m \). Samples in the new space are \( y = w^T x \), which is \( W_{\text{Fractal}} \in R^{m \times d} (180 \times d) \).

### 2.2 Convolvional neural network

CNN is one of the most dominating methods of deep learning, in which several input layers are trained efficiently. For minimizing the preprocessing, CNN uses a range of multi-dimensional perceptions. The three main layers of CNN are convolution layer, pooling layer, and fully connected layer. These different layers perform different functions.

For the backward and forward propagation training, there are two stages in architecture. For the movement of information in forward direction, only forward step is used. In this process, the input information is obtained at
the output layer after passing from hidden layer. For generation of output, the input value is sent by input layer to the hidden layer. If there is the case of backward propagation then calculation of network error can be done. During this process, in first stage, input data are fed to the defined network. The error value along with network is returned with a cost of function diagram to the updated network weights (as shown in Figure 1). CNN consists of various types of hidden layers described as next.

2.2.1 | Layer of convolution

In convolution network, the most essential part is convolution layer and output of this layer can be understood as 3-D stack of neurons. With the working of these different layers, CNN works in different kernels to convolve the input image and maps with central features.

The main features of the operation of convolution are:

- Weight sharing mechanism is used to reduce the number of factors, in each feature map results.
- To deviations in the position of the object, it provides stability.
- Connection between the neighbor pixels can be understood by local connection.

2.2.2 | Activation functions

When we feed the input in current neuron then the activation function is used as a mathematical gate to get the desired output to the next layer. There are several types of activation functions in deep learning, but the sigmoid and hyperbolic tangent is the most common in use. The output of the hyperbolic tangent function is in between 1 and −1. The sigmoid function can receive the input from $+\infty$ to $-\infty$ and the outputs may be in between 0 and 1. These features of these two functions are the cause for less use in CNN. Due to this reason, system may become unstable and the loss in image data may happen in results. In recent time, Rectified Linear Unit (ReLU) functions have been implemented most. The purpose of this function is to provide the nonlinear behavior to the network. With the help of this function, we can enter all pixels values in the image and it will make all negative values zero. To define a nonlinear part of CNN, we have used ReLU.\textsuperscript{16}

2.2.3 | Max pooling

Due to minor changes in the information (images), identification of those changes in network can be done with the help of max pooling. Therefore, use of max pooling has many effects on the neural network. The main and effective task during the subtraction of sample task, max pooling is used to allow extra space of the images to recognize the features of the images. Max and average are the two main types of pooling techniques, using max pooling we can get into deeper layers of the CNN. In deep learning, when arrived at last step in each level, sampling has to be reduced. In this manner, pooling technique provides good results. Using this, we can improve the storage capacity also in spatial domain.

Figure 1 shows the framework of the CNN architecture. This figure shows the sequence of the data, which is
provided as input and the middle part, which has convolution, max pool layer, and the output classes.

2.3 | Explanation and formulation of presented methods

To detect and diagnose the infection based on medical image processing, there are number of techniques, which have been suggested. Key objective of this paper is to develop and design a new system for recognizing COVID-19 infected persons by utilizing their lungs images. Figure 2 shows the intangible diagram of the planned work. For diagnosis and segmentation of the infected image, we have done three analysis, which is shown in the conceptual format. In the primary step, we have extracted the feature of images using fractal methods. For classification of the patient’s images, we have used CNN method. In second step, architecture of CNN is used to classify the patients based on the lungs images. In final step, we have trained the network for the segmentation of diseased area in the lungs. In result and discussion section, each part of the architecture is explained.

Figure 2 shows the block diagram of the intended model, which has different blocks used in the proposed model.

3 | PERFORMANCE ANALYSIS

In data mining science, following factors are used to estimate the efficacy of the classification.

- True negative (TN): Healthy image is appropriately identified.
- True positive (TP): Patient is properly detected.
- False negative (FN): The patient is wrongly diagnosed.
- False positive (FP): The healthy image is wrongly diagnosed.

In proposed work, to calculate the overall performance of the designed model, we have used fall out and Jaccard similarity value. Along with this, five parameters are used to calculate the results of classification: Specificity(S), Accuracy (ACC), Sensitivity (R), miss rate, and S-dice. The explanation of these parameters is given below.

\[
\text{Specificity (S)} = \frac{TN}{TN + FP} \quad (8)
\]

\[
\text{Accuracy (ACC)} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (9)
\]

\[
\text{Sensitivity (R)} = \frac{TP}{TP + FN} \quad (10)
\]

![Block diagram of the intended model](image)
Miss rate = \frac{FN}{FN + TP} \quad (11)

S - dice = \frac{2TP}{2TP + FN + FP} \quad (12)

To calculate the overall performance, the parameters are:

\[
\text{Fall-out} = \frac{FP}{FP + TN} \quad (13)
\]

\[
\text{Jaccard - similarity} = \frac{TP}{FP + FN + TP} \quad (14)
\]

where TP is true positive,

TN is true negative,

FP is false positive, and

FN is false Negative.

Figure 3 shows the relation between image length and histogram, which is drawn from the method of fractal feature extraction.

In Figure 4, the architecture of DNN with different layers on fractal feature has been shown.

In Figure 5, results of the DNN method have been shown. This figure is presented in two parts (a) and (b). Part (a) is having mean square error and part (b) shows the error probability in DNN method.

Output labels and scatter plot and confusion matrix in DNN is presented in Figure 6A,B, respectively.

To describe the performance of classifier, confusion matrix has been used. Evaluation criteria on group of experimental values and the actual values are compared using confusion matrix.

Figure 7 is having the CNN architecture for identification of COVID-19 using lung images of patients. In this figure, the images of COVID-19 patients and non-COVID-19 images have been used.

4 | RESULTS AND ANALYSIS

This segment of the paper explains the performance of different approaches. This paper has presented three different methods as discussed in earlier sections also. The first section explains the dataset used. In second section, we have described the classification outcomes based on DNN architecture on fractal features extracted from the lungs descriptions. Next section contains the outcomes of binary classification using CNN architecture. In results and discussion section, we have described the identification of the infected area of the images, which is based on image segmentation. To evaluate the presented models, we have explained different matrices, using Equations (8)–(13).
Figure 8 shows the results of training iterations versus accuracy and loss values.

Overlapped area of predicted and ground truth, which is split by the area of the anticipated segmentation plus the ground truth segmentation has been defined in the part of image segmentation.

Figure 9A,B show the values of confusion matrix for binary classification training set and test set.

### 4.1 Datasets

The dataset for the COVID-19 images is available publicly on various platforms. For fractal feature extraction, we have used chest x-ray images. We have also used a dataset of CT images of lungs. For testing and validation purpose, we have used the data, which is available publicly. The whole data are categorized into two classes.
First the data of COVID-19 infected persons and second for non-COVID-19 persons or normal persons. The use of this data is in classification or identification of COVID-19 infection and segmentation of the data for the detection of infected area.18–21

4.2 | DNN and fractal features extraction for identification of COVID-19

This section explains the utilization of DNN architecture, presented for the fractal aspect drawing out from the

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**FIGURE 7** Convolution neural network (CNN) architecture for identification of COVID-19 using lung images of patients

**FIGURE 8** Training iterations versus accuracy and loss values
images of chest x-ray. Using this method, histogram of the images is extracted as shown in Figure 3. The red color line is showing the result of sum of functions. For this, we have calculated the normal distribution functions and calculation of those functions provided in the histogram. In this modeling, we have used four functions in small number with high accuracy. This task is done by modeling the histogram with Gaussian function. All the characteristics of the images are the variables of the Gaussian function and all images of the dataset have been processed with same process. Hence, the dataset of the classification is converted into a matrix through the usage of all four features. In Figure 4, architecture of the DNN training presents the input layer as features and output layers as labels. To generate the single output, input layer takes four features for each data request. Sigmoid activation function has been applied after each hidden layer. Figure 5A,B illustrate mean square error and error probability. In Figure 6B, the COVID-19 images are labeled as 1 while non-COVID-19 images are labeled with 0 and this is the outcome of DNN method for classification. Figure 6A is an output R2 for which related classification is 75%.

Table 1 shows performance analysis of DNN outcomes. Figure 6B presents the performance analysis results and these results are in the form of confusion matrix. Dataset consists of 812 images, out of which 437 are of COVID-19 patients and 383 are of non-COVID-19 patients. Out of 437 images of COVID-19, 383 (87.6%) are identified accurately while 54 (12.4%) images are identified as non-COVID-19 patients. From non-COVID-19 images, out of 375 images, 300 images were diagnosed correctly, that is, (80%), while 75 images (20%) images are incorrectly diagnosed. Hence, the sensitivity of the system of classification is 84.7% with an accuracy of classification of 84.11%. The presented model shows 69.9% matching/similarity between COVID-19 and other images. The related factors of these outcomes are shown in Table 1. Comparison of the output with CNN method is explained in next section of the paper.

### 4.3 Identification of COVID-19 infected humans via CNN technique

This section of paper demonstrates the outcomes of CNN architecture using lungs chest x-ray images. The classification is divided into two parts, first the positive cases of COVID-19 and second the normal images of the lungs. To analyze the presented model, we have used various evaluation matrices. Figure 7 illustrates the architecture of the presented CNN model for identification of COVID-19 infected persons. In this model, a total of 16 layers are

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**Table 1** Performance analysis of fractal features using deep neural network (DNN) architecture with binary classification

| Metric                  | Values   |
|-------------------------|----------|
| Accuracy (ACC)          | 0.8411   |
| Specificity (S)         | 0.8362   |
| Similarity              | 0.6993   |
| Sensitivity or recall (R)| 0.8474   |
| Miss rate               | 0.1525   |
| Fall out                | 0.2000   |
| S-dice                  | 0.8230   |
there with three convolution layers. 75% of images from the dataset have been used for the purpose of training of the network and remaining 25% of images are used for testing the model. Accuracy and loss value as a function of training are shown in Figure 8.

The final trained model is evaluated for the train and test datasets. Confusion matrices for predictions are shown in Figure 9. This model, out of 203 images, predicts 192 images accurately during the test set. Therefore, the result in terms of accuracy is 94.6%. The false negative rate of the model has been calculated to be 2%, which represent the success in raising the alarm for COVID-19 cases.

Table 2 shows the output of evaluation metrics for classification task. The test set results are based on confusion metrics and these are 2% miss rate and 8.8% fallout.

Using this model, the specificity of 91.1% has been recorded, which shows that how accurate the model is in identifying cases of COVID-19. Achieved fallout value shows that the model is capable of not predicting the non-COVID-19 case as a COVID-19 case. For binary classification, F1 score achieved by this model is 0.9452. The presented model has high accuracy and sensitivity for the classification of the images. Using this model, we can diagnose the disease with greater accuracy. However, DNN sensitivity is 84.7%, but if we compare the fallout of DNN and CNN then we cannot ignore the DNN method. Therefore, from the results of the proposed work, it can be stated that the CNN model has great prospects in identifying COVID-19 infected humans. In the next section, process for detection of infected area is described, using segmentation method for CT scan images.

### 4.4 Recognition of infected area from the CT scan images of lung for COVID-19

This section contains the outcomes of presented model of CNN segmentation. Figure 10 describes the design of the process used for segmentation. In this method, the infected images are labeled by “255” for the patients of COVID-19 and “0” value shows the result for non-COVID-19 images. In the input images, there are three main regions. Each region has its significance. First, black region shows the area by which human can breathe the air. If there is any disturbance in this region then the respiratory system of the human can be disturbed/affected. Second, dark gray region of the images shows the connection of trachea, bronchus, and bronchioles of respiratory system. The light gray region in images shows the infection of COVID-19. The main challenge of the

| Metric             | CNN   | DNN   |
|--------------------|-------|-------|
| Accuracy (ACC)     | 0.9458| 0.8411|
| Specificity (S)    | 0.9105| 0.8362|
| Similarity         | 0.8962| 0.6993|
| Sensitivity or recall (R) | 0.9047| 0.8474|
| Miss rate          | 0.0010| 0.1525|
| Fall out           | 0.0010| 0.2000|
| S-dice             | 0.9452| 0.8230|

**FIGURE 10** Design of convolution neural network (CNN) model for segmentation of COVID-19
model is to recognize this region. To provide the high potential for our model, we have used the images with more different colors in image as compared to almost similar color. With this, we have devolved a model to detect the infected regions with more accuracy. Output layer of the explicated design shows the ground truth images of the infected regions.

In Figure 10, infected images are in the first column. Output layer’s images (ground truth images) are shown in second column. Third column has results of images detected with infected region. For whole process, we have taken 75% of images for the training and remaining 25% of images are used for testing. In the last column, we have shown the output of the segmentation (after ignoring some small spots) and these are same as ground truth images. These results defines that the presented model is efficient in detecting the infected area with high precision. Figure 11 shows the segmentation outcomes in the form of images. Figure 12A–D shows the outputs of the segmentation methods in the form of parameters. In this figure, receiver operating characteristics (ROC) curve is plotted between the rate of true positive and false positive rates. In segmentation algorithm, each image has unique criterion. Figure 12A is showing the high efficiency of the ROC curves. Figure 12B–D shows the high performance region, accuracy of the segmented images, and average number of accuracy of all images, respectively. The average of the accuracy for all the images is 88.4%. Jaccard value shows the overlapping region of the resulting image and the ground truth images. Fluctuation in the

![Figure 11](image_url)  
**Figure 11** Segmentation detection of lung images for COVID-19 patients
input value is 0.4, which is due to leaving small black spots in resulted images.

In Figure 11, segmentation detection of lung images for COVID-19 patients with its ground truth and predicted image has been shown.

In Figure 12, the results of the segmentation have been shown in four different parts (A), (B), (C), (D).

5 | STATE-OF-THE-ART COMPARISON

Image processing and classification is an emerging technique and in recent times have started being extensively used in the medical sector in diagnosing various diseases that can be identified through the processing and classification of medical imagery. Proposed model of identifying COVID-19 infection through feature extraction fairly competes with other such techniques used in identifying same diseases. But the benefits that the proposed model offers can be helpful in diagnosing COVID-19 not just to doctors but also to the patients and common people.

A state-of-the-art comparison of the proposed system to existing COVID-19 diagnosis systems using image classification is given below (Table 3):

In previous methods, the authors were limited to a specific type of images. Using the proposed model, we can detect the infected tissues in different types of lungs images. The new insight that is obtained due to the proposed approach is that there is no limitation for the types of images. We can use any of the x-ray images, MRI and even CT scans.
CONCLUSION

This paper describes three deep learning approaches for segmenting and classifying lung images in order to identify the COVID-19-tainted area. Two methods, DNN and CNN, are used to diagnose the disease. CT scan images and fractal feature of the images have been used for classification and segmentation. The classification result shows high accuracy (94.6%) and sensitivity (90.5%) with the use of CNN architecture and accuracy 84.11% and sensitivity 84.7% with the DNN method. At present, the strategy for conclusion of COVID-19 is RT-PCR. This process is time consuming and not available for many patients due to its expenses. Therefore, the presented method can provide a better alternate to diagnose COVID-19 as compared to existing method. Another contribution of the presented paper is to detect the infected area of the lungs. For this, we have used preprocessed ground truth images of output layer. Furthermore, this network can be used to separate the infected region for the treatment. Due to it, growth of the infection in lungs can also be monitored and can be controlled by providing accurate treatment within time. Hence, it can be stated that this is the right time to use AI technology in the field of medicine to assist the doctors and with its help a better diagnosis can be provided to the patients.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

ACKNOWLEDGEMENT

The authors would like to thank National Institutes of Health (NIH) for uploading their datasets in Kaggle repository.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in https://www.kaggle.com/allen-institute-for-ai/CORD-19-research-challenge?select=Kaggle [17].

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