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Detect and envision of pandemic disease exposure using CNN

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ABSTRACT

COVID-19 has emerged as a pandemic, affecting millions globally with its high transmission rate, especially in colder climates. The virus's multiple mutations have made it progressively harder to detect and manage. Despite widespread awareness of preventive measures such as masks and sanitizers, early detection remains critical. Traditional methods like blood tests are time-consuming, and existing studies utilizing fuzzy K-means clustering, principal component analysis (PCA), stochastic discriminant analysis (SDA), decision trees (DT), and support vector machines (SVM) have faced limitations, including small datasets, insufficient accuracy, inadequate medical data, weak methodologies, and failure to consider primary symptoms. This work proposes a deep learning (DL) convolutional neural network (CNN) architecture utilizing CT scan images of the lungs for the rapid and accurate identification of COVID-19 infections. The approach leverages the Visual Geometry Group 16 (VGG16) model to extract significant features, such as size and color differences, from computed tomography (CT) scan images, facilitating a swift and precise diagnosis. The VGG16 model, implemented using the Keras library on top of TensorFlow, processes the preprocessed images through neural network layers to classify the images as COVID-19 positive or negative. The proposed model demonstrates a high accuracy rate of 94.12%, indicating that this method is both efficient and reliable for detecting COVID-19, offering a significant improvement over conventional diagnostic techniques and existing studies.

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1. INTRODUCTION

The COVID-19 pandemic, which began in Wuhan, China in December 2019, has spread globally, infecting over 23 million people, with around 16 million recoveries and 0.8 million deaths [1]-[5]. The disease is highly contagious, transmitted through human interaction, coughing, and sneezing [6], [7]. Common symptoms include fever, cough, respiratory issues, and loss of senses, typically appearing 5 to 14 days after exposure. Infected individuals need to be isolated for at least two weeks under medical supervision [8]. The pandemic has led to severe economic crises worldwide. Since no vaccine is available, prevention is critical [9], [10]. The absence of an automated COVID-19 diagnosis process during pandemic leads to significant challenges for both medical persons and patients [11].

Existing studies that employ techniques like fuzzy K-means clustering, principal component analysis (PCA), stochastic discriminant analysis (SDA), decision trees (DT), and support vector machines (SVM) have encountered significant challenges. These existing techniques used smaller datasets leading to low accuracy, and the use of insufficient medical data that does not fully capture patient conditions. These shortcomings highlight the need for improved methodologies and larger, more comprehensive datasets to enhance the reliability and effectiveness of medical diagnostics.

Automating COVID-19 testing through advanced technologies, including deep learning (DL) and convolutional neural networks (CNNs), can enhance the accuracy and speed up diagnosis process by using computed tomography (CT) scan images. This kind of approach reduces human intervention and errors in diagnosis process. Advanced technologies such as CNNs and Visual Geometry Group 16 (VGG16) are being utilized to scan the CT images of lungs for detecting COVID-19. CNNs are highly effective in image processing tasks due to their ability to automatically and adaptively learn spatial hierarchies of features from input images. VGG16, a specific deep convolutional network architecture, is renowned for its simplicity and depth, making it particularly well-suited for the classification of complex images. By employing these technologies, the proposed system can analyze lung CT scans with high accuracy, enabling quick and reliable COVID-19 diagnosis dealing the drawbacks of existing studies. DL models trained on large datasets of CT scan images can automatically and accurately detect COVID-19 related abnormalities in the lungs. Such models not only speed up the diagnosis process but also improve patient outcomes. The main contributions of this work is as follows:

- Analyze and assess the impact of pandemic diseases, particularly focusing on COVID-19 variants.
- Design a system to efficiently detect COVID-19 patients using CT scan images.
- Implement a CNN and VGG16 to predict COVID-19 cases from CT scan images.
- Test the system to ensure its effectiveness and accuracy in identifying COVID-19 cases.

The structure of the paper is as follows: section 2 states the related work with a summary table. Proposed methodology is addressed in section 3, which includes dataset preparation, preprocess, feature extraction, and DL model development. Section 4 presents the results and analysis, including both training and testing outcomes. Finally, section 5 contains the conclusion.

2. RELATED WORK

Pasin and Gonenc [12] proposed a system that mainly focuses on automatic identification of effected countries with the COVID-19 pandemic using fuzzy K-means and K-prototype algorithms. The limitation of this work is its inability to predict the disease. Shvetcov *et al.* [13] developed a mobile app, which can be used to examine the users by considering the specific timepoints in line with COVID-19. The main drawback of this system is it neglects patient symptoms for mental and physical health monitoring. The work proposed by Scheim *et al.* [14] focuses on detecting COVID-19 through human red blood cell (RBC) images by analyzing blood clots, hypoxia and myocarditis. Chu *et al.* [15] proposed a novel feature selection technique minimum redundancy maximum relevance (mRMR) permute that can be used to predict SARS-CoV-2 infection. The main limitation of this work is its low accuracy and less number of instances were considered to train and the test model. Arshad *et al.* [16] used DL based methods for detection of COVID-19. Meraihi *et al.* [17] deals with identification of corona virus using SVM, and CNN methods. The text data, Chest X-Ray, CT scan and clinical data are used to obtain features and detect corona virus. The limitation is that the smaller dataset is used to train the model. Additionally, the model’s accuracy is relatively low (65%), which leads to errors in the identification process. Paul *et al.* [18] studied, examined and analyzed COVID-19 related works, which are related to machine learning (ML), artificial intelligence (AI) and DL. This work addressed types of data used by the researchers, techniques and size of datasets. Zoabi *et al.* [19] proposed a system to detect the COVID-19 cases in the national wide of Israeil. The authors proposed ML framework by considering the 51,831 test cases. The main limitation of this work is the lack of discussion on ML techniques and weak methodology report. Solayman *et al.* [20] proposed a system based on ensemble methods to predict the pandemic disease. SMOTE technique is used for data preprocessing. The main limitation of this work is that incomplete methodology, and not considered the image data. Rashid *et al.* [21] discussed the role of ML in diagnosis of pandemic disease. This work addressed that average accuracy of the tasks through ML is 92.9%. The main limitation of this work is lack of discussion on practical implementations. Table 1 summarizes the existing techniques and their performances.

Table 1. Summary of related work

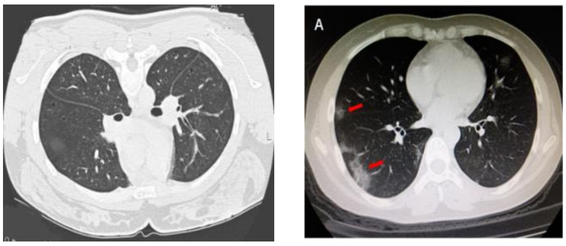
Author	Method	Type of modality	Performance	Task	Volume of dataset
Pasin and Gonenc. [12]	K-prototype, fuzzy K-means	Clinical test and vaccines reports	96.2%	Identifies effecting countries	10 countries, 2 clusters
Shvetcov *et al.* [13]	K-means, PCA, SDA, DT	Mental health diagnoses	91%	Health monitoring	400 instances
Scheim, *et al.* [14]	Non-ML	Blood cells	96%	Diagnosis	Not addressed
Chu *et al.* [15]	Hybrid	blood biomarkers and radiomics	86%	Predict	137-170 instances
Arshad *et al.* [16]	DL	Chest X-ray	NA	Diagnosis	Not specified
Meraihi *et al.* [17]	SVM, CNN	Text data, CT images, X-rays, clinical data	65%	Diagnosis, predict	160
Paul *et al.* [18]	ML, DL, AI (Not specified)	Text data, CT images, X-rays, clinical data	NA	Survey	Not specified
Zoabi *et al.* [19]	ML (Not specified)	Not specified	95%	Detect	51,831
Solayman *et al.* [20]	Ensemble	Text data	92%	Predict	2742,596
Rashid *et al.* [21]	ML (Not specified)	Not specified	92%	Survey	14 research articles
Proposed method	VGG-16	Chest-CT	94.1%	Diagnosis	2482

3. PROPOSED METHOD

As our proposed model addresses the global pandemic issue named COVID-19, it should be trained with appropriate datasets to achieve high accuracy in performance [22]. The CT scan dataset used for training the proposed model is sourced from Kaggle. Our proposed system employs VGG16 model that extracts key features such as size and colour differences in the scanned reports from the given datasets [23], [24]. Based on these features and some subtle variations, the model predicts whether the input images are related to COVID-19 or not. This innovation is designed to allow people to upload their CT scan images into the testing folder to predict whether they have COVID-19 or not. Once the image is uploaded, then the model will pre-process it to fit into its architecture's size.

3.1. Dataset collection

The dataset collected from Kaggle, contains 1,050 CT scan images used to build a model for COVID-19 detection. It includes scan reports of both COVID-19 and non-COVID-19 patients as shown in Figure 1. Figure 1(a) depicts non-COVID-19 CT scan image and Figure 1(b) represents COVID-19 positive CT scan image. The CT scan images are of human lungs. The dataset includes 700 images, with 350 showing COVID-19 positive and 350 showing COVID-19 negative cases.



(a) (b)

Figure 1. Sample images of the dataset (a) non-COVID-19 lung CT scan and (b) COVID-19 positive lung CT scan

3.2. Pre-processing

The dataset needs to be pre-processed before applying it to the model because the images colour or the size of the image would be different. The pre-processing technique is important as there would be cluttered and blur images. Here all different size images are converted into 224×224 pixels of same size images. The outcome of the pre-processing is the final training set. The pre-processing steps are performed by using Algorithm 1.

Algorithm 1. Dataset preparation

```
Input to the algorithm: Dataset
Output of the algorithm: Processed Dataset
Step 1: Store the Dataset in Di.
Step 2: Import Di.
```

```
Step 3: Read Di.
Step 4: Checking cluttered and blurred images from Di.
Step 5: Store those cluttered and blurred in Qi.
Step 6: Checking dimension errors in Di.
Step 7: Store those dimension errors in Li.
Step 8: Final Dataset Si = Di-Qi-Li.
```

Our proposed model uses 80% of dataset for training and 20% of dataset for testing [25]. The proposed model will learn from the training images and predicts the output decision in the testing folder as shown in Figure 2.

Figure 2. Training and testing sets

3.3. Feature extraction

In this step, desired features are extracted from the pre-processed dataset. In this process, 2482 CT scan images are analyzed. As shown in Figure 3, people first upload a CT scan image, which undergoes preprocessing to remove raw content. The image is resized to 224×224 in the VGG16 architecture. Key features are then extracted to determine if the person has COVID-19. If tested with COVID positive, precautions are advised. The dataset, consisting of lung CT scan reports collected from various sources. The dataset is then split into three parts: training, validation, and testing sets. The neural network learns from the training data [10]. The training part includes different CNN layers like convolution layers of 3×3 filters, pooling layers of 2×2 filters, fully connected layer and SoftMax to classify the output (COVID-19 or non-COVID-19). The model uses the training data to predict whether the input CT scan indicates COVID-19.

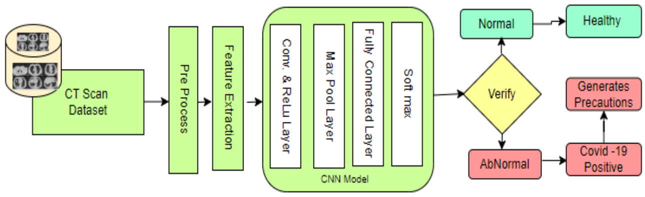


Figure 3. Proposed methodology

3.4. Convolution neural network

In DL, CNN comes under deep neural network. It is mostly used to analyze the images. It is also called a shift variant or space invariant artificial neural network based on their architecture and characteristics [26]. CNN contains input layer, output layer and in between some hidden layers [27]. It consists of four main layers namely convolution layer, pooling layer, fully connected layer and SoftMax [28] as in Figure 4.

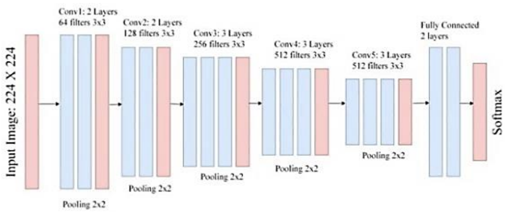


Figure 4. VGG16 architecture

3.4.1. Convolution layer

The convolution layer in the CNN analyzes CT scan images using multiple kernels that cover the depth of input volume [29]. Each kernel processes different image parts by multiplying its values with corresponding pixel values, summing them to produce a single value, called the scalar product as illustrated in Figure 5. The kernel moves across the entire image as shown in Figure 6, repeating this process to create a filtered output called the feature map shown in Figure 7. The feature map highlights important features like texture, edges, and anomalies in the CT scan images, which are crucial for detecting COVID-19-related patterns, such as lung abnormalities or specific radiological signs of the virus, aiding in accurate diagnosis [30]. The functionalities of convolution layer are implemented by using Algorithm 2.

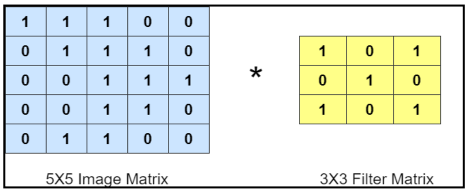


Figure 5. Image matrix multiplied with filter matrix

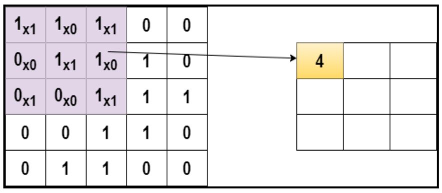


Figure 6. Convolved feature matrix (C)

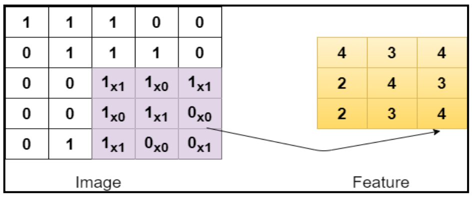


Figure 7. 3×3 convolved feature matrix (C)

Algorithm 2. The functionalities of convolution layer

Input to the algorithm: Image
Output of the algorithm: Convolved feature image
Step 1: Taking the input image from Si.
Step 2: Consider it as Image Matrix $I_{l \times b \times h}$.
Step 3: Consider the filter matrix $F_{fl \times fb \times h}$.
Step 4: Now perform the operation I x F.
Step 5: Store the result in Convolve Feature Map $C_{l \times b \times h}$ = I x F where the dimension of the C is obtained by applying formula $C_l = I_l - F_l + 1$, $C_b = I_b - F_b + 1$, $C_h = 1$.
Step 6: Next goes to Stride, it moves the required number of pixels in the input image matrix I.
Step 7: If the filter matrix F does not fit in input image matrix, then pad the image with additional data A, that can be obtained by using the formula, $A = \frac{I - F + 2P}{S} + 1$.

3.4.2. Pooling layer

Max pooling summarizes features like texture, edges, and anomalies in CT scan images by selecting the maximum value from each region covered by a smaller pooling kernel [31]. This process reduces the spatial dimensions of the feature maps by about half shown in Figure 8, preserving the most significant information and reducing computational complexity. The result highlights key features essential for identifying COVID-19 related abnormalities. Algorithm 3 implements the functionalities of max pooling layer.

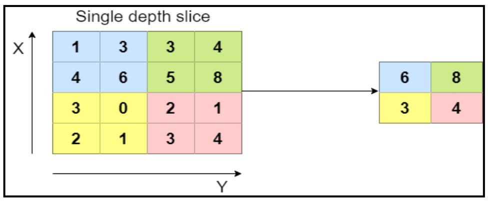


Figure 8. Max pool with 2×2 filters and stride

3.4.3. Fully connected layer

The fully connected layer in the CNN model connects each neuron to every neuron in the previous layer [30], enabling high-level reasoning by aggregating complex features from CT scan images. Its output is then used by the SoftMax layer to classify the images and determine the presence of COVID-19. A fully connected CNN model is shown in Figure 9. The functionalities of fully connected layer are illustrated in Algorithm 4.

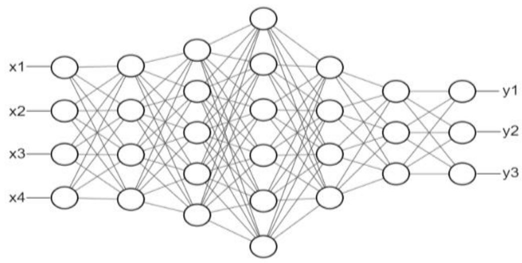


Figure 9. Fully connected layer

3.4.4. SoftMax

The activation layer transforms summarized data into the output format using an activation function. Traditional functions like sigmoid and hyperbolic tangent struggle with complex functions and suffer from vanishing gradients in deep networks. Therefore, ReLU is commonly used in CNNs due to its effectiveness in overcoming these issues [32]. The operations of SoftMax algorithm are shown in Algorithm 5.

Algorithm 3. Functionalities of max pooling layer

Input to the algorithm: Convolved feature image.
Output of the algorithm: max pooled feature image.
Step 1: Now the convolved image C from the convolution layer reaches pooling layer.
Step 2: It extracts the maximum elements from the convolved future map C.
Step 3: The maximum element from C can be chosen with integration of 2 x 2 filter (D) and Stride(S) of 2.
Step 4: Generally, formula for finding max pool is given by $\frac{(C-D)}{S}+1$
Step 5: This result in a max pool feature image ($Z_{i \times j}$) = (C - D).

Algorithm 4. Functionalities of fully connected layer

Input to the algorithm: max pooled feature image.
Output of the algorithm: a model of combined features.
Step 1: In this layer, max pooled feature image ($Z_{i \times j}$) is taken.
Step 2: Now this flattened into vectors (X_i) before passing into FC layer.
Step 3: These vectors (X_i) are fed to the fully connected layers.
Step 4: These X_i are combined in fully connected layers to create a model.
Step 5: The outcome is fed to the softmax.

Algorithm 5. Operations of SoftMax algorithm

Input to the algorithm: a model of combined features.
Output of the algorithm: classify the affected person.
Step 1: The output from the FC layer (Y_i) is passed to the softmax for the final result.
Step 2: In this the negative inputs from FC layer are neutralized to 0.
Step 3: Step 2 increases the efficiency of this layer by not activating all neurons at same time.
Step 4: The activation function is given by f(x) = max (0, x).
Step 5: This layer is used to classify the result (T or T^1) i.e whether the person is affected with COVID-19 or not.

4. RESULTS AND DISCUSSION

This section evaluates the performance of proposed system. Our results demonstrate that the proposed system achieves an accuracy of 94.12%. CNN delivers high accuracy in image processing [32], [33].

4.1. Performance analysis

The performance of the proposed system is evaluated by considering various parameters. Furthermore, a comparative analysis of the proposed system with existing techniques is also conducted to justify its performance. This evaluation highlights the strengths and effectiveness of the proposed system in achieving the desired outcomes

4.1.1. Training results

The CT scan reports of both COVID-19 and non-COVID-19 are considered as a dataset. As the Figure 10 shows the data set comprises of 340 images as a training set and 340 images of validation set. After training, the model is tested to measure its accuracy. So, for that purpose 20 images are loaded into testing set to measure the performance of the model. Furthermore, the model uses 50 epochs and each epoch with batch size of 60. It provides the accuracy and loss score for each epoch in the Figures 11 and 12.

```
Found 340 images belonging to 2 classes.
Time:  0:03:11.592751
Found 340 images belonging to 2 classes.
Found 340 images belonging to 2 classes.
Found 20 images belonging to 2 classes.
Train on 340 samples, validate on 340 samples
```

Figure 10. Number of samples

```
Epoch 48/50
340/340 [==============================] - 0s 882us/
step - loss: 0.1315 - acc: 0.9324 - val_loss: 0.0869 -
val_acc: 0.9412
Epoch 49/50
340/340 [==============================] - 0s 890us/
step - loss: 0.1250 - acc: 0.9441 - val_loss: 0.0877 -
val_acc: 0.9412
Epoch 50/50
340/340 [==============================] - 0s 906us/
step - loss: 0.1226 - acc: 0.9382 - val_loss: 0.0874 -
val_acc: 0.9412
```

Figure 12. Number of epochs

```
Epoch 1/50
340/340 [==============================] - 1s 3ms/step
- loss: 1.1207 - acc: 0.5147 - val_loss: 0.5818 -
val_acc: 0.7706
Epoch 2/50
340/340 [==============================] - 0s 1ms/step
- loss: 0.6923 - acc: 0.6206 - val_loss: 0.5380 -
val_acc: 0.7265
Epoch 3/50
340/340 [==============================] - 0s 981us/
step - loss: 0.6566 - acc: 0.6500 - val_loss: 0.6876 -
val_acc: 0.5618
```

Figure 11. Number of epochs

4.1.2. Testing results

This section focuses on the results, describing the model's training process, including training rate, duration, and prediction outcomes. After training, the model undergoes a testing phase to assess its performance. Figure 13 depicts three key aspects: model accuracy, loss percentage, and prediction time [18].

```
340/340 [==============================] - 0s 185us/step
[INFO] accuracy: 94.12%
[INFO] Loss: 0.0873521322312573
Time:  0:00:16.845690
```

Figure 13: Number of epochs, accuracy, loss and time taken to test

4.2. Graphical results

Data Visualization is crucial for evaluating model performance. Figure 14 depicts the accuracy of both training and validation set. Accuracy is mentioned on y-axis and epochs on x-axis. Figure 15 illustrates loss calculation of both training and validation. Loss parameter is mentioned on y-axis and epoch is mentioned on x-axis.

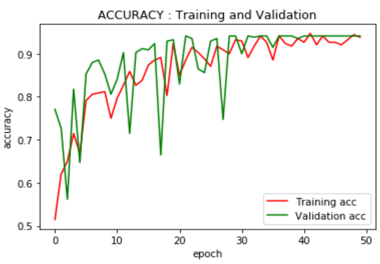


Figure 14. Accuracy

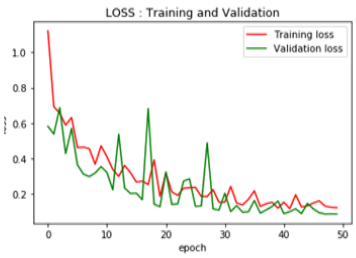


Figure 15. Loss

The proposed method is compared with existing techniques by using various parameters as summarized in Table 2. A black box testing [19] is used to evaluate the model and same is illustrated using Table 3. The final status is determined by comparing the predicted outcome with the actual outcome.

Table 2. Comparison analysis table

Authors	Model	Nature of dataset	Accuracy/ Prediction	Data size
Abdel-Basset *et al.* [26]	Improved marine predators' algorithm (IMPA)	Chest X-ray	66.26%	654
Waheed *et al.* [29]	Resnet	Chest X-ray	72.38%	374
Agrawal *et al.* [31]	VGG-16	Chest X-ray	97%	1,014
Elaziz *et al.* [33]	Resnet	Chest X-ray	94.2%	1,800
Rehman *et al.* [34]	Auxiliary classifier generative adversarial network (ACGAN)	Chest X-ray	95%	1,124
Proposed method	VGG-16 and CNN	Chest CT scan	94.12%	2,482

Table 3. Case study test unit

System: Envision of COVID-19 pandemic exposure using deep learning
Test id: #01
Test preference: Medium
Section name: COVID-19 detection
Test technique: Black box
Description: Testing the CT scan reports
Pretest: Chest CT scan image

S.No.	Type of test	Data to the test	Predicted outcome	Real outcome	Pass/Fail	Comment
1.	COVID-19 detection	COVID-19 affected CT scan	COVID-19: positive	COVID-19: positive	Pass	Nil
2.	Non-COVID-19 detection	Healthy persons CT scan	COVID-19: negative	COVID-19: negative	Pass	Nil
3.	Chest CT scan detection	Chest CT scan	Valid CT scan image	Valid CT scan image	Pass	Nil
4.	Blurry image	Blurry mage	Discarded in preprocessing	Discarded in preprocessing	Pass	Nil
5.	X-ray	X-ray	COVID-19: Positive	COVID-19: Negative	Fail	Nil

The uniqueness of this model lies in its ability to predict whether a person is affected by COVID-19 based on their CT scan reports. The model outputs an image displaying the diagnosis: if the patient has COVID-19, it will show "COVID-19: positive" along with precautions like "quarantine and sanitizing." Similarly, if the patient is healthy, the status will be "COVID-19: negative" with precautions such as "Use mask and maintain social distance". These results are illustrated in Figure 16, where Figure 16(a) represents the original CT images, and Figure 16(b) highlights the detected COVID-19 symptoms along with recommended precautions.

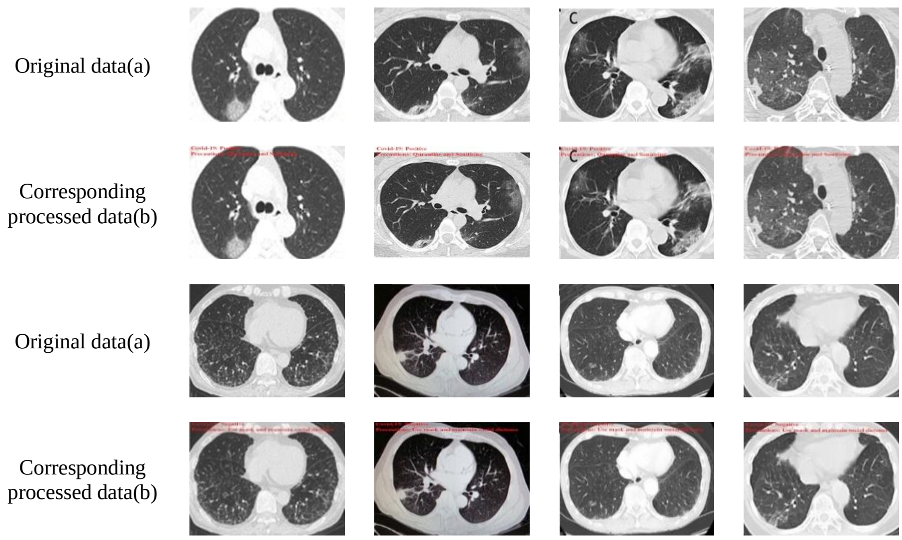


Figure 16. COVID-19 image illustration (a) original images and (b) COVID-19 symptoms spotted and listed precautions

5. CONCLUSION AND FUTURE SCOPE

We proposed CNN based model to predict the COVID-19 from the CT scan images. The proposed model uses VGG16 that automates the process of COVID-19 prediction with less computational resources. In pandemic situation, this type of innovations will predict the COVID-19 positive cases in lesser time. Our experimental results justify that proposed model achieved an accuracy rate of 94.12% on 50 epochs. Further, the accuracy can be enhanced by adjusting the data size and epochs count. The features obtained by this model are status of COVID-19 and precautions which need to be followed to overcome that disease. The proposed model has ability to learn complex patterns, extract deep features from the given CT scan images and predict the output with high accuracy. Our proposed model is implemented using Keras library on the top of TensorFlow. Our experimental results demonstrate that the proposed model outperforms existing approaches, aiding medical professional in early disease detection and treatment. Future work includes applying this model to various medical images and developing a user-friendly mobile app for automated disease prediction.

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