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A Two-Stage Method for Diagnosing COVID-19, Leveraging CNN, and Transfer Learning on CT Scan Images

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ABSTRACT

Lung infection represents one of the most perilous indicators of Covid-19. The most efficient diagnostic approach entails the analysis of CT scan images. Utilizing deep learning algorithms and machine vision, computer scientists have devised a method for automated detection of this disease. This study proposes a two-stage approach to identifying lung infection. In the initial stage, image features are extracted through a transfer learning framework employing ResNet50, with the last two layers being fixed. Subsequently, a CNN neural network is constructed for image detection and categorization in the second stage. By employing superior image feature selection and minimizing non-informative features, this proposed method achieves impressive accuracy metrics: 98.99% accuracy, 98.91% sensitivity, and 99.10% specificity. Furthermore, a comparative analysis is conducted between this method and six other architectures (Inception, InceptionResNetV2, ResNet101, ResNet152, VGG16, VGG19), with and without transfer learning. The findings demonstrate that the proposed method attains 98% accuracy on test data, without succumbing to overfitting.

Keywords— ***Natural Network, Convolution, Deep Learning, Covid 19, CT Scan Radiographs.***

1. Introduction

The COVID-19 epidemic emerged in China and rapidly disseminated across the globe. To date, numerous researchers from diverse disciplines, including medicine and technology, have conducted studies to detect the disease and develop a vaccine for it [1]. One expedited method for detecting this disease is through medical imaging [2]. This automated technique enables rapid detection and treatment of the epidemic by analyzing medical images without human error.

Computer scientists scrutinize medical images and classify them according to health categories. Specifically, for COVID-19, deep learning methods are employed. Among the most effective convolutional neural network (CNN) architectures for identifying and classifying COVID-19 are DenseNet201, DenseNet121, ResNet50, and VGG16 [3]

The accuracy parameter is crucial in disease diagnosis, particularly when working with real-world datasets where the number of parameters is extensive and the collected data may not be normalized, necessitating numerous corrections. Existing methods have been insufficient in simultaneously evaluating accuracy, sensitivity, and specificity. This study aims to introduce a novel method for diagnosing COVID-19 using transfer learning techniques with architectures such as ResNet50, VGG, Inception, and Res-Net on a real dataset comprising over 2400 images, aiming to achieve high accuracy, sensitivity, and specificity.

In our research, we initially employed DenseNet201, DenseNet121, ResNet50, and VGG16 architectures on a dataset named SARS-CoV-2 CT Scan. The accuracy results of these algorithms were 44.48%, 44.86%, 55.13%, and 44.87%, respectively. These results indicated that the method did not achieve high accuracy or performance on other evaluation metrics such as sensitivity and specificity for detecting COVID-19. The low diagnostic

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accuracy, below 60%, can be attributed to the lack of normalization in some authentic datasets, rendering the outcome unacceptable for disease diagnosis.

To address this, we propose a two-stage method for detecting lung infection, a critical indicator of COVID-19. In the first stage, image features are selected using transfer learning architecture on ResNet50, with the last two layers being frozen. In the second stage, a CNN is constructed for image detection and classification. By selecting superior image features and reducing non-informative features, the proposed method improves evaluation parameters by at least one percent, achieving an accuracy of 98.99%, sensitivity of 98.91%, and specificity of 99.10 %.

The present study is organized as follows. Section 2 provides literature review, Section 3 provides transfer learning, Section 4 provides the proposed method, Section 5 the proposed transfer learning method , Section 6 provides features of layers of the proposed method literature review, Section 7 provides simulation & results and finally Section 8 provides the conclusion.

2. Literature Review

Since 2000, a lot of research has been done on the use of medical images for the diagnosis of different illnesses. Due to the prevalence of COVID-19 in 2019, research received a significant boost, and many attempts were made for the automated detection of COVID-19 via diagnostic images.

Bullock et al. presented a general review of the detection of COVID-19. They used medical images to diagnose the disease [4]. Although they were among the first researchers who applied this technique, the main problem they had was the low number of images used. Tao et al. believed that in clinical trials carrying samples of patients is necessary [5]. Considering that medical images are easily accessible, using them can facilitate the analyzing process for COVID-19 diagnosis.

Yee et al. examined diagnostic images of 9 patients who were afflicted with COVID-19 [6]. Their study showed that only 33% of abnormal observations in initial X-rays had the disease, while a much higher percentage had an abnormal observation in CT scans, and were found to have the disease. The result from Yichang et al. showed that compared to X-ray images, a CT scan was more accurate in detecting COVID-19 [7].

Zhang et al. used a CNN method with DenseNet to process CT scans [8,9]. For evaluation, a Dataset of diagnostic images of 275 people who have COVID-19 and 195 people who did not have it, was used. They achieved in binary classification in two classes an accuracy and F1 score of more than 85.3%.

Loey et al. also used five different methods of convolutional neural networks, including AlexNet, VGG16, VGG19, GoogleNet, and ResNet50 to process CT scan images [10]. The CT scan dataset of different people, including 746 images (349 images of people with COVID-19 and 397 healthy people), was used for evaluation. The results showed the superiority of ResNet50 architecture with 82.91% accuracy.

In a similar study, Goses et al. used a deep-learning network to process CT scan images [11]. Their study showed 99.6% precision, 98.2% sensitivity, and 92.2% correct diagnoses.

Wu et al. integrated deep learning and classification techniques to analyze CT scan images [12]. They used 750 CT scan pictures for the evaluation (400 of those with COVID-19 and 350 of persons without COVID-19). The JCS system that was used to classify sensitivity, demonstrated 95% accuracy, 93% accurate detection, and a score of 78.3% for identifying COVID-19 instances.

Ahuja et al. used different deep learning methods based on the transmission from CT scan images that were composed of three levels. They presented a three-stage model for improving the accuracy of the diagnosis, including increasing data, forming a CNN model with pre-training, and localization of anomalies in CT scan images. This technique showed better accuracy in prediction [13].

Khan et al. [14] proposed a CNN method to diagnose the radiographic patterns with the name STM-RESNet from medical images. They used a systematic method of region and edge with the CNN method with three stages of split, transform, and merge, and the dataset of CoV-NonCoV-15k. Using three evaluation parameters to detect this dataset, they achieved sensitivity, specificity, and accuracy parameters to be 0.97%, 96%, and 96.53%, respectively.

Banerjee et al. [15] proposed an ensemble method based on deep learning for the diagnosis of COVID-19 with chest X-ray images. The method was an assist Computer-Aided Detection for medical images. They used a mixed method containing Random Forest (RF) and CNN methods, and four evaluation parameters including accuracy, recall, precision, and F1-Score on the COVID-19 dataset to achieve 98.13%, 100%, 92.59%, and 96.15% respectively.

Alamoodi et al. [16] offered a systematic review of assessing sentiment papers on COVID-19 infection and other infectious illnesses including epidemics, pandemics, and outbreaks. They used five databases, namely, IEEE Explore, Web of Science, PubMed, and Science Direct. The systematic review contained four stages: Identification, Screening, Eligibility, and Included. They found 28 articles and classified them into four major categories: Lexicon-based models, Machine learning-based models, Hybrid-based models, and Individuals. Despite a low number of studies in this regard, the current data is needed for scientists to fight similar outbreaks in the future.

Heidari et al. [17] introduced deep learning approaches and fine-tuned the AlexNet model to automatically classify CXR images and categorize them as either "COVID" or "Normal." They evaluated the model using three parameters: accuracy, specificity, and sensitivity, on an online COVID dataset, achieving an accuracy of 99.26%, a sensitivity of 95%, and a specificity of 99.7%.

Torabipour et al. [18] introduced four deep learning approaches by modifying pre-trained CNN models to automatically classify CXR images as either "COVID" or "Normal." They evaluated the models using four parameters: accuracy, recall, precision, and F1-Score on the COVID-19 dataset, achieving results of 99.62%, 99.63%, 99.63%, and 99.63%, respectively.

Shayegan [19] proposed a combined method of scientometric analysis and brief review to study published articles that utilized ensemble learning approaches for detecting COVID-19. Articles were sourced from the Scopus database and subjected to a two-step process. Initially, a concise review of the gathered articles was performed, followed by scientometric and bibliometric analyses. The analysis revealed that convolutional neural network (CNN) was the most commonly used algorithm, with support vector machine (SVM), random forest, ResNet, DenseNet, and Visual Geometry Group (VGG) also frequently employed. Furthermore, China emerged as a significant contributor to the top-ranking categories in this research field.

3. Transfer Learning

The This is a method based on deep Learning for machine vision in image processing. This method can freeze some layers in CNN algorithms such as VGG16, VGG19, and Resnet50. It is used when there are not enough images for disease detection. In this research, the transfer learning method is used to solve the problem. This method uses a convolution neural network with the weight of the ImageNet dataset, which can freeze the classification layer, and replace it with the proposed CNN network (20).

3.1. Convolutional Neural Network

A convolutional neural network is a sub-method of deep learning which is used for image processing and machine vision. It has four important layers of convolution layer, pooling layer, normalization layer, and fully connected layers [21]. Different known convolutional neural network architectures include Alex-net, LeNet-5, VGG16، ResNet-50, and DenseNet121[22].

3.2. ResNet-50 Architecture

One of the deepest convolutional neural network architectures is ResNet-50 with higher accuracy and precision than CNN architecture. This method has 50 convolutional layers and 26 blocks [23].

4. Proposed Method

This research proposes a three-stage technique: At first, a dataset is uploaded, and data are preprocessed. In the second stage, the main method is formed, and present data are trained. In the last stage, CT scan images are classified into two types: with COVID-19 and healthy. The process of COVID recognition is then automatically done (See Figure 1).

4.1. Dataset

The SARS-COV-2 Ct-Scan Dataset used in this research [24] has 2482 CT scan images containing 1252 CT scan images with COVID-19 and 1230 CT scan images without it. In this research, 80% of images (1985) were for training the method, and 20% of images (497) were for testing it.

5. The Proposed Transfer Learning Method

Figure 2 shows an overview of the proposed methodology which was used in this research. The details are presented below.

5.1. Uploading Dataset and Pre-Processing

Uploading Dataset: A dataset named "Dataset SARS-Cov-2" comprising CT scan lung images is uploaded into a Python simulator.

Pre-processing: (a) All images are realized to 3x224x224 pixels and normalized. (b) The data are divided into two classes COVID and healthy. (c) The data are split into 80% for learning and 20% for validation.

5.2. First Stage (Feature Selection)

Input images with 3x224x224 pixels perform feature selection using Resnet50 with transfer learning and decrease the image features for improved classification in the subsequent CNN method.

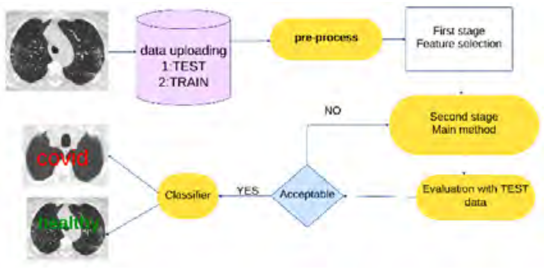


Figure. 1. The Research Methodology

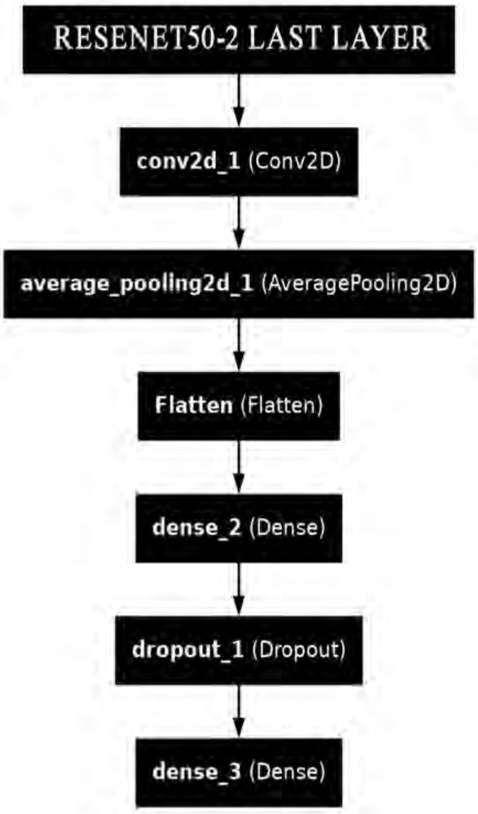


Figure. 2. The proposed methodology in Python.

5.3. Second Stage (creating the main method)

A new CNN method is used with a hidden layer (convolutional layer with 3x3 filters and a 4x4 pooling layer), a flattening layer, and two fully connected layers for classification into COVID-19 and healthy classes.

5.4. Classification Stage

Dataset images are processed with the proposed method and classified into COVID and healthy classes.

Table 1 shows the structure of the proposed transfer learning method in Python.

5.5. Train Data

Images are trained in the dataset using the proposed method for 100 epochs.

6. Features of Layers of the Proposed Method

In this part different layers of our proposed method are described:

6.1. Convolutional Layer

The convolutional layer is the most important in CNN and the input images are multiplied by some of the filters and the output will be a feature map [22]. The feature map is the result of the Convolutional layer and is shown in Eq(1):

Table 1. Implementation of the proposed method

Raw	***Name Of Layer***	***Parameter***	***Output***	***Name of The Layer***
First	Input Layer	0	(None, 224, 224, 3)	Input_1
	Resnet50 Architecture With Transfer Learning Technique	0	(None, 7, 7, 2048)	Resnet50-2 Last Layer
Second	Convolutional Layer	55299	(None, 7, 7, 3)	Conv2d_1
	Subsampling Layer	0	(None, 1, 1, 3)	Average_Pooling2d
	Flattening Layer	0	(None, 3)	Flatten
	Fully Connected Layers With 64 Neurons	256	(None, 64)	Dense_1
	Layer Dropout	0	(None, 64)	Dropout_1
	Fully Connected Layers With 2 Neurons	130	(None, 2)	Dense_2
Total Prams	23,643,397			
Trainable Prams	23,590,277			
Non-Trainable Prams	53,120			

6.2. Convolutional Layer

The convolutional layer is the most important in CNN and the input images are multiplied by some of the filters and the output will be a feature map [22]. The feature map is the result of the Convolutional layer and is shown in Eq(1):

$$C_i^{(l)} = B_i^{(l)} + \sum_{j=1}^{a_i^{(l-1)}} K_{i.j}^{(l-1)} * C_J^{(l)} \quad (1)$$

where

$B_i^{(l)}$: it is a bias

$K_{i.j}^{(l-1)}$: a filter with a*a

$C_i^{(l)}$: feature maps

$C\,i\,(l-1)$: it is the size of the input image

The result of applying the ReLU activation function

in the feature maps is shown in Eq(2-3).

$$Y_i^{(l)} = Y\left(C_i^{(l)}\right) \quad (2)$$

$C_i^{(l)}$: Output of the convolutional layer

$Y_i^{(l)}$: Output

$$Y_i^{(l)} = max\left(0.Y_i^{(l)}\right) \quad (3)$$

$0.\ Y_i^{(l)}$: The input

$Y_i^{(l)}$: The output

6.3. Fully Connected Layer

The fully connected layer is used for the classification and the activation function is softmax, as shown in Eq (4):

$$y_i^{(l)} = f\left(z_i^{(l)}\right).\ where\ z_i^{(l)} = \sum_{i=1}^{m_i^{(l-)}} w_{i.j}^{(l)}\, y_i^{(l-1)} \quad (4)$$

$w_{i.j}^{(l)}$: Weights of Neurons.

$f\left(z_i^{(l)}\right)$: The Activation Function [22].

7. Simulation & Results

In this part, the proposed method is simulated on Python V.3.8 software with the GPU. We used the CPU Intel Core i7 and 20 GB RAM.

7.1. Accuracy and Loss of Data

With the first proposed method to train with 100 epochs and the data divided to train (1985 images) 80% and test (497 images) 20%, we reached 98% accuracy and loss %.2. The result of the simulation is illustrated in Figure 3. Figure (3-a) shows the accuracy of the method (horizontal access represents the number of tests and vertical access represents accuracy) As seen in Figure (3-a), the accuracy of the proposed method is over 98% with 100 epochs showing the strength of the proposed method. Figure (3-b) illustrates the loss of method (horizontal access represents the number of tests and vertical access represents the number of errors). As seen in Figure (3-b), the loss of the proposed method is below 2% with 100 epochs which shows the strength of the proposed method.

7.2. Evaluation

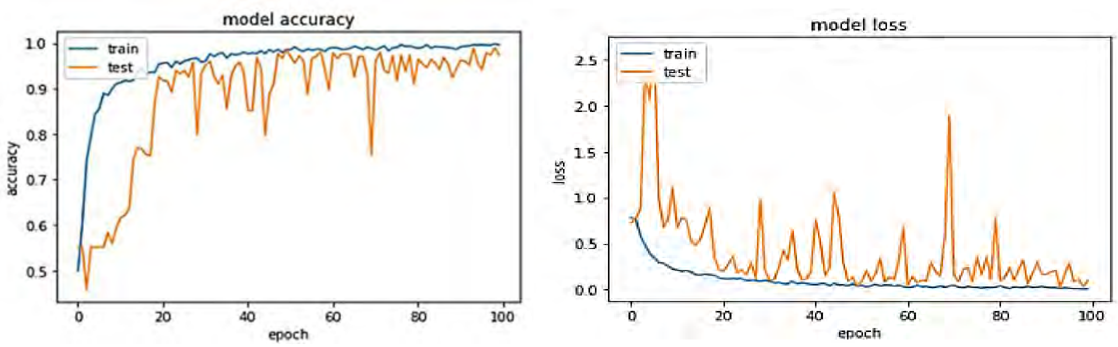
Three parameters of accuracy, sensitivity, and specificity were used for Evaluation. Accuracy is considered the objective function, which is the sum of sensitivity and specificity parameters. These parameters are obtained from a confusion matrix. This matrix is an m*m table with the following characteristics:

TP: Positive cases that are correctly classified

TN: Negative cases that are correctly classified

FN: Negative cases that are incorrectly classified

FP: Positive cases that are incorrectly classified (20).



(a). Accuracy of the proposed method

(b). Loss of the proposed method

Figure. 3. Accuracy and Loss of the proposed method

Accuracy: These criteria represent the general accuracy and show the percentage of test data that are correctly classified (25), Eq(5):

Accuracy=(TP+TN)/(TP+FP+TN+FN) (5)

Sensitivity: This is the percentage of positive cases that are correctly distinguished as positive (24), Eq(6):

Sensitivity=TP/(TP+FN) (6)

Specificity: This is the proportion of negative cases that are correctly recognized in the tests as negative (21), Eq(7):

Specificity=TN/(TN+FP) (7)

The confusion matrix of the method, which has two portions labeled real and predicted, includes data on how COVID-19 and healthy people are classified. This matrix is shown in Figure 4 and Table 2 in two parts real and predicted, and the characteristics are as follows: TP=221, TN=271, FP=2, and FN=3.

The results from the confusion matrix show that applying the proposed method leads to 98.99% accuracy, 98.91% sensitivity, and, 99.10% Specificity.

7.3. Comparing the proposed method with other models

In this part, we compare the proposed method with 6 transfer learning methods (inception, InceptionResNetV2, resnet101, ResNet152, vgg16, vgg19). At first, we replaced 6 transfer learning methods with resnet50 in our method and simulated them in Python, with the same data set and 100 epochs, and got three evaluation parameters (Accuracy, Sensitivity, Specificity) for every model. The result of the comparison is illustrated in Figure 5. Figure 5 shows the comparison of results of the transfer-learning method (horizontal access represents the evaluation parameter and vertical access the model names). Figure 5 illustrates the strength of the suggested technique by displaying the best accuracy among the comparison models for the accuracy of the proposed method.

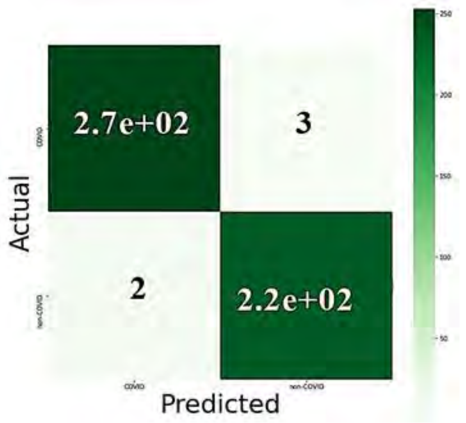


Figure. 4. Confusion Matrix

Table 2. Classification Report

Predicted Classification	*Real Data*		
Covid	Healthy		Dataset
3	271	Healthy	
221	2	Covid	

Figure 5. The comparison results of the transfer-learning methods Table 3 shows a comparison of the proposed method with six transfer learning. It illustrates the presented method accuracy to be 98.99, inception transfer learning accuracy to be 98.39, inception ResNetV2 learning accuracy to be 98.38, ResNet101 transfer learning accuracy to be 97.99, ResNet152 transfer learning accuracy to be 98.79, Vgg16 transfer learning accuracy 97.77, and Vgg19 transfer learning accuracy to be 97.99. As can be seen, this method has the highest accuracy compared to the known models.

In the following, we compare the accuracy of the proposed method with six transfer learning methods in Figure (6); Figure (6-a): Accuracy of the Inception model, Figure (6-b): Accuracy of the InceptionResNetV2 model, Figure (6-c): Accuracy of the ResNet101 model, Figure (6-d): Accuracy of the ResNet152 model, Figure (6-e): Accuracy of the VGG16 model, Figure (6-f): Accuracy of the VGG19 model, Figure (6-g): Accuracy of the proposed method.

In these figures, the horizontal axis represents the number of tests, and the vertical axis represents the accuracy. As observed in Figure 6g, the accuracy of the proposed method exceeds 98%, highlighting the robustness of the proposed approach.

Finally, to prove the power of the proposed method and transfer learning a comparison is made between the proposed method with a deep learning

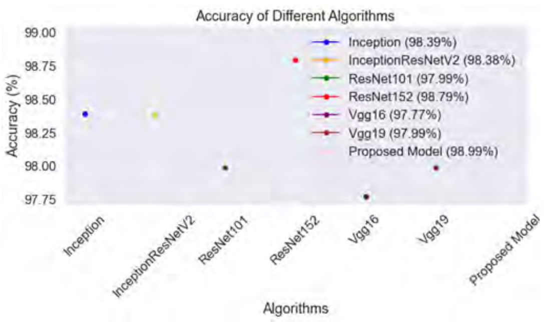
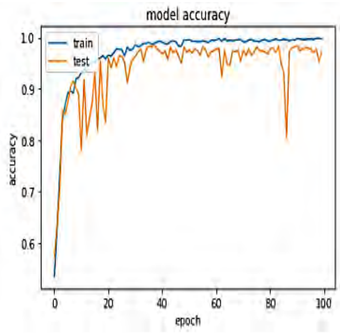
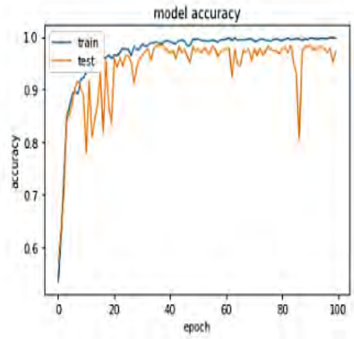


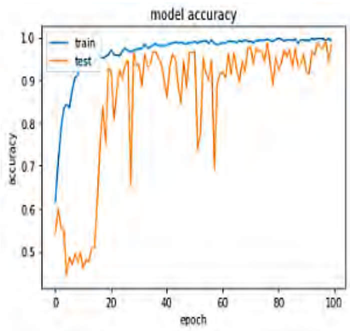
Figure. 5. The comparison results of the transfer-learning methods



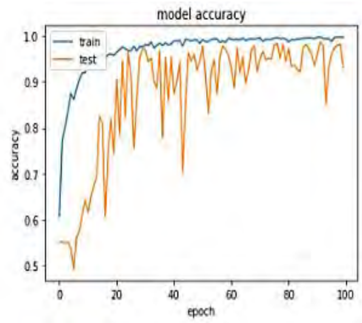
a) accuracy of inception model



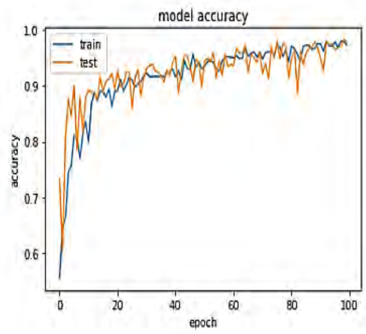
b) accuracy of inception mode



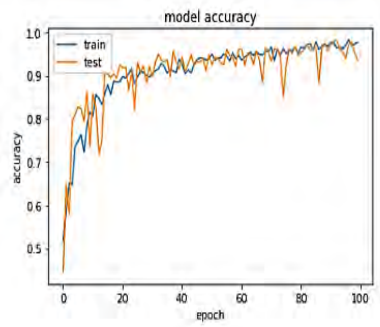
c) accuracy of resnet101 model



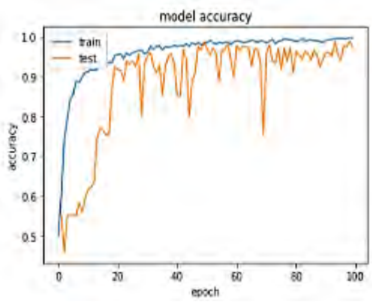
d)accuracy of ResNet152 model



e) accuracy of vgg16 model



f)accuracy of vgg19 model



g) accuracy of proposed method

Figure. 6. The Accuracy Of The Proposed Method With Other Method

method (not transfer learning), such as the convolutional neural network model, and with DenseNet201 architecture and one layer of convolution with 3*3 filter and other deep learning models, such as VGG16, Resnet50, and DenseNet121, without frozen layer and transfer learning. To do it, the same dataset and 100 times training were used. The results are presented in Table 4 and Figure 7.

Table 3. The compariso of results

Models	*Accuracy*	*Sensitivity*	*Specificity*
Inception	98.39	99.22	97.52
InceptionResNetV2	98.38	99.22	97.52
ResNet101	97.99	97.45	98.65
ResNet152	98.79	99.27	98.21
Vgg16	97.77	96.35	99.55
Vgg19	97.99	97.45	98.65
Proposed Model	98.99	98.91	99.10

Table 4. Comparison Result (proposed method with other deep learning methods)

Models	*Accuracy %*	*Sensitivity%*	*Specificity%*
DenseNet201	44.87	0	1
VGG16	44.86	0	1
Resnet50	55.13	1	0
Densnet121	44.87	0	1
CNN+ DenseNet121	90.34	90.51	90.13
proposed method	98.99	98.91	99.10

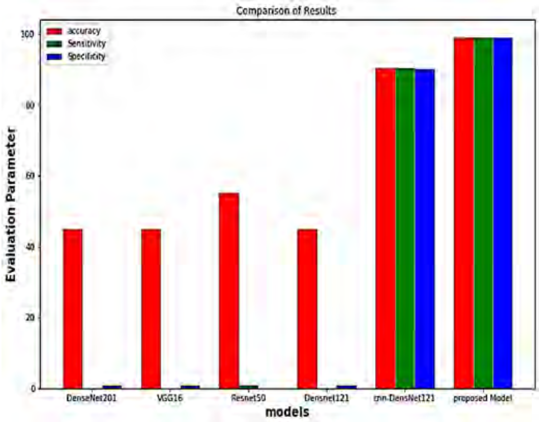


Figure. 7. The comparison of results

Table 4 and Figure 7 show that the proposed method is better in 3 parameters evaluation (Accuracy, Sensitivity, specificity) than 98% but these parameters in other deep learning Methods reach only a maximum of 55 %. A hybrid model of convolutional neural network and DensNet121 displays 90 %, proving that the proposed method can detect COVID-19 very well.

8. Conclusion

This study introduces a two-stage method for diagnosing COVID-19, comprising feature selection in the first stage (ResNet50 pre-training and 2 frozen layers) and replacing one convolutional neural network layer as the main method. The evaluation of the proposed method yielded significant results, including an accuracy of 98.99%, sensitivity of 98.91%, and specificity of 99.10% for COVID-19 diagnosis.

In comparison to other transfer learning methods such as Inception, InceptionResNetV2, ResNet101, ResNet152, VGG16, and VGG19, our proposed method demonstrated superior performance, with a 1% improvement in evaluation parameters. Particularly, the proposed method significantly outperformed other deep transfer learning models like DenseNet201, VGG16, and ResNet50, achieving a higher accuracy of 98% compared to their 55%.

In discussing the research limitations and the complexity of the proposed method, several considerations emerge. The first limitation concerns the accessibility and quality of the dataset used. In this regard, the dataset named "Dataset SARS-Cov-2" may have limitations in terms of sample size, diversity, or labeling accuracy, potentially affecting the overall generalizability of the results. Additionally, while the proposed method performs well on the specific dataset used, its generalization capability to new data warrants further investigation.

Furthermore, challenges associated with transfer learning, including domain adaptation issues and biases inherited from pre-trained models, are important and should be addressed with appropriate strategies. The complexity of the method, especially involving deep learning techniques like ResNet50 and CNNs, poses challenges in terms of computational resources, training time, and hyperparameter tuning, which need to be carefully considered for practical deployment.

Ultimately, the proposed method holds promise for deployment in hospitals and medical centers as an automated AI system in medical decision support. This method can potentially mitigate losses, enhance COVID-19 detection capabilities, and serve as a medical assistant in underserved areas where only CT scan devices are available.

Declarations

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Authors' contributions

TT: Study design, acquisition of data, interpretation of the results, statistical analysis, drafting the manuscript; MG: Study design, interpretation of the results, drafting the manuscript, revision of the manuscript; AG: Supervision, drafting the manuscript.

Conflict of interest

The authors declare that there is no conflict of interest.

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