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COVID-19 Detection using Transfer Learning Approaches through Chest X-ray Images

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The outbreak of the novel coronavirus brought the world to a halt, affecting the health care system worldwide. Thus, the need for a rapid and accurate detection method emerged to help stop the high death rates. The use of convolutional neural networks with chest X-ray screening has been demonstrated to be effective in early COVID-19 diagnosis. Therefore, in this study, four distinct transfer learning models were investigated to detect COVID-19 in two-class (case 1) and three-class (case 2) classifications. In both cases, the classifications were carried out on a balanced dataset. In case 1, a binary classification was performed between COVID-19 patients and non-infected X-rays, while in case 2, a multi-classification between COVID-19, viral pneumonia patients, and non-infected X-rays was presented. The confusion matrices obtained from each model evaluated the models' performance. The test results are presented in terms of accuracy, precision, recall, and F1-Score. The results demonstrated that the visual geometry group–16 model had the highest accuracy in both scenarios compared to other models, with a binary classification accuracy of up to 99% and a multi-classification accuracy of up to 94%.

1. Introduction

The novel Corona Virus, which is known as the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), first broke out in Wuhan, China, as a pneumonia outbreak in December 2019. It was declared by the World Health Organization as a pandemic on March 11th, 2020 [1]. The SARS-CoV-2 virus has spread worldwide, rapidly affecting people of all ages [2].

Since the healthcare systems were overwhelmed with the increasing number of cases, governments required citizens to wear face masks in some countries and enforced social distancing to slow the spread of the virus. The symptoms of SARS-CoV-2 vary from mild symptoms such as fever, coughing, tiredness, sore throat, nose congestion, and aches and pains to severe symptoms such as chest pain, difficulty breathing, and pneumonia, which are thought to be the main causes of death, with some reported positive asymptomatic cases. In severe cases, patients need to be put on oxygen support, which increases the need for more intensive care units, which are extremely expensive and burden governments further [3], [4].

Several diagnostic methods are used to detect SARS-CoV-2, such as Complete Blood Count, C-Reactive Protein test, D-Dimer test, and Ferritin level. However, these blood screens are very deceiving and inaccurate in the early detection of SARS-CoV-2, although they can be useful in late or severe cases. Therefore, there is a need for a more accurate, reliable, and early diagnosis method, leading to the use of several methods, such as a) Reverse Transcriptase Polymerase Chain Reaction (RT-PCR), which is very expensive, requires specialised medical expertise, and is less sensitive, b) X-Ray imaging, c) Computerized Tomography (CT) scans, which are more affordable than RT-PCR, widely available at hospitals, and can be used for rapid detection. However, the diagnosis of the SARS-CoV-2 virus using X-rays or CT scans depends mainly on the experience of the radiologist, and can be an even harder task when the number of patients is large [2], [4]-[6]. Due to the rapid virus spread, early diagnosis is crucial to prevent the deterioration of the patients' health, which can reduce the number of deaths. In addition, the complete dependence on human intervention to diagnose and assess many daily cases is an extremely time-consuming process. Employing artificial intelligence, image classification with deep learning–based methods, and transfer learning, enables the development of a model to distinguish between SARS-CoV-2 cases, viral and bacterial pneumonia, and normal cases with higher accuracy using X-ray images.

Over the last few decades, machine learning algorithms have rapidly grown in medical applications, such as image classification in cancer disease problems and computer-aided diagnosis. These algorithms have helped physicians and radiologists make early diagnoses, leading to better medical care for patients [7].

Many traditional machine learning algorithms have achieved good results, such as random forest, support vector machine (SVM), and Bayes. These methods require previous medical knowledge to determine the region of interest to be examined, which in turn is used to select a set of useful features that have a significant effect on the final classification decision [8], [9]. This process is time consuming and highly complicated compared to the convolutional neural network (CNN) model, which is commonly used in deep learning and requires neither medical knowledge nor manual extraction of image features. CNN can automatically learn and calculate the features and then use that knowledge for classification [10], [11].

Deep convolutional neural networks need a large dataset to be trained well before making predictions that can only perform a single task. As a result, the training process requires a lot of time and energy [12]. This is the driving force behind transfer

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learning. Transfer learning is used to improve a learner from a pretrained model on a large dataset by transferring knowledge to another model to be trained [13]. To achieve faster training, transfer learning techniques are used in deep CNNs where the dataset is not large [14]. The main concept of transfer learning is using models trained on large datasets such as ImageNet [1]. Then it modifies the Softmax and classification layers to be re-used as a starting point with another model to perform a new task. Keras provides free access to many of the best ImageNet image recognition models, such as visual geometry groups (VGG), Inception, and ResNet [5].

Figure 1 shows the difference in learning processes between traditional machine learning techniques that try to learn each task from scratch and the transfer learning techniques that try to transfer knowledge from a previous task to a new task [11].

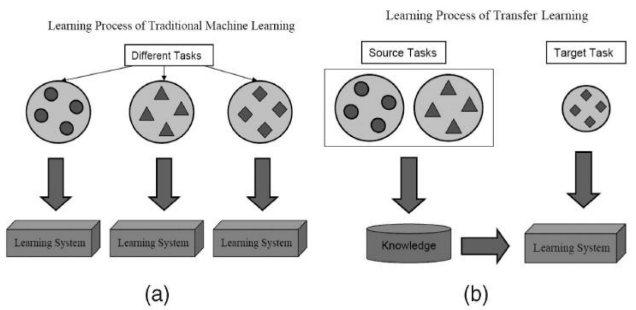


Fig. 1. Two types of learning processes: (a) traditional machine learning and (b) transfer learning.

Several approaches have been introduced in the past two years to use machine learning in rapidly screening and diagnosing the medical images of COVID-19-infected lungs. PK Sethy et al. suggested using a traditional SVM learning methodology to solve the problem by extracting and feeding the deep features from a fully connected layer of a CNN to the SVM. This approach was supposed to reduce the necessity of a larger dataset but came at the cost of accuracy [3].

Conversely, S Patil et al. preferred pretraining models to avoid COVID-19 data scarcity. They used four pretrained models to achieve high accuracies in that task. They showed that using a more suitable dataset with further model-tuning could lead to promising results on the same problem [4]. MK Pandit et al. followed in a similar direction and tested a pretrained model on a small dataset of chest radiographs with some fine-tuning [5].

Moreover, M. Ahsan et al. proposed and tested six modified deep learning models to classify COVID-19 infection based on chest X-ray images. They extended their study to include a small balanced and a larger imbalanced dataset, illustrating the impact on the results when the models were trained on each one and demonstrated the effectiveness of deep learning models [6]. Another study conducted by K El Asnaoui et al. compared the recent deep learning model architectures in detecting and classifying coronavirus pneumonia [7].

2. Research Methodology

In this section, the dataset and the data preprocessing steps used in this research are described. In addition, optimized CNN models are proposed for transfer learning to classify chest X-ray images to identify infected patients. Then, the results obtained from different transfer learning models, namely VGG16, VGG19, ResNet101, and ResNet50, are compared [3].

Simonyan and Zisserman from the Oxford Robotics Institute created the VGG network (VGGNet) to reduce the number of parameters in convolutional layers to enhance training time [15]. The VGGNet incorporates a tiny multiple of 3 × 3 kernel filters to improve image feature extraction functionality [16]. VGGNets are available in two versions: VGG16 and VGG19, which differ in depth and number of layers. The VGG16 has 16 weighted layers, whereas the VGG19 has 19, making it more complex. 224 × 224 RGB image convolutional layers are employed as input image size in both VGG16 and VGG19. Each network has a different size because VGG16 is 528 megabytes and VGG19 is 549 megabytes [17], [10].

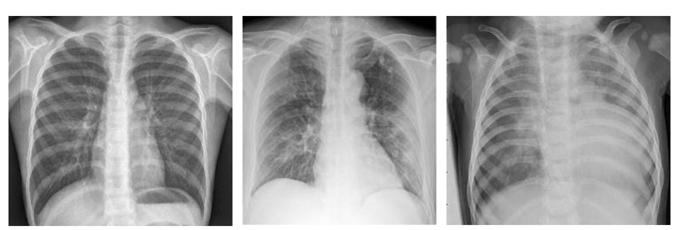
Kaiming created a class of residual neural network models (ResNets) [15]. ResNets are formed by actively reformulating the layers to obtain accuracy from great depths. This results in a strong convergence characteristic. Therefore, ResNet is roughly eight times deeper, while being less complicated. than the prior model (VGGNet) [18]. This is accomplished using “learning residual functions” that employ skip connections to leave certain levels and go to the next. Various versions of ResNet# architectures are being developed; “#” represents the number of layers utilized. This study utilized ResNet50 and ResNet101. ResNet50 accepts input pictures with heights and widths that are multiples of 32 and channel widths of 3 [10].

2.1. Dataset

In this research, an X-ray image dataset, from the Guangzhou Women and Children’s Medical Center, of healthy patients and patients with viral pneumonia and COVID-19 was used [19]. The dataset consists of 1583 images of normal patients, 4273 images of patients with viral pneumonia, and 576 images of patients with COVID-19. The total data size is 1.048 GB and the average size of them is 606 KB. In the represented work, two different cases were compared with the same number of images trained and tested for each case as follows:

a) The results of 576 images with normal, COVID-19, and viral pneumonia X-rays were compared in a multi-classification case.
b) The results of 576 images with normal and COVID-19 X-rays were compared in a binary classification case.

Figure 2 (a), (b), and (c) show a sample of images of patients with normal, viral pneumonia, and COVID-19 X-rays from the dataset, respectively.



(a) (b) (c)

Fig. 2. Sample of the used dataset

In the represented work, since the number of images of patients with COVID-19 was 576, the same number of X-rays of normal patients and patients with viral pneumonia were randomly selected out of 1583 and 4273 images, respectively. The ratio of images trained was 80% of the total used images, whereas 20% of the used images were tested.

Table 1 shows the testing scheme of this research, in which four different transfer learning models were used.

Table 1 Testing Scheme

Case	Label	No. of X-ray images/class	Used Image	Train	Test
Binary-classification	COVID-19	576	576	460	116
	Normal	1583	576	460	116
Multi-classification	COVID-19	576	576	460	116
	Normal	1583	576	460	116
	Viral Pneumonia	4273	576	460	116

2.2. Preprocessing

Gray images, by default, were the proposed dataset, which were converted to RGB images in all models [16]. Based on the standards assigned for the pretrained model, the images were normalized. Therefore, before applying the chest X-rays as input, they were resized to 224 × 224 RGB images to enhance the model's performance, [10], [20].

2.3. Pretrained Model

A pretrained network is a previously trained network on a larger dataset, which is mostly enough to extract unique features from the trained models. In the represented work, VGG16, VGG19, ResNet101, and ResNet50 were trained and tested in Google Colaboratory as the pretrained models, and these models were considered the base models, which is available in Keras and TensorFlow libraries. For each base model, an untrained head was applied. The modified architecture of the models was as follows:

a) First, the models were structured with the pretrained networks without the fully connected (FC) layer (untrained head).
b) A solely new connected layer with average pooling 2D layer (4 × 4) was added on top of the pretrained model → Flatten → Dense → Dropout (0.3) → Dense with "softmax" activation, as shown in Figure 2.
c) The convolutional weight was frozen in the training phase so that only the FC layer would train during the experiment.

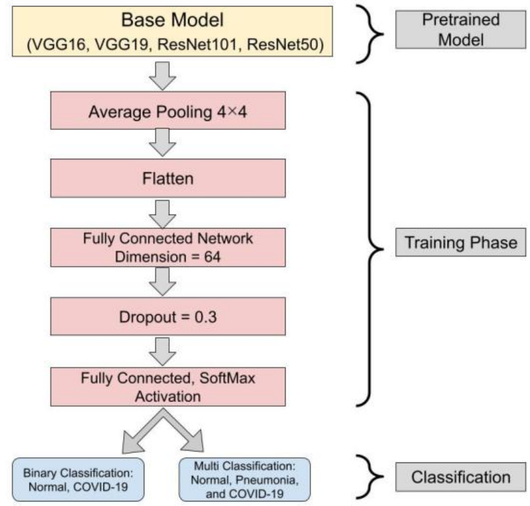


Fig. 3. The Model Architecture

Typically, the pretrained model consists of multiple layers with various parameters such as kernel size, hidden layers, number of filters, and neurons. Specifically, in this study, three main parameters were taken into consideration—batch size, epochs, and learning rate. For both cases, the batch size, epochs, and learning rate were 100, 40, and 0.001, respectively.

3. Results

The test results are exhibited in terms of the confusion matrix (CM), which visualizes the results predicted by the classification process. From the CM, the accuracy, precision, recall, and F1-Score are the main indicators of the model's overall performance calculated from equations 1, 2, 3, and 4, respectively.

$$Accuracy = \frac{t_p + t_n}{t_p + t_n + f_p + f_n} \tag{1}$$

$$Precision = \frac{t_p}{t_p + f_p} \tag{2}$$

$$Recall = \frac{t_p}{t_n + f_p} \tag{3}$$

$$F1\text{-}score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

where,

True positive (t_p) = COVID-19 classified as patients. False positive (f_p) = Healthy people classified as patients. True negative (t_n) = Healthy people classified as healthy. False negative (f_n) = COVID-19 classified as healthy.

3.1 Case 1

The training and test results are shown in Table 2 and Table 3, respectively.

Table 2 Training results of case 1

Model	Accuracy	Precision	Recall	F1-score	Time consumed

					(s)
VGG16	**99.46%**	**99.46%**	**99.46%**	**99.46%**	**5952**
VGG19	**98.37%**	**98.38%**	**98.37%**	**98.37%**	**6299**
ResNet101	**95.98%**	**95.98%**	**95.98%**	**95.98%**	**6447**
ResNet50	**98.80%**	**98.81%**	**98.80%**	**98.80%**	**6299**

Table 3 Testing results of case 1

Model	Accuracy	Precision	Recall	F1-score
VGG16	**99.14%**	**99.14%**	**99.14%**	**99.14%**
VGG19	**98.28%**	**98.28%**	**98.28%**	**98.28%**
ResNet101	**95.26%**	**95.53%**	**95.26%**	**95.25%**
ResNet50	**97.84%**	**97.85%**	**97.84%**	**97.84%**

- *Confusion Matrix (CM)*

Figure 3 shows the test CM of VGG16, VGG19, ResNet101, and ResNet50. VGG16 exhibited the best results compared to the other models, with only one false result in both COVID-19and normal images. In contrast, VGG19 had two false COVID-19 and normal image results. Meanwhile, ResNet101 classified 10 COVID-19 patients as healthy, and one healthy person as a COVID-19 patient, while ResNet50 classified three COVID-19 images as healthy and two healthy people as a COVID-19 patient. Testing accuracies of 99.14%, 98.28%, 95.26%, and 97.84% were achieved for VGG16, VGG19, ResNET101, and ResNET50, respectively. From Figure 4, it is shown that the accuracy obtained from the VGG16 is better than the VGG19, which is better than ResNET101, which is better than ResNET50, in terms of classifying COVID-19 patients.

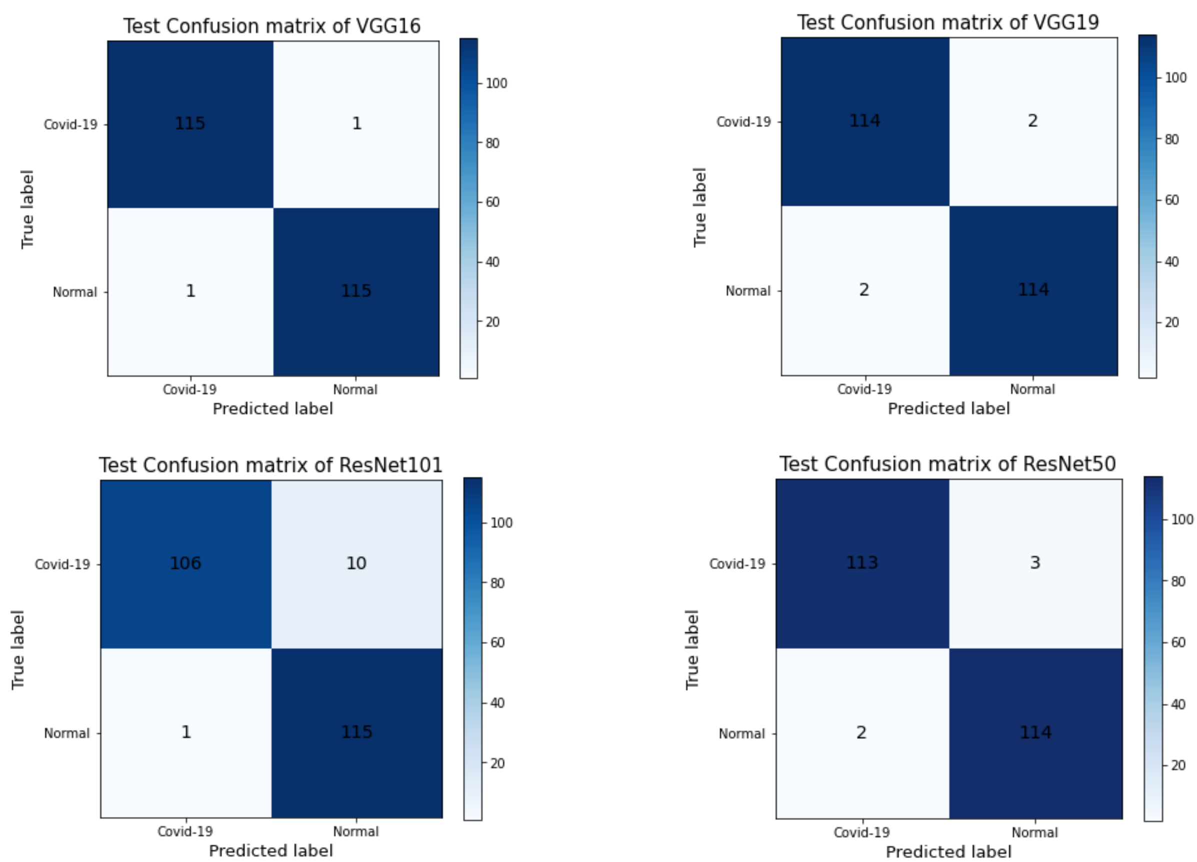


Fig. 4. Confusion Matrices of case 1

- *Model Loss*

The training and validation losses of the four different models at each epoch are shown in Figure 5. From the figure, it can be noted that the validation losses were lower than the training losses in ResNet101 and ResNet50, and the losses in VGG16 and VGG19 were much lower than those in ResNet101 and ResNet50 toward the end.

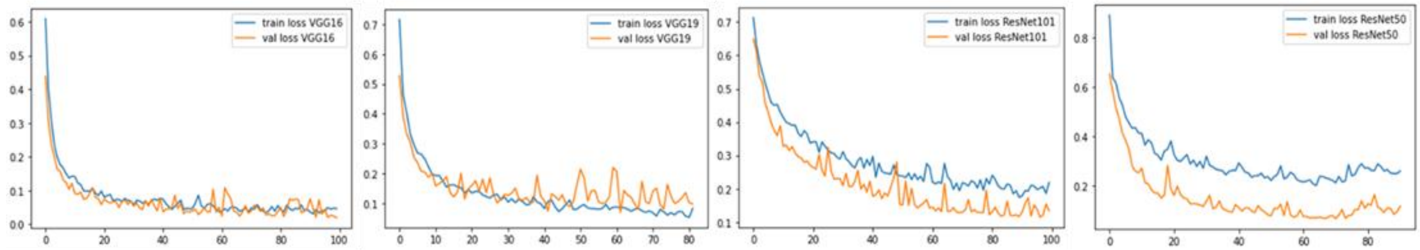


Fig. 5. Training and validation loss in case 1

- *Model Accuracy*

Figure 6 shows the training and validation accuracy of the four used models at each epoch. The models VGG16, VGG19, ResNet50, and ResNet101 show promising results in the training and validation data. For the VGG16 model, the train accuracy is 98.80% and the validation accuracy is 99.14% at epoch 76.

For the VGG19 model, the train accuracy is 97.28% and the validation accuracy is 98.71% at epoch 67.

For the ResNet50 model, the validation accuracy reached its highest peak of 98.28% at epochs 61, 62, 68, and 90.

For the ResNet101 model, the train accuracy is 92.17% and the validation accuracy is 95.69% at epochs 89 and 94.

This result shows that the four models can obtain high results for the validation dataset from the training dataset.

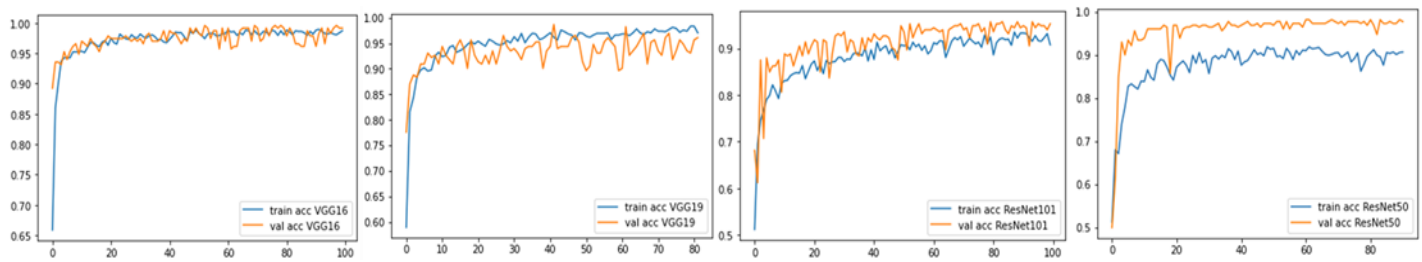


Fig. 6. Training and validation accuracy in case 1

3.2. Case 2

The training and test results are shown in Table 4 and Table 5, respectively.

Table 4 Training results of case 2

Model	Accuracy	Precision	Recall	F1-score	Time Consumed (s)
VGG16	94.86%	94.95%	94.86%	94.86%	8106
VGG19	94.57%	94.70%	94.57%	94.59%	7749
ResNet101	88.42%	88.67%	88.41%	88.43%	8694
ResNet50	88.20%	88.47%	88.19%	88.28%	8351

Table 5 Testing results of case 2

Model	Accuracy	Precision	Recall	F1-score
VGG16	94.25%	94.29%	94.25%	94.25%
VGG19	93.10%	93.14%	93.10%	93.10%
ResNet101	87.07%	87.09%	87.07%	86.93%
ResNet50	87.36%	87.56%	87.36%	87.18%

- *Confusion Matrix*

Figure 7 shows the test CM of the four used models. It is noted that VGG16 outperformed the other models acquiring 94.25% testing accuracy and classifying one COVID-19 patient as healthy and three as viral pneumonia patients. In contrast, VGG19 classified two COVID-19 patients as healthy and two COVID-19 patients as viral pneumonia patients, the same as ResNet101. ResNet50 exhibited the lowest accuracy in viral pneumonia classification, classifying 24 viral pneumonia patients as healthy, and ResNet101 classified 18 healthy people as viral pneumonia patients achieving 87.07% and 87.36% accuracy, respectively

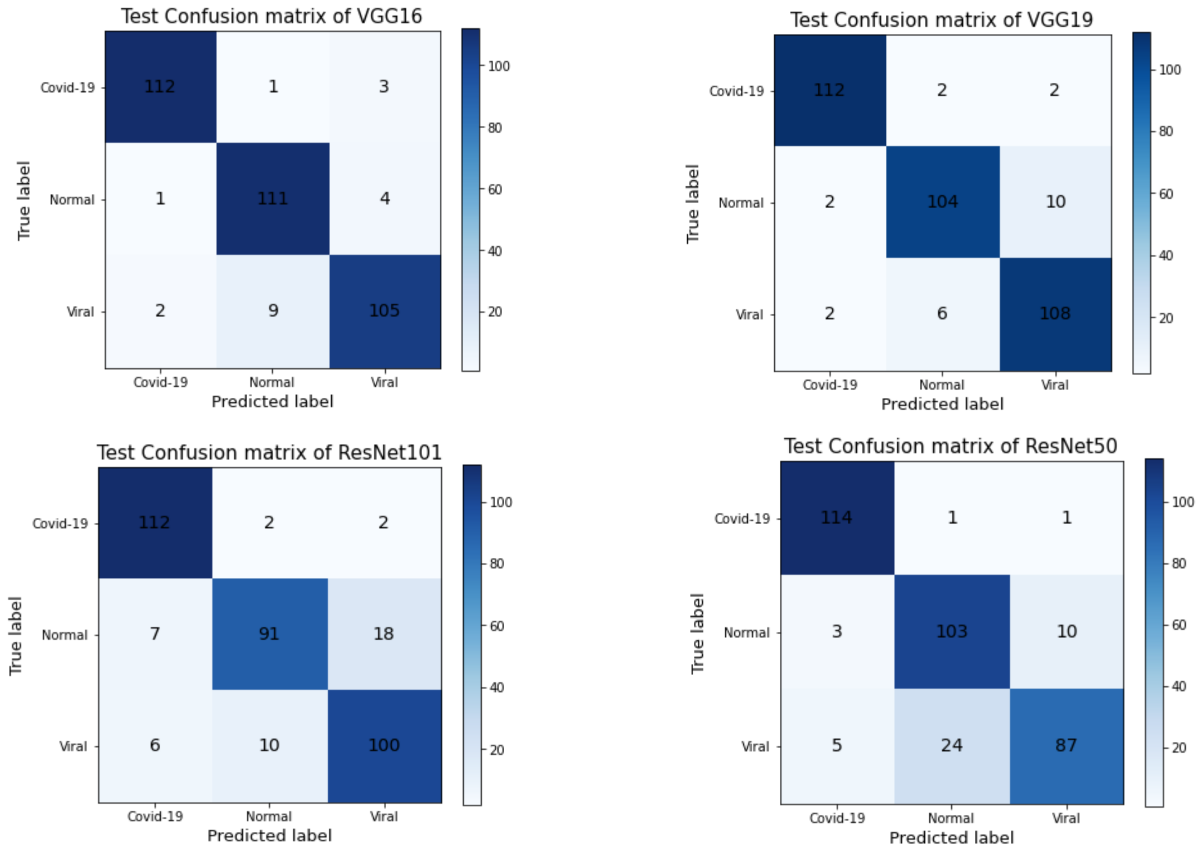
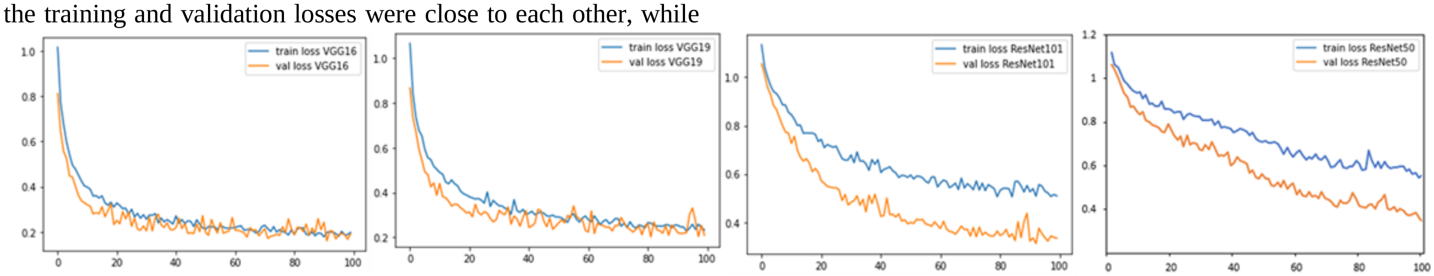


Fig. 7. Confusion Matrices of case 2

- *Model Loss*

Figure 8 shows the training and validation losses of the four used models at each epoch. In VGG16 and VGG19, the values of the training and validation losses were close to each other, while in ResNet101 and ResNet50, the validation loss values were less than the training loss values.



- **Figure 8: Training and validation loss in case 2**

- *Model Accuracy*

Figure 9 shows the training and validation accuracy of the four used models at each epoch. VGG16 and VGG19 demonstrated higher validation accuracy (93.39% and 91.38%) at epochs 99 and 82, respectively. In VGG16 and VGG19, the train and validation accuracies were similar, while in ResNet50 and ResNet101, the validation accuracy was higher than the training accuracy.

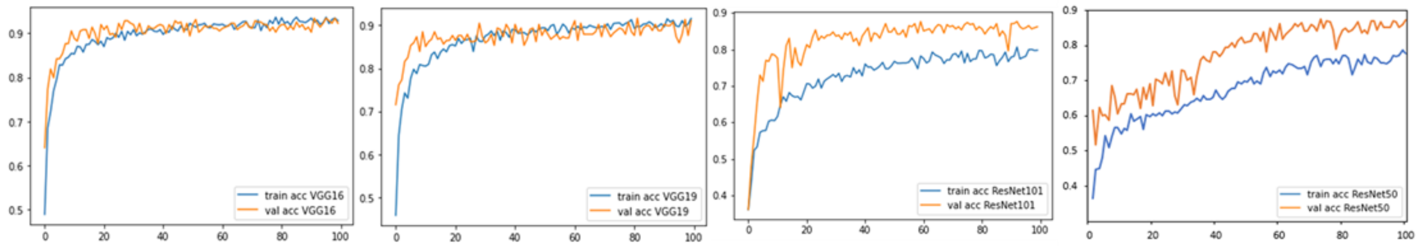


Fig. 9. Training and validation accuracy of case 2

Table 6 Comparison of results in case 1

	M. Ahsan et al. [4]	Patil & Golellu [21]		I. Rodrigues et al. [22]	A. Shankar et al. [23]	M. Pandit et al. [24]	In the represented work
Data set	1845	599	2481	1560	586	728	1152
VGG16	99%	99.5%	96.41%	99.1%	-	96%	99.14%
VGG19	97%	98.8%	95.2%	96.41%	100%	-	98.28%
ResNet101	96%	-		-	-	-	95.26%
ResNet50	93%	-		81.9%	95.33%	-	97.84%
Average accuracy							
VGG16 and VGG19	-	99.15%	95.8%	-	-	-	98.71%
VGG19 and ResNet50	-	-		-	97.66%	-	98.06%
VGG16, VGG19 and ResNet50	-	-		92.47%	-	-	98.42%
VGG16, VGG19 ResNet101 and ResNet50	96.25%	-		-	-	-	97.63%

Table 7 Comparison of results in case 2

	M. Ahsan et al. [4]	I. Rodrigues et al. [22]	A. Shankar et al. [23]	H. Alasasfeh et al. [10]	M. Pandit et al. [24]	In the represented work
Data set	2905	2905	659	657	1428	1728
VGG16	91%	91.07%	-	95%	92.53%	94.25%
VGG19	-	91.33%	98.67%	95%	-	93.10%
ResNet101	-	-	-	-	-	87.07%
ResNet50	-	46.37%	94.67%	33%	-	87.36%
Average accuracy						
VGG19 and ResNet50	-	-	96.67%	-	-	90.23%
VGG16, VGG19 and ResNet50	-	76.25%	-	74.33%	-	91.57%

- *Result Comparison*

Due to the COVID-19 pandemic, globally, researchers seek to achieve higher accuracy in different testing issues to help in the differentiation between different cases. Therefore, in this paper, four models are tested and compared with related works to demonstrate the good quality of our work.

In case 1, using 576 images, the accuracies achieved with VGG16, VGG19, ResNet101, and ResNet50 were 99.14%, 98.28%, 95.26%, and 97.84%, respectively, compared to the results achieved by M. Ahsan et al. using 1845 images with the same pretrained models and achieved 99%, 97%, 96%, and 93%, respectively [4].

S. Patil and A. Golellu used VGG16 and VGG19 and acquired 99.5% and 98.8% accuracy using 599 images and 96.41% and 95.2% accuracy using 2481 images, respectively [21]. I. Rodrigues et al. used VGG16, VGG19, and ResNet50 on 1560 images and acquired 99.1%, 96.41%, and 81.9% accuracy, respectively [22]. A. Shankar et al. acquired 100% and 95.33% accuracies using VGG19 and ResNet50, respectively [23], while M. Pandit et al. achieved 96% accuracy using VGG16 [24]. Table 6 summarizes the model results comparison of case 1.

In case 2, the accuracies achieved using VGG16, VGG19, ResNet101, and ResNet50 were 94.25%, 93.1%, 87.07%, and 87.36%, respectively. M. Ahsan et al. acquired 91% accuracy using VGG16 on 2905 images [4], while I. Rodrigues et al. used 2905 images using VGG16, VGG19, and ResNet50 and acquired 91.07%, 91.33%, and 46.37% accuracy, respectively [22]. A. Shankar et al. achieved 98.67% and 94.67% accuracy using VGG19 and ResNet50, respectively [23]. H. Alasasfeh et al. used VGG16, VGG19, and ResNet50 on 657 images and acquired 95%, 95%, and 33% accuracy, respectively [10]. M. Pandit et al. achieved 92.53% accuracy using VGG16 [24]. Table 7 shows the results comparison of case 2.

To attain fair comparison, a new metric called average accuracy for all models is added in Tables 6 and 7. According to Table 6,

- In the case of VGG16, [24] has a lower accuracy (96%) than the proposed model (99.14%).

- For VGG16 and VGG19, [21] for both data sizes have an average accuracy of 99.15% and 95.8%, respectively, compared to the proposed models (98.71%).
- For VGG19 and ResNet50, [23] has a lower average accuracy (97.66%) than the proposed models (98.06%).
- For three test models (VGG16, VGG19, and ResNet50), [22] has a lower average accuracy (92.47%) than the proposed models (98.42%).
- Finally, when the four test models of VGG16, VGG19, ResNet101, and ResNet50 are tested, [4] has a lower average accuracy (96.25%) than the proposed models (97.63%).

From the above comparison, the presented study achieved a higher average accuracy than the other mentioned reference studies, except for Ref [21]. Perhaps [21] achieved better results, but it used only two models. According to Table 7,

- In the case of VGG16, references [24] and [4] have lower accuracy (91%and 92.53%, respectively) than the proposed model (94.25%).
- For VGG19 and ResNet50, [23] has an average accuracy of 96.67% compared to the proposed models (90.23%).
- For three test models (VGG16, VGG19, and ResNet50), references [22] and [10] have lower average accuracy (74.33% and 76.25%, respectively) than the proposed models (91.57%).

From the above comparison, the presented study achieved a higher average accuracy than the other mentioned reference studies, except for Ref [9]. Perhaps [9] achieved better results, but it used only two models.

4. Conclusion

This study presented a deep learning–based transfer learning approach for automatically detecting SARS-CoV-2 infection from chest X-ray images. Four deep learning models (VGG16, VGG19, ResNet101, and ResNet50) were trained and tested to classify normal and COVID-19 patients in case 1, and normal, COVID-19, and pneumonia patients in case 2 using a balanced dataset of 576 chest X-ray images for each type. It was observed that VGG16 outperformed the other deep learning models in both cases. The classification accuracies in case 1 were 99.14%, 98.28%, 95.26%, and 97.84% for VGG16, VGG19, ResNet101, and ResNet50, respectively. Meanwhile, in case 2, classification accuracies were 94.25%, 93.1%, 87.07%, and 87.36% for VGG16, VGG19, ResNet101, and ResNet50, respectively.

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