Deep transfer learning CNN based approach for COVID-19 detection

Wazir Muhammad [1, *], Zuhaibuddin Bhutto [2], Syed Ali Raza Shah [3], Jalal Shah [2], Murtaza Hussain Shaikh [4], Ayaz Hussain [1], Imdadullah Thaheem [5], Shamshad Ali [1]

[1]Department of Electrical Engineering, Balochistan University of Engineering and Technology, Khuzdar, Pakistan
[2]Department of Computer System Engineering, Balochistan University of Engineering and Technology, Khuzdar, Pakistan
[3]Department of Mechanical Engineering, Balochistan University of Engineering and Technology, Khuzdar, Pakistan
[4]Department of Information Systems, Kyungsung University, Busan, South Korea
[5]Department of Energy Systems Engineering, Balochistan University of Engineering and Technology, Khuzdar, Pakistan

A R T I C L E   I N F O

A B S T R A C T

Recently, the novel coronavirus (Covid-19) and its different variants have spread rapidly across the world. Early-stage detection of COVID-19 is a challenging task due to the limited availability of Covid testing kits to the public. Conventionally, reverse transcription-polymerase chain reaction (RT-PCR) is the reliable test for the detection of COVID-19 which is time-consuming and costly. The aim of this work is to identify the COVID-19 symptoms with the help of a deep learning algorithm using chest X-Ray images. In order to improve the quality of chest X-Ray images, authors have further modified the pre-trained model with some extra CNN layers, such as the first layer is the average pooling layer and the other two are dense layers followed by ReLU with softmax activation function. The experimental results have been carried out on publicly available chest X-Ray images of COVID-19 to mark COVID-19 patients as positive and negative datasets. For evaluation purpose, we have used benchmark of pre-trained models such as VGG-16 (Visual Geometry Group), VGG19, Xception, ResNet152, ResNet152v2, ResNet101, ResNet101v2, DenseNet201, DenseNet169 and DenseNet121. On the benchmark datasets, viz. COVID-19 X-Ray images, an average improvement in terms of training/validation accuracy, precision, recall, and F1-scores scores were 95%, 94%, 99/88%, 99/88%, and 93/92% respectively. The results provide sufficient evidence that deep learning can be used efficiently for the detection of COVID-19 symptoms.

1. Introduction

The Coronavirus disease endures by the presence of acute syndrome coronavirus 2 (SARS-CoV-2) first emerged in 2019 at Wuhan, China which has dispersed to the other countries with a commute of infected people (Wu and McGoogan, 2020), and within no time, this disease has taken the shape of a global pandemic. The number of reported cases has reached 25 million as of early September 2020 with more than 0.86 million deaths worldwide because of the COVID-19. World Health Organization (WHO) terms the formal name of this virus to be coronavirus disease (COVID-19), initially called "2019 novel coronavirus" (Strzelecki, 2020). The symptoms of COVID-19 include runny nose, fever, headache, and cough (Covid et al., 2020). This virus has caused deaths in people, those particularly with a weak immune system (Singhal, 2020). It has caused serious implications on our daily life. The rapid increase in the number of cases leads to the urgency of fast diagnosis, effective testing, and enduring treatment. To control the spread of disease, there is a need for a fast diagnosis with accuracy so that people carrying COVID can be isolated in time, thus the spread can be slowed down. Presently, the detection of COVID-19 in the medical field is attained by reverse transcription-polymerase chain reaction (RT-PCR) based testing which is recommended as an effective diagnostic approach now. However, there are some fallbacks that include the limited sensitivity and scarcity in the availability of testing kits in the pandemic region (especially in developing countries) which has not only proved to be burdensome for the medical staff but also ignites the spread of the disease.

Recent research in the radiological field shows that computed tomography (CT) can be applied for the diagnosis of COVID-19 due to its high sensitivity and accuracy as compared to RT-PCR. The COVID-19 affects the lungs like pneumonia but induces lesions in the bilateral lung which is composed of ground-glass opacities (GGO), which has highlighted the significance of Chest X-ray (CXR) images or CT images for the identification of COVID-19. CT scan provides a convenient and economical solution as a diagnostic tool that is fast and reliable, thus presenting an alternative for RT-PCR. The diagnostic model can become more effective and reliable when incorporated with modern techniques of artificial intelligence and machine learning, thus preventing human error, and generating massive results within no time considering the pandemic situation.

The rest of the paper is organized as follows. Section 2 gives a brief introduction to related work. Section 3 discusses the proposed transfer learning model. Experimental results are presented in Section 4 and in Section 5, the Conclusion and Future work are discussed.

2. Related works

The World Health Organization (WHO) announced in February 2020 that a new virus known as COVID-19 had begun to spread quickly in various countries. COVID-19 is usually diagnosed because of pneumonia-like symptoms, which can be detected through genetic and imaging studies. Deep learning-based convolutional neural networks (CNNs) has significant applications in various field such as image super-resolution, satellite imaging, security surveillance, and medical image classification tasks (Tajbakhsh et al., 2016; Peled and Yeshurun, 2001; Muhammad et al., 2020; 2021a; 2021b; Muhammad and Aramvith, 2019; Shi et al., 2013). Promising results of deep learning in the field of medical diagnosis have urged scientists to use it for COVID-19 detection as well. For, instance, some researchers have deployed a deep convolutional neural network technique to perceive the indication of COVID-19. Sethy and Behera (2020) deployed a novel methodology for discontenting and categorizing pneumonia infection from X-ray images. The primarily trained models are incorporated to retrieve the characteristics from X-ray images. Ismael and Şengür (2021) used deep learning-based approaches for COVID-19 detection on the basis of chest X-ray images. The authors used the fine-tuned ResNet50 model and recorded it to 92.6% accuracy. The features obtained from ResNet50 (He et al., 2016) with support vector machine (SVM) classifier (Qian et al., 2010) produce reliable results. Wang et al. (2020a) introduced a model of deep learning-based CNN for coronavirus detection which they call COVID-NET. In the proposed model, authors randomly select a medical image for COVID-19 detection and achieved 85.2% accuracy with 0.83 specificities and 0.67 of sensitivity. A model of VB-Net deep learning is proposed by Shan et al. (2020) which integrates to segment the infection regions of COVID-19 patients within CT scan images. The training dataset used the images of 549 with different scenarios of disease obtained from different sources. The achieved accuracy is up to 91.6%. Hemdan et al. (2020) presented 7 different deep neural network architectures for COVID-19 classification. In Jain et al. (2021), the authors used 3 pre-trained models like Inceptionv3, Xception, and ResNet models to maximize the accuracy up to 97.97%, but not include the VGG19 (Simonyan and Zisserman, 2014) and DenseNet201 (Huang et al., 2017) architectures. Stephen et al. (2019) proposed a model that detects and classifies cases of pneumonia. The training dataset depends on the collection of chest X-ray images (Kermany et al., 2018). The experimental results report 2.88% training loss, 95.31% training accuracy, validation loss is 18.35% and validation accuracy is 93.73%. In Varshni et al. (2019), the authors used five pre-trained convolutional neural network models, VGG16 Network architecture (Simonyan and Zisserman, 2014), ResNet50 (He et al., 2016), DenseNet-121 (Huang et al., 2017), DenseNet-169 and Xception Network architecture to extract the features. The pre-trained networks are used as a feature extractor followed by a different type of classifier which encloses Random Forest, K-nearest neighbor, Naıve Bayes, and SVM incorporated for the identification of pneumonia from X-ray images. In Narin et al. (2021), the transfer learning technique has been deployed for the identification of COVID-19. They utilized an initially trained model of Inception-v3 (Szegedy et al., 2016) and ResNet50. Experimental results showed that the ResNet50 model presented the best results when compared to Inception-v3.

Apostolopoulos and Mpesiana (2020) proposed a medical image-based deep learning neural network architecture. In this study, the authors split the dataset into three groups depending upon classification and nature which include a normal, pneumonia, and COVID-19 dataset. During their study, they have integrated five primarily trained models and accomplished accuracy up to 98.75% for the binary categorization task. Khan et al. (2020) proposed a model known as CoroNet, which is based on Xception pre-trained architecture. The authors claimed 89.6% overall accuracy on four different classes. Homayouni et al. (2021) used the deep learning approach to detect the anomaly in COVID-19 time-series datasets. Ayan and Ünver (2019) proposed the Xception (Chollet, 2017) and VGG16 (Simonyan and Zisserman, 2014) based deep convolutional neural network models which are based on Pneumonia chest X-ray images. In their work, a dataset containing nearly 5800 chest X-ray images is retrieved from the Kermany et al. (2018). Their approach classifies 4200 images as pneumonia and the remaining images as a pneumonia-free case. The investigational results for VGG-16 network architecture report 85% sensitivity, and 86% precision.

3. Proposed transfer learning model

The design and development of a new model based on CNN are complex, and time-consuming tasks. Integrating primarily trained models is a quick and efficient method to be adopted as compared to the consideration of developing a new CNN model (Özcan and Baştürk, 2019). In this paper, the authors proposed a new transfer learning type model that integrates a deep CNN framework for the identification of the COVID status through X-ray images. Fig. 1 presents an overall network architecture of the proposed method and integrates five initially trained deep CNN architectures; namely

VGG16, VGG19, ResNet50, Inceptionv3, and Xception with the addition of three layers. The first layer is the average pooling layer and the other two are dense layers followed by ReLU and Softmax activation function. The last layer of each pre-trained model is removed and replaced by the trainable part which consists of a fully connected/dense layer with a dropout is 0.5. For binary classification purposes. This layer has 2 units with sigmoid output to classify the output of COVID-19 as a Positive or Negative Class. Some characteristics of initially trained models are demonstrated in Table 1. The details of pre-trained deep CNN models are given in Table 1.
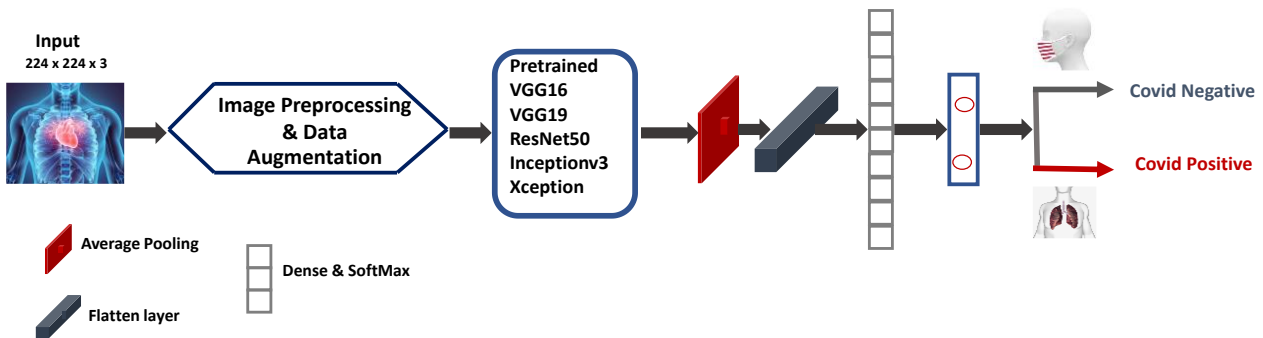

Fig. 1: Proposed design for COVID-19 detection and classification

3.1. VGG16 and VGG19

VGG16 and VGG19 (Simonyan and Zisserman, 2014) is a deep CNN type network architecture proposed by Simonyan and Zisserman (2014) and successfully trained on the ImageNet dataset (Deng et al., 2009) consists of 14 million images belongs to 1000 different types of classes. In the ILSVRC-2014, (Russakovsky et al., 2015) the model achieves 92.7% top-5 test accuracy. It replaces the large kernel size of AlexNet (Krizhevsky et al., 2012) with 3x3 filters. The training time of VGG16 and VGG19 is completed in weeks and the NVIDIA Titan GPUs have been utilized. The network depth of VGG16 and VGG19 has 16 and 19 layers.

3.2. ResNet50

ResNet50 (He et al., 2016) is a deep convolutional neural type network that depends on 50 deep layers. ResNet50 is trained on more than one million images obtained from the database of ImageNet (Deng et al., 2009). The model can classify different images into 1000 categories, such as animals, pencils, mice, and keyboards. The input size of the pre-trained network is 224-by-224.

3.3. InceptionV3

Inceptionv3 (Szegedy et al., 2016) is a deep CNN network that has 48 deep CNN layers and is trained on the ImageNet database (Deng et al., 2009). The pre-trained model can classify the images into different 1000 types of subcategories, like animals, keyboard, pencil, and mouse. Millions of images

provide rich feature representations. The input size of the image in the network is 299-by-299.

3.4. Xception

In 2017, Google introduced the new architecture named Xception network (Chollet, 2017), which stands for the extreme version of an Inception. In this architecture, the standard convolution operation is replaced by depth-wise separable convolution, which is better than Inceptionv3. Xception model is trained on the ImageNet dataset as well as on the JFT dataset (Chowdhury et al., 2020). Xception network achieves 0.790 Top1-accuracy and 0.945 Top-5 accuracy. The input size of the image in the network is 299-by-299.

4. Experimental results

The proposed transfer learning type model is designed in Python 3.7 using deep learning library Keras backend as a TensorFlow. All experimental results are conducted on the computer of the Intel Xeon processor (2 GHz) with a RAM of 16 GB. All pre-trained model weights are updated with the mini-batch size is 32 and the initial learning rate is 0.0003. The proposed model has been tested in the two classes, such as COVID-19 Positive and COVID-19 Negative class.

4.1. Collection of data

For the experimental procedure and assessment, we have deployed two categories of image sets which enclose COVID-Negative and COVID-Positive.

Since COVID-19 is a new research area, therefore the number of images related to COVID-19 is still limited. To overcome this limitation, we combine two available datasets that are publicly accessible consisting of COVID-19(COVID-Positive) and normal images with no COVID generally named as COVID-Negative. The said dataset for COVID-19 X-ray images is openly made available by Cohen et al. (2020). The authors gathered the images from different open access sources. The next dataset of COVID-19 images is developed by medical doctors' teams from Bangladesh and Qatar University (Cohen et al., 2020). The recent version of the COVID-19 image dataset having more than two hundred X-ray images is accessible from the Kaggle website. In the training phase, the dataset of 200 COVID-Negative images and 230 of COVID-Positive images are considered. In the test dataset, COVID-Negative is 150 images and 203 is the COVID-Positive images.

4.2. Data augmentation

While classifying both traditional as well as deep learning approaches, the training dataset has an important role in determining the performance of the model. In order to enhance the performance and to overcome the issue of over-fitting, we have used data augmentation techniques in the form of rotation, flipping, and shearing as shown in Fig. 2.

4.3. Feature map visualization of COVID-19 image in the layers

In Fig. 3, we analyzed the segment of the image for which the CNN by complementing the segments in the original images. The values in the activation maps can be normalized between the range of 0 and 1, in case they have a different range.

Table 1: Evolution of pre-trained deep transfer learning based CNN models

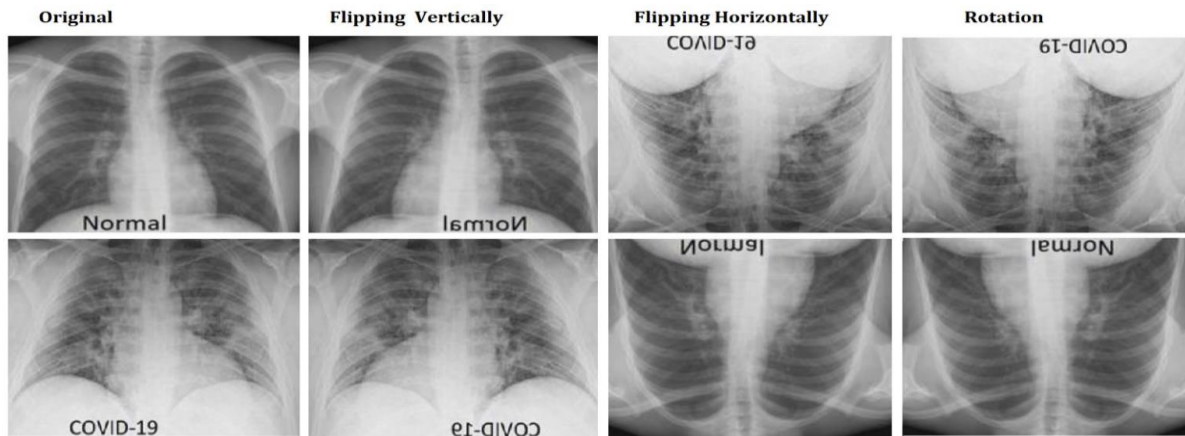| Pre-trained Model	Input Size	Size (MB)	No: of Parameters (M)	Top-1 Accuracy	Top-5 Accuracy
VGG16 (Simonyan and Zisserman, 2014)	$224 \times 224 \times 3$	528	138	0.713	0.901
VGG19 (Simonyan and Zisserman, 2014)	$224 \times 224 \times 3$	549	143	0.713	0.900
ResNet50 (He et al., 2016)	$224 \times 224 \times 3$	98	25	0.749	0.921
Inceptionv3 (Szegedy et al., 2016)	$299 \times 299 \times 3$	92	23	0.779	0.937
Xception (Chollet, 2017)	$299 \times 299 \times 3$	88	22	0.790	0.945

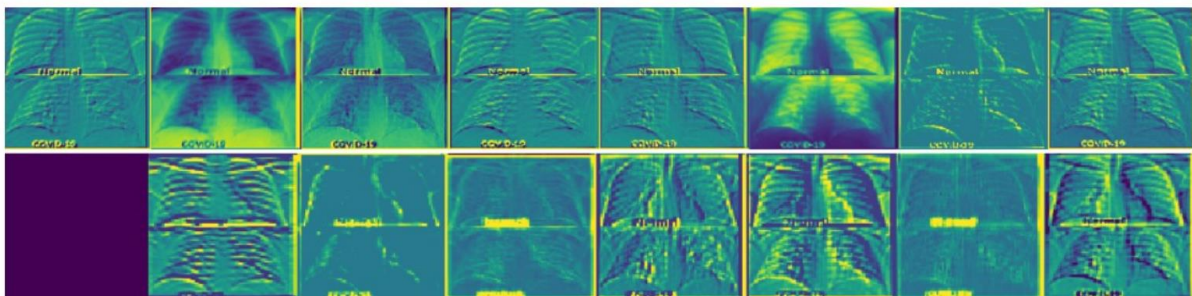**Fig. 2:** Data augmentation on the original image

Fig. 3: Feature activation map of different layers

4.4. Evaluation parameters

Accuracy is a performance evaluation metric to predict the correctness of the classification model and is given by Eq. 1.

$$Accuracy(\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \qquad (1)$$

Sensitivity is the ability of a test to correctly identify all those who have positive COVID-19 and is given by Eq. 2.

$$Sensitivity\ (\%) = \frac{TP}{TP+FN} \times 100 \qquad (2)$$

Precision means how many samples are classified correctly as a positive outcome of all positives and is calculated by Eq. 3.

$$Precision\ (\%) = \frac{TP}{TP+FP} \times 100 \qquad (3)$$

Specificity is the ratio between how many samples are correctly classified and how many samples are negatives and is calculated by Eq. 4.

$$Specificity\ (\%) = \frac{TN}{TN+FP} \times 100 \setminus \qquad (4)$$

F1-score also known as F-score is to measures the accuracy of tests. F-score is calculated from the value of recall and precision and has the highest value is 1, which indicates the perfect measurement of recall and precision.

$$F_1 Score\ (\%) = 2 \times \frac{Precision \times Sensitivity}{(Precision+Sensitivity)} \qquad (5)$$

In Table 2, we evaluate the performance of two classes, such as COVID-Negative and COVID-Positive. All transfer learning-based deep CNN model achieves different precision, recall, and F1 scores.

4.5. Comparison evaluation with state-of-the-art-methods

Comparison analysis of the proposed method with other state-of-the-art methods is presented in Tables 2 and 3. Results are clearly seen that the proposed methodology obtained remarkable performance in terms of quality metrics.

Table 2: Performance comparison of different pre-trained models in terms of training, validation loss, accuracy, precision, recall, and F$_1$ scores

Classification Models	Training Loss		Training Accuracy		Precision	Recall	F1 Score
	Training	Validation	Training	Validation	Infected/ Uninfected	Infected/ Uninfected	Infected/ Uninfected
VGG16	0.0428	0.5913	0.9878	0.8261	0.91/0.75	0.77/0.90	0.83/0.82
VGG19	0.0271	0.5351	0.9878	0.8696	1.00/0.77	0.77/1.00	0.87/0.87
ResNet50v2	0.0625	0.0097	0.9756	1.0000	1.00/1.00	1.00/1.00	1.00/1.00
Xception	0.0085	0.9948	0.9898	0.9231	1.00/0.71	0.69/1.00	0.82/0.83
ResNet152	0.5047	0.3913	0.7317	0.9565	1.00/0.91	0.92/1.00	0.96/0.95
ResNet152v2	0.0420	0.0012	0.9756	1.0000	1.00/1.00	1.00/1.00	1.00/1.00
ResNet101	0.2570	0.0708	0.8780	1.0000	1.00/1.00	1.00/1.00	1.00/1.00
ResNet101v2	0.0301	0.0110	0.9878	1.0000	1.00/1.00	1.00/1.00	1.00/1.00
DenseNet201	0.0518	0.0004	0.9634	1.0000	1.00/1.00	1.00/1.00	1.00/1.00
DenseNet169	0.0169	0.3215	1.0000	0.9130	1.00/0.83	0.85/1.00	0.92/0.91
DenseNet121	0.0084	1.0288	1.0000	0.8261	1.00/0.71	0.69/1.00	0.82/0.83
Average	0.0956	0.3596	95%	94%	99%/88%	88%/99%	93%/92%

Table 3: Performance comparison with state-of-the-art methods

Proposed Algorithm	Network Architecture	Test Images	Accuracy
(Wang et al., 2020b)	COVID-Net	53 COVID-19 (+) 5526 COVID-19(-) 8066 Normal	92.4%
(Hemdan et al., 2020)	COVIDX-Net VGG19 DenseNet201	25 COVID-19 (+) 25 Normal	90.0%
(Abbas et al., 2021)	Deep CNN (DeTrac)	105 COVID-19 (+) 80 Normal 11 SARS	93.1%
(Mobiny et al., 2020)	DECAPS + Peekaboo	746 COVID-19 (+) and (-)	87.6%
(Hall et al., 2020)	Resnet50 and VGG16	102 COVID-19 (+) and pneumonia patients	89.2%
Proposed (Our)	Xception	203 COVID-19 (+) 150 COVID-19 (-)	94.5%

Furthermore, training accuracy and loss curves as shown in Fig. 4. The training of all pre-trained transfer learning models has been carried out up to 500 epochs. It can be seen from Fig. 4 that the highest training accuracy is obtained by Xception models. In the loss curves, it can be observed that the loss values decrease in the pre-trained models during the initial training stage. It can be said that the Xception model loss values decrease rapidly approaches to zero.

5. Conclusion and future work

The drastic increment in the number of patients affected with COVID-19 and its worldwide spread demands an efficient diagnosis and testing to overcome the pandemic. Early-stage diagnosis of this virus will help people with fast recovery and slow down the process of spreading. Computed tomography (CT) when integrated with advanced machine learning approaches can produce good results with considerable accuracy thus eradicating the cost and need for extensive medical staff. In this paper, we have used a transfer learning approach with two categories of X-ray images named COVID-19 negative and COVID-19 positive. Transfer learning provides a superior response in terms of precision, sensitivity, and F$_1$ score. In future work, authors have used transfer learning of the deep CNN model approach with a larger benchmark training as well as a testing dataset.
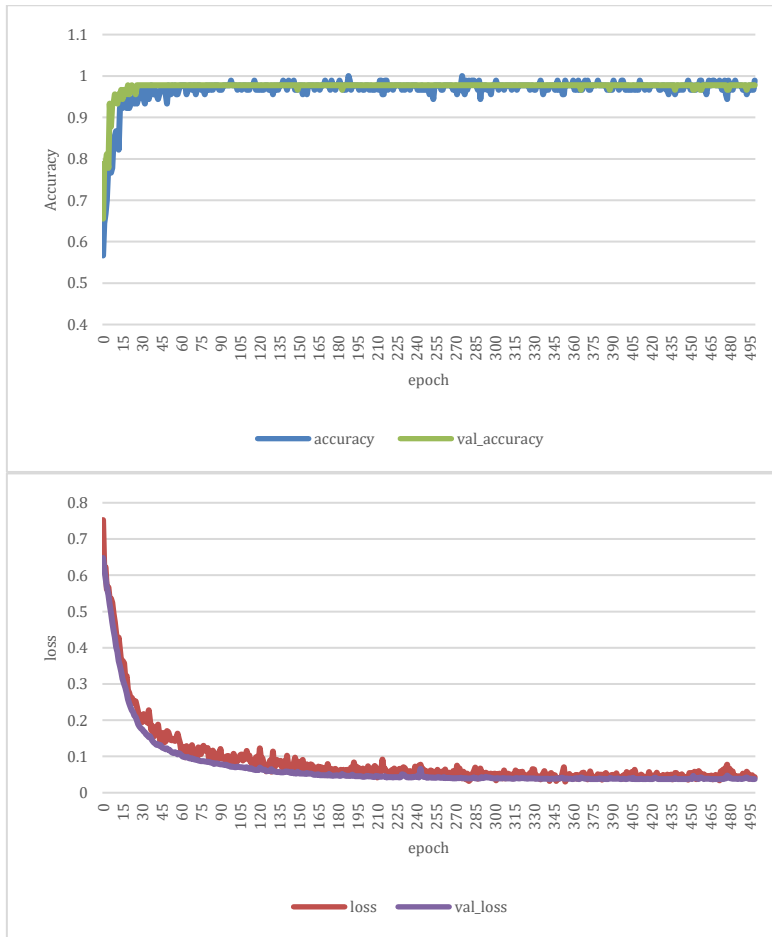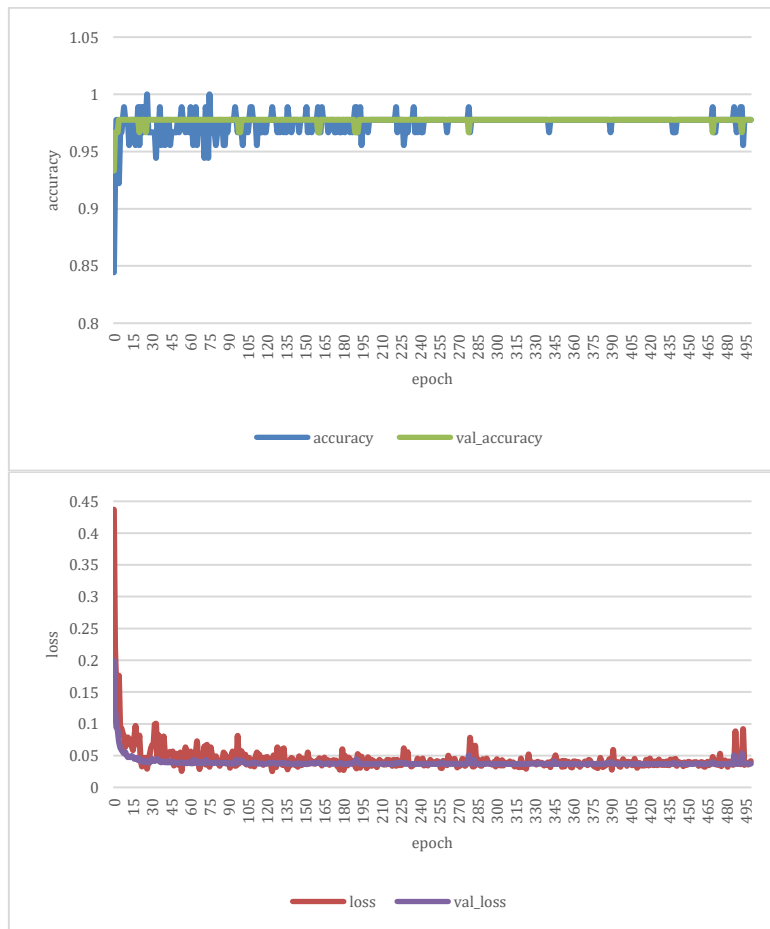
(a) VGG16
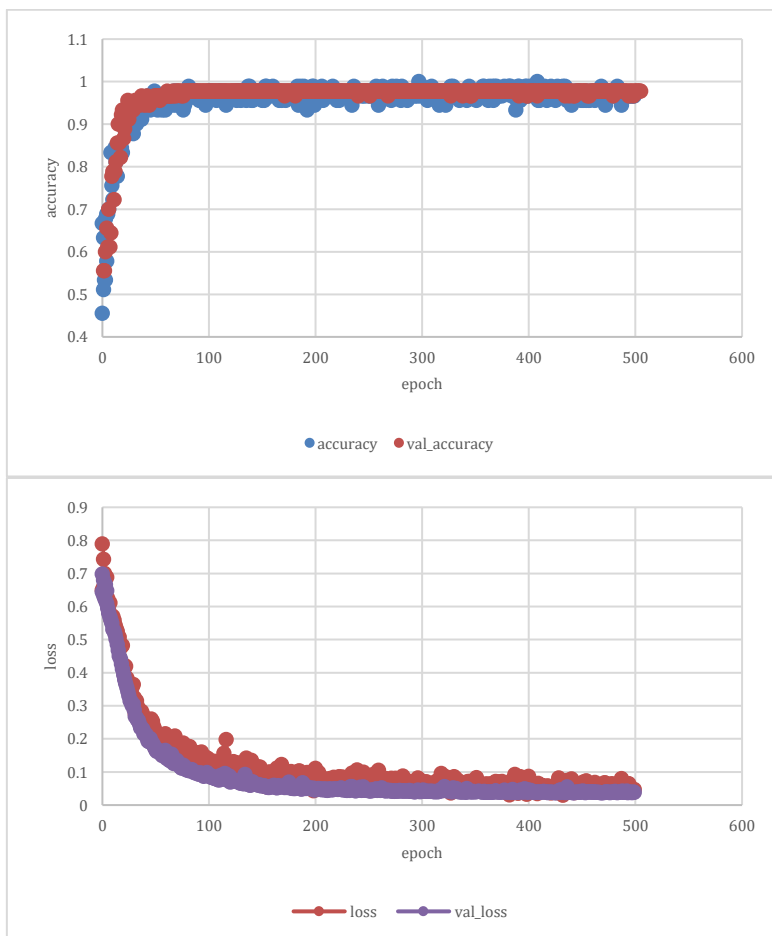
(b) VGG19
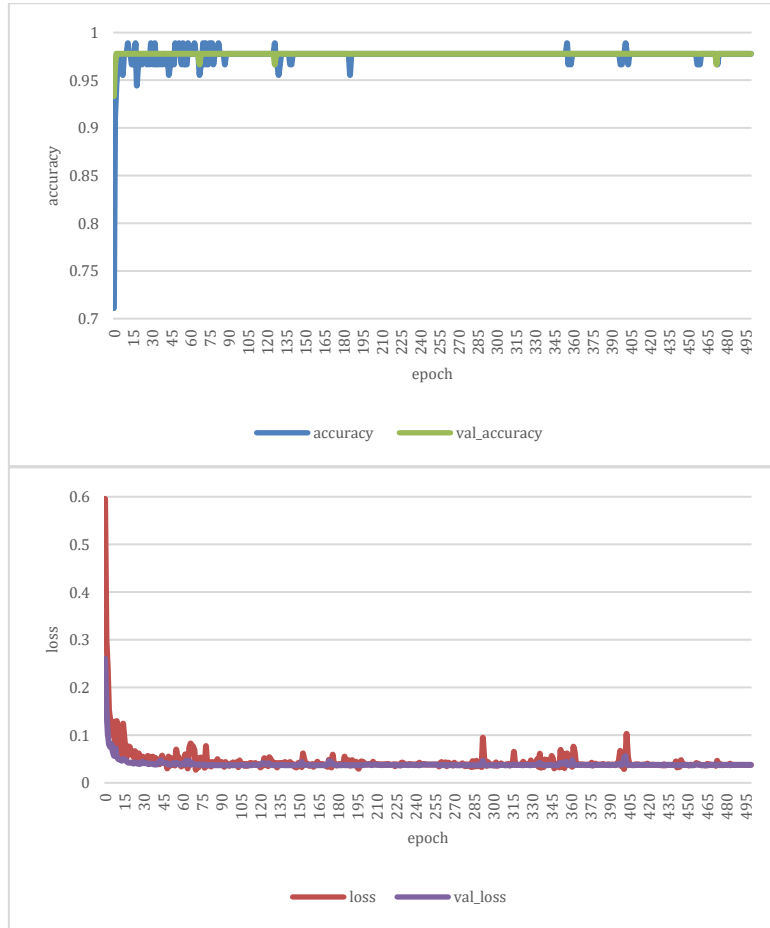
(c) ResNetv50

(d) Xception

Fig. 4: Accuracy and loss curves for VGG16, VGG19, ResNet50v2, and Xception transfer learning models

Acknowledgment

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Abbas A, Abdelsamea MM, and Gaber MM (2021). Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. Applied Intelligence, 51(2): 854-864.
https://doi.org/10.1007/s10489-020-01829-7
PMid:34764548 PMCid:PMC7474514

Apostolopoulos ID and Mpesiana TA (2020). Covid-19: Automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. Physical and Engineering Sciences in Medicine, 43(2): 635-640.
https://doi.org/10.1007/s13246-020-00865-4
PMid:32524445 PMCid:PMC7118364

Ayan E and Ünver HM (2019). Diagnosis of pneumonia from chest X-ray images using deep learning. In the 2019 Scientific Meeting on Electrical-Electronics and Biomedical Engineering and Computer Science, IEEE, Istanbul, Turkey: 1-5.
https://doi.org/10.1109/EBBT.2019.8741582
PMid:30711875

Chollet F (2017). Xception: Deep learning with depthwise separable convolutions. In the Conference on Computer Vision and Pattern Recognition, IEEE, Honolulu, USA: 1251-1258.
https://doi.org/10.1109/CVPR.2017.195

Chowdhury ME, Rahman T, Khandakar A, Mazhar R, Kadir MA, Mahbub ZB, and Islam MT (2020). Can AI help in screening viral and COVID-19 pneumonia? IEEE Access, 8: 132665-132676. https://doi.org/10.1109/ACCESS.2020.3010287

Cohen JP, Morrison P, Dao L, Roth K, Duong TQ, and Ghassemi M (2020). Covid-19 image data collection: Prospective predictions are the future. arXiv:2006.11988.
https://doi.org/10.48550/arXiv.2006.11988

Deng J, Dong W, Socher R, Li LJ, Li K, and Fei-Fei L (2009). ImageNet: A large-scale hierarchical image database. In the Conference on Computer Vision and Pattern Recognition, IEEE, Miami, USA: 248-255.
https://doi.org/10.1109/CVPR.2009.5206848

Hall LO, Paul R, Goldgof DB, and Goldgof GM (2020). Finding covid-19 from chest x-rays using deep learning on a small dataset. arXiv:2004.02060v4.
https://doi.org/10.36227/techrxiv.12083964.v2

He K, Zhang X, Ren S, and Sun J (2016). Deep residual learning for image recognition. In the Conference on Computer Vision and Pattern Recognition, IEEE, Las Vegas, USA: 770-778.
https://doi.org/10.1109/CVPR.2016.90 **PMid:26180094**

Hemdan EED, Shouman MA, and Karar ME (2020). COVIDX-Net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images. arXiv:2003.11055v1.
https://doi.org/10.48550/arXiv.2003.11055

Homayouni H, Ray I, Ghosh S, Gondalia S, and Kahn MG (2021). Anomaly detection in COVID-19 time-series data. Computer Science, 2(4): 1-17.
https://doi.org/10.1007/s42979-021-00658-w
PMid:34027432 PMCid:PMC8132285

Huang G, Liu Z, Van Der Maaten L, and Weinberger KQ (2017). Densely connected convolutional networks. In the Conference on Computer Vision and Pattern Recognition, IEEE, Honolulu, USA: 4700-4708.
https://doi.org/10.1109/CVPR.2017.243
PMCid:PMC5598342

Ismael AM and Şengür A (2021). Deep learning approaches for COVID-19 detection based on chest X-ray images. Expert Systems with Applications, 164: 114054.
https://doi.org/10.1016/j.eswa.2020.114054
PMid:33013005 PMCid:PMC7521412

Jain R, Gupta M, Taneja S, and Hemanth DJ (2021). Deep learning-based detection and analysis of COVID-19 on chest X-ray images. Applied Intelligence, 51(3): 1690-1700.
https://doi.org/10.1007/s10489-020-01902-1
PMid:34764553 PMCid:PMC7544769

Kermany DS, Goldbaum M, Cai W, Valentim CC, Liang H, Baxter SL, and Zhang K (2018). Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell, 172(5): 1122-1131.
https://doi.org/10.1016/j.cell.2018.02.010 **PMid:29474911**

Khan AI, Shah JL, and Bhat MM (2020). CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. Computer Methods and Programs in Biomedicine, 196: 105581.
https://doi.org/10.1016/j.cmpb.2020.105581
PMid:32534344 PMCid:PMC7274128

Krizhevsky A, Sutskever I, and Hinton GE (2012). ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25: 1097-1105.

Mobiny A, Cicalese PA, Zare S, Yuan P, Abavisani M, Wu CC, and Van Nguyen H (2020). Radiologist-level covid-19 detection using CT scans with detail-oriented capsule networks. arXiv:2004.07407v1.
https://doi.org/10.48550/arXiv.2004.07407

Muhammad W and Aramvith S (2019). Multi-scale inception based super-resolution using deep learning approach. Electronics, 8(8): 892.
https://doi.org/10.3390/electronics8080892

Muhammad W, Aramvith S, and Onoye T (2021a). Multi-scale Xception based depthwise separable convolution for single image super-resolution. PLOS ONE, 16(8): e0249278.
https://doi.org/10.1371/journal.pone.0249278
PMid:34424911 PMCid:PMC8382202

Muhammad W, Bhutto Z, Ansari A, Memon ML, Kumar R, Hussain A, and Ali S (2021b). Multi-path deep CNN with residual inception network for single image super-resolution. Electronics, 10(16): 1979.
https://doi.org/10.3390/electronics10161979

Muhammad W, Ullah I, and Ashfaq M (2020). An introduction to deep convolutional neural networks with Keras. In: Mahrishi M, Hiran KK, Meena G, and Sharma P (Eds.), Machine learning and deep learning in real-time applications: 231-272. IGI Global, Pennsylvania, USA.
https://doi.org/10.4018/978-1-7998-3095-5.ch011

Narin A, Kaya C, and Pamuk Z (2021). Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. Pattern Analysis and Applications, 24: 1207–1220.
https://doi.org/10.1007/s10044-021-00984-y
PMid:33994847 PMCid:PMC8106971

Özcan T and Baştürk A (2019). Static image-based emotion recognition using convolutional neural network. In the 27th Signal Processing and Communications Applications Conference, IEEE, Sivas, Turkey: 1-4.
https://doi.org/10.1109/SIU.2019.8806408

Peled S and Yeshurun Y (2001). Superresolution in MRI: Application to human white matter fiber tract visualization by diffusion tensor imaging. Magnetic Resonance in Medicine: An

Official Journal of the International Society for Magnetic Resonance in Medicine, 45(1): 29-35. https://doi.org/10.1002/1522-2594(200101)45:1<29::AID-MRM1005>3.0.CO;2-Z

Qian H, Mao Y, Xiang W, and Wang Z (2010). Recognition of human activities using SVM multi-class classifier. Pattern Recognition Letters, 31(2): 100-111. https://doi.org/10.1016/j.patrec.2009.09.019

Russakovsky O, Deng J, Su H, Krause J, Satheesh S, Ma S, and Fei-Fei L (2015). ImageNet large scale visual recognition challenge. International Journal of Computer Vision, 115(3): 211-252. https://doi.org/10.1007/s11263-015-0816-y

Sethy PK and Behera SK (2020). Detection of coronavirus disease (covid-19) based on deep features. Preprints 2020, 2020030300. https://doi.org/10.20944/preprints202003.0300.v1

Shan F, Gao Y, Wang J, Shi W, Shi N, Han M, and Shi Y (2020). Lung infection quantification of COVID-19 in CT images with deep learning. arXiv:2003.04655v3. https://doi.org/10.48550/arXiv.2003.04655

Shi W, Caballero J, Ledig C, Zhuang X, Bai W, Bhatia K, and Rueckert D (2013). Cardiac image super-resolution with global correspondence using multi-atlas patch match. In the International Conference on Medical Image Computing and Computer-Assisted Intervention, Springer, Nagoya, Japan: 9-16. https://doi.org/10.1007/978-3-642-40760-4_2 **PMid:24505738**

Simonyan K and Zisserman A (2014). Very deep convolutional networks for large-scale image recognition. In the ICLR 2015: 3rd International Conference on Learning Representations 2015, San Diego, USA: 1-14.

Singhal T (2020). "Rationalization of empiric antibiotic therapy"– A move towards preventing emergence of resistant infections. The Indian Journal of Pediatrics, 87: 945–950. https://doi.org/10.1007/s12098-019-03144-7 **PMid:31912460**

Stephen O, Sain M, Maduh UJ, and Jeong DU (2019). An efficient deep learning approach to pneumonia classification in healthcare. Journal of Healthcare Engineering, 2019: 4180949. https://doi.org/10.1155/2019/4180949 **PMid:31049186 PMCid:PMC6458916**

Strzelecki A (2020). The second worldwide wave of interest in coronavirus since the COVID-19 outbreaks in South Korea, Italy and Iran: A google trends study. Brain, Behavior, and Immunity, 88: 950–951. https://doi.org/10.1016/j.bbi.2020.04.042 **PMid:32311493 PMCid:PMC7165085**

Szegedy C, Vanhoucke V, Ioffe S, Shlens J, and Wojna Z (2016). Rethinking the inception architecture for computer vision. In the IEEE Conference on Computer Vision and Pattern Recognition, IEEE, Las Vegas, USA: 2818-2826. https://doi.org/10.1109/CVPR.2016.308

Tajbakhsh N, Shin JY, Gurudu SR, Hurst RT, Kendall CB, Gotway MB, and Liang J (2016). Convolutional neural networks for medical image analysis: Full training or fine tuning? IEEE Transactions on Medical Imaging, 35(5): 1299-1312. https://doi.org/10.1109/TMI.2016.2535302 **PMid:26978662**

Varshni D, Thakral K, Agarwal L, Nijhawan R, and Mittal A (2019). Pneumonia detection using CNN based feature extraction. In the IEEE International Conference on Electrical, Computer and Communication Technologies, IEEE, Coimbatore, India: 1-7. https://doi.org/10.1109/ICECCT.2019.8869364

Wang L, Lin ZQ, and Wong A (2020a). Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. Scientific Reports, 10(1): 1-12. https://doi.org/10.1038/s41598-020-76550-z **PMid:33177550 PMCid:PMC7658227**

Wang W, Xu Y, Gao R, Lu R, Han K, Wu G, and Tan W (2020b). Detection of SARS-CoV-2 in different types of clinical specimens. JAMA, 323(18): 1843-1844. https://doi.org/10.1001/jama.2020.3786

Wu Z and McGoogan JM (2020). Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: Summary of a report of 72 314 cases from the Chinese center for disease control and prevention. JAMA, 323(13): 1239-1242. https://doi.org/10.1001/jama.2020.2648 **PMid:32091533**