Benchmarking Multiple Deep Learning Models for Enhanced COVID-19 Detection

Sadeem Alharthi, Shahad Alqurashi, Manal Alamir, Manal AlGhamdi, Tahani Alsubait

College of Computer and Information Systems, Umm Al-Qura University, Makkah, Saudi Arabia

Summary
Due to the recent emergence of COVID-19, chaos and economic destruction have spread all around the world. As this is considered a novel virus, lack of resources and limitations of planning to cope with this pandemic have greatly impacted many lives and many people have lost their loved ones due to this situation. Thus, there is a need for some innovation of science and AI to handle this task on hand. It has become very necessary to investigate the use of the latest deep learning modeling techniques to discover efficient ways of detection of this novel virus. In this paper, we used publicly available datasets to apply some deep learning modeling techniques including VGG19, Xception, Resnet50 and GoogleNet in a transfer learning manner. Using such models eases the process of detection of the disease from chest X-rays to classify the patients based on their status: either COVID-19 or pneumonia chest/normal patients. The achieved preliminary results are promising. In particular, the Xception model achieves the highest performance with 99%, whereas the accuracy of the VGG19, ResNet50 and the InceptionV3 are 98%, 98%, and 90% respectively.

Key words:
COVID-19, Corona Virus, Chest X-Ray, Convolutional Neural Network, Deep Neural Network

1. Introduction

Corona virus (COVID-19) pandemic scope has grown rapidly and by looking at the severity of this pandemic and death rates we can find out that badly affected areas has increased over time. Many countries have declared emergency and the pandemic have affected normal daily life routines worldwide. It is mainly considered a respiratory disease which can infect the lungs to a greater extent. There are many health- related departments all around the world working day and night to get a working vaccine for the novel virus, as soon as possible, and some vaccines are already in the clinical trials phase. To control the extent of this disease and its impact, it is really important to test people at great speeds. So far, the testing methods that exist are all considered complex laboratory work [3], [16]. The polymerase chain reaction assay (RT-PCR) is the basic standard for Coronaviruses diagnosis, sometimes resulting in high false-negative levels because of the lengthy time consumed to confirm COVID-19 cases [9]. Therefore, there is a need to develop alternative means of testing or detection of the virus. Computed Tomography (CT) and Chest X-Ray (CXR) [3], [16] can help in a major part in confirming COVID-19 cases, especially in the state of infected children and pregnant women [9], as noted changes in the lungs appear specifically in COVID-19 patients. These symptoms appear to be common in most COVID-19 patients [1]. Many medical cases are scanned by using X-ray machines such as bone dislocations, fractures, pneumonia, lung infections, and tumors. One type of advanced X-rays is a CT scan, which allows to check images of the inner soft tissues and the highly soft structure of the active body part and organs [15]. However, using an X-ray machine is faster, cheaper, less harmful and easier than CT. Failure to immediately recognize and cure COVID-19 might produce a rise in mortality rates [15]. We focused on using the X-ray imaging modality for probable COVID-19 patients.

Deep learning techniques have shown promising results over the past few years to perform radiological tasks by impulsive analyzing of multiple medical images [9]. They are very good at learning the representation of complex images and differentiating between images and objects due to their ability to learn the underlying features. As deep learning models need a lot of data to grasp the knowledge of some specific field and its general representation, so most of the studies use transfer learning concepts as it does not need data in bulks and you can fine-tune pre-trained models on your new datasets [15].

In this paper, we have proposed to use transfer learning from pre-trained models and Chest X-ray images for the automatic prediction of COVID-19. For this purpose, we have benchmarked different models, namely Xception, modified Visual Geometry Group Network (VGG19), ResNet50, and InceptionV3 pre-trained models to get a higher detection accuracy of the disease for a collected X-ray dataset.

This paper is organized as follows: Section 2 presents previous work related to this research. Section 3 provides our experimental setup. Section 4 presents the network architecture. Section 5 shows experimental results and comparative analysis between Xception, VGG19, Resnet50, and InceptionV3 pre-trained models' performance. Finally, in Section 6, the conclusion and future work directions are briefed.

Manuscript received August 5, 2020
Manuscript revised August 20, 2020

2. Related Work

Many researchers are working to get an automated Corona Virus detection method using CT scans and X-rays by employing existing computer vision and deep learning methods. ResNet50, InceptionV3 and Inception-ResNetV2 are pre- trained convolutional neural network (CNN) models that have been recently employed for the detection of Corona Virus and pneumonia infected patients using chest X-ray radiographs. Narin et al. [15] achieved 97% accuracy for Inception v3, 98% accuracy for ResNet50 and 87% for Inceptin-ResNet V2. They performed these experiments on 100 images (50 normal and 50 COVID-19 patients).

Similarly, Muhammad et al. [5] collected a dataset of CT scans and performed experiments on different pre-trained models and showed that the best accuracy was produced by SqueezeNet model at around 98%. Cohen et al. [7] gathered a collection of images related to pneumonia and COVID- 19. They have collected almost 123 X-ray images for frontal view. Ahmed H. [8] reported that some of the features of COVID- 19 patients' chest X-rays exhibit pneumonia like features and have some similarity. In the study by Xuanyang et al. [21] data mining techniques were used to distinguish SARS (Severe Acute Respiratory Syndrome) and typical pneumonia based on X-ray images. Adam et al. [6] studied the comparison of CT scans of different asymptomatic patients infected by Corona Virus from China. The study aimed to analyze the cases according to different day intervals, starting from the time the symptoms started to appear. Similarly, Ng M. et al. [16], Bai et al. [3] and Ai et al. [1] compared CT scans of COVID-19 patients from China and tried to find the common findings among them. In general, medical examinations findings were pointing towards common symptoms and damages.

Ioannis et al. [2] presented an approach for detecting COVID-19 based on transfer learning. The used dataset contains 728 X-ray images split as 227 COVID-19 subjects and 504 normal subjects. They obtained an accuracy of 98% by using VGG19. Prabira et al. [17] utilized SVM with different transfer models (GoogleNet, ResNet101, VGG19, ResNet50, ResNet18, Inceptionresnetv2, Inceptionv3, AlexNet, Xception- Net, VGG16 and DenseNet201). The used dataset contains 50 images composed of 25 COVID-19 subjects and 25 normal subjects. Their highest accuracy was achieved using ResNet50 with 95%, compared to 93% achieved using the Xception model.

3. Experimental Setup

We used Keras API which contains all the pre-trained models along with required ImageNet weights. The models were trained on original ideas and parameters that are used in standard ImageNet classification modeling tasks. We downloaded the model weights from the Keras standard documentation link. In addition, we download weights of Xception from [13], VGG19 from [12], Resnet50 from [11], and InceptionV3 from [10]. We used Colab GPU machine for training our model having 1080 titan x GPU along with 12 MB RAM.

3.1 Dataset

We have collected a dataset from open access repositories for COVID-19 chest X-ray images [7] and pneumonia chest X-ray images [14]. Initially, we had 213 images of COVID-19 cases including chest X-rays and CT scans and we extracted only X-rays (187 images) to analyze them. Then we randomly selected 200 other chest X-rays in which 100 belong to normal patients and 100 belong to pneumonia patients. So, we got our dataset of different cases and considered two categories to train our model which are: COVID-19 patients and normal/pneumonia patients. The split of data is shown in Table 1.

Table 1: Split of dataset in terms of category

Total	Covid19	Pneumonia/ Normal)
387	187	100/100 = 200

Also, we split the dataset further into training, validation and testing sets. We keep 20 images for validation, 10 from each category. 54 images were used for testing, 27 from each category. The rest of the images were used for training purposes. Split of the dataset is shown in Table 2.

Table 2: Split of dataset into train, validation and test data.

Data	Total	Covid19	Pneumonia
Training	300	150	150
Validation	23	10	13
Testing	54	27	27

3.2 Data preprocessing

As we have only 300 samples in the training set and knowing that deep learning models need more data to train and generalize well on testing data, hence, we applied data augmentation on only training images and convert 300 training images into 600 training images by applying different trans- formation and rotation techniques. Some of the data samples are shown in Fig.1.

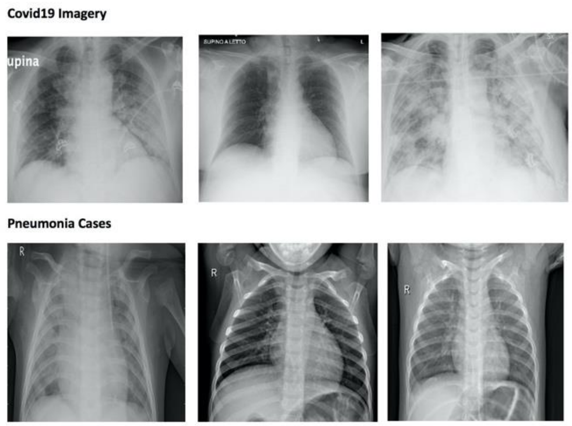

Fig. 1 Image of Covid19 and Pneumonia patient

3.3 Performance Metrics

We used 5 metrics for evaluating the performance of the utilized transfer learning models. These are Accuracy, Precision, Recall, F1-Score and Area under the ROC Curve (AUC). Definitions of these metrics are presented below.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{3}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{4}$$

TP, TN, FN, and FP given in Equations 1 – 4 represent the number of True Positives, True Negatives, False Negatives and False Positives, respectively. Based on the used model and test dataset, TP and TN represent the number of images that are correctly labeled as positive (COVID-19) for TP and negative (i.e., normal) for TN. FP is the number of wrongly predicted cases, i.e., normal cases that are mislabeled as (COVID-19) cases. FN is the proportion of positive images (COVID-19) that are mislabeled as negative (i.e., normal). All of that at the image level.

4. Network Architecture

As we know, a model could take a few days to train from scratch and it needs tons of data samples to train. So, if we have a small dataset, which is common in the medical field, then there is a need of a mechanism to overcome this problem. Transfer learning comes to solve this kind of problem where it allows us to use pre-trained models to train on new datasets and fine tune CNN layers with very small learning rates in order to use it for data predictions. In this study, we used some pre-trained models to get the classification task solved. In particular, we used Xception, VGG19, ResNet50 and GoogleNet models.

4.1 Xception model

Xception [4] model is the modified version of the Inception model introduced by Google. They improve the Inception model architecture by changing Inception modules with depthwise separable convolutions. Depth-wise separable convolution is the combination of depth-wise and pointwise convolution. Pointwise 1x1 convolution is applied first then nxn depthwise convolution. Xception model is implemented without non-linearity Rectified Linear Units (ReLU). The architecture of depth wise operations is shown in Fig. 2.

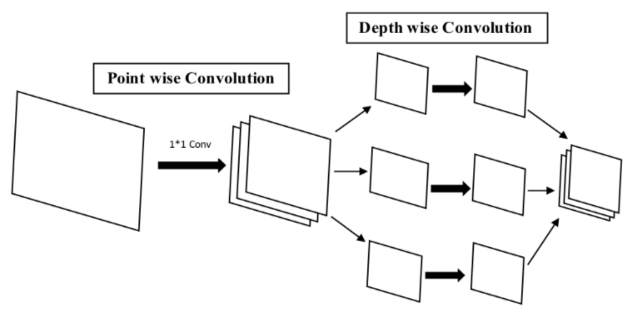

Fig. 2 The Modified Depth-wise Separable Convolution used as an Inception Module in Xception, so called "extreme" version of Inception module (n=3 here)

For training the Xception model, we first downloaded a pre- trained model from Keras repository. Then, we removed its top layers and appended GAP (Global average pooling) layer and 3 FC (Fully-Connected) layers of size 1024, 512 and 1 neurons, respectively. We use ReLU activation function for FC layers except for the last layer where we use Sigmoid. Loss function is binary cross entropy along with SGD optimizer, having learning rate of 0.001 with decay rate of 0.1 to minimum 0.00001.

4.2 VGG19 model

As the time passes, researchers have tried and proposed different length CNN architecture models. Some are length wise deep and some are depth wise. So, to implement the transfer learning function on our required dataset, we chose VGG19 [18], which is just an extension of VGG16 containing 19 overall layers instead of 16. It contains almost similar 5 blocks of convolutional layers, with 1st and 2nd block containing 2 CNN layers each, and 3rd, 4th and 5th block containing 4 CNN layers each. So in total we have 16 CNN layers with 3 dense layers. The architecture of the model is illustrated in Fig.3.

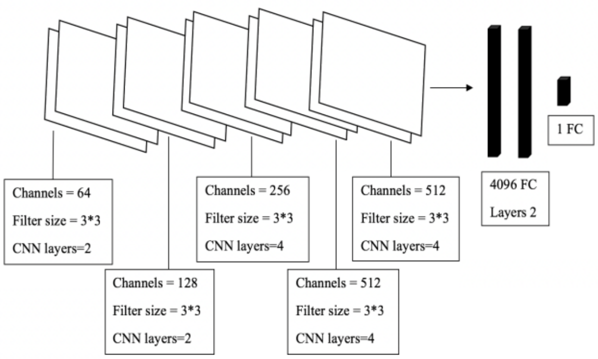

Fig. 3 VGG19 architecture containing 3*3 size filters stacked one after each other in blocks

In this experiment we use VGG19 pre-trained on ImageNet with 1000 classes. We first remove its top FC layers of size 4096 and 1. We append a global average pooling layer (GAP) after the last Convolutional layer and add 2 FC layers of size 256 and 1 because the task at hand is a binary classification. Important parameters and other settings that we have kept for the training of this model are shown in Table 3 and the architecture of our VGG19 model is presented in Fig. 4. We have trained the model for 10 epochs and has achieved reasonably good accuracy with low training and validation loss.

Table 3: Important parameters of VGG19 architecture

Freeze Layers	All CNN layers pre-trained on ImageNet
Training Layers	Last 2 FC layers added by our-self
Loss Function	Binary Cross Entropy
Optimizer	SDG (learning rate = 0.001, momentum = 0.9)
Activation Function	ReLU for all FC except last (Sigmoid)

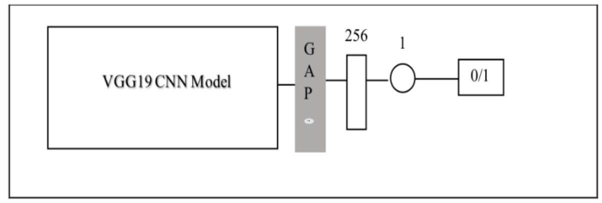

Fig. 4 Flow diagram of our model structure VGG19 CNN structure with GAP and 2 dense layers

4.3 Reset50 model

At the Large-Scale Visual Recognition Challenge (ILSVRC- 2015), Kaiming He et al. used the so-called Residual Neural Network (ResNet) and introduced a novel architecture with “skip connections” and heavy batch normalization. Skip connections, also known as gated units or gated recurrent units, are considered among the recent successful elements which have been applied in RNNs shown in Fig.5. Using this unique architecture, the model was able to train a NN with 152 layers [20].

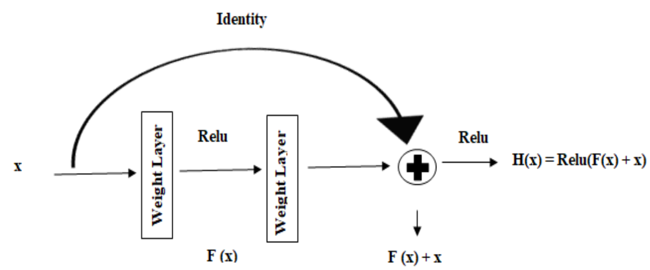

Fig. 5 Residual learning: a building block

The identity connection between the layers is used to construct a simple residual network. The reported performance of this architecture outperforms human-level performance with a top-5 error rate of 3.57% on ImageNet dataset [20].

We are using Resnet50 to classify the cases as either COVID-19 patients or pneumonia chest/normal patients. We added the Global Average Pooling layer for feature extraction that gives us a 2048-dim feature vector that contains very crucial information about the image. We then used a sequential neural network having layers with a number of neurons 1024,512 and 1. We used the (ReLU) activation function in all input and intermediate layers and used Sigmoid function on the last layer to do binary classification. The loss function is binary cross-entropy along with SGD optimizer having a learning rate of 0.001 and Nesterov momentum of 0.9.

4.4 GoogleNet or InceptionV3

InceptionV3 is an advanced version of Google net or InceptionV1 with some minor changes in optimizers and inception block. It uses the Inception module which is nothing just a concatenation of output feature maps from different kernels applying on previous module output. So this concatenated output goes into another inception module and so on. This model works pretty well and gave a 5.6% top validation error rate [19].

To train this model we simply loaded a Keras pre-trained model with ImageNet weights and with no top. We then add GAP layer to average feature maps pixels value. Then we add 3 dense layers of size 1024,512 and 1. Loss function if binary cross-entropy and optimizer we use are Adam with a learning rate of 0.001.

5. Results

The pre-trained models (Xception, VGG19, ResNet50, and InceptionV3) have been used on train, validation and test sets from the chest X-ray images. Accuracy and loss values of train, validation and test sets of the pre-trained models are given in Table 4. Due to the fading number of COVID19 chest X-ray images and to avoid overfitting for all pre-trained models, the model has been trained to 100th epoch during the training step.

Table 4: Explaining Results achieved from Xception, VGG19, Resnet50, and InceptionV3 models

Models	Data	Loss	Accuracy
Xception	Train	0.07	97%
	Validation	0.01	100%
	Test	0.02	99%
VGG19	Train	0.03	99%
	Validation	0.03	95%
	Test	0.07	98%
Resnet50	Train	0.02	99%
	Validation	0.004	100%
	Test	0.08	98%
InceptionV3	Train	0.23	89%
	Validation	0.12.	92%
	Test	0.06	90%

The curve related to accuracy and loss for each model is illustrated in Fig. 6 and Fig. 7. When analyzing the loss curves, it is noted that the loss values in all four pre-trained models were decreased through the training phase. We can say that ResNet 50 model approaches to zero and decreases loss values faster. We found that for each pre-trained model that one instance of Pneumonia positive class is wrongly classified while no instances or samples of the COVID-19 class are wrongly classified which is more important as classifying COVID-19 patients into normal pneumonia is more dangerous. In more detail, Table 5 shows comparison of different metric results achieved from transfer learning methods. We used 5 metrics for the performances of three transfer learning models. These are Accuracy, Precision, Recall, F1-Score and Area under the ROC Curve (AUC) as we mentioned in section performance metrics. It can be seen that the ResNet50 and VGG19 models have similar performance in accuracy, precision, recall and F1 Score which is 98%.

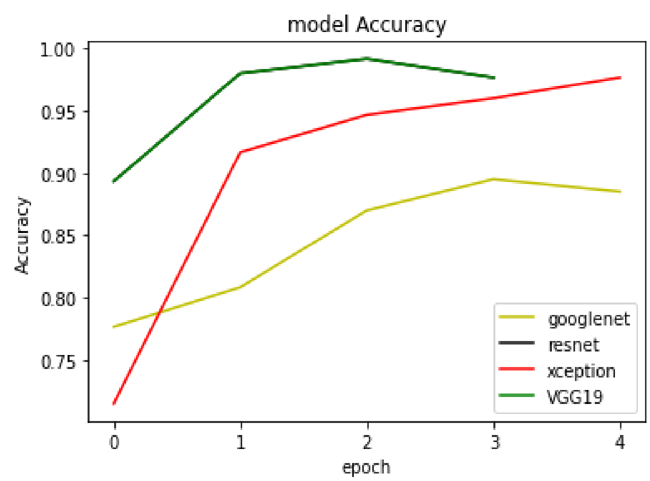

Fig. 6 Accuracy of each pre-trained models

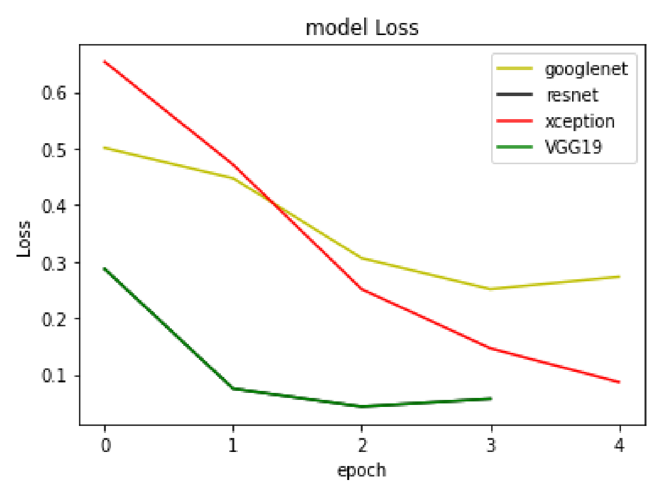

Fig. 7 Loss curve of each pre-trained models

Table 5: Comparison of Accuracy, precision, Recall, F1 Score and AUC

Models	Accuracy	Precision	Recall	F1 Score	AUC
VGG19	98%	98%	98%	98%	0.98
Resnet50	98%	98%	98%	98%	1.0
Xception	99%	99%	100%	99%	1.0
InceptionV3	90%	90%	88%	89%	0.9

We also present comparison of ROC curves which is a good estimation to judge which model is separating data more efficiently in Fig. 8. So far, we have seen that we have achieved 99% testing accuracy from Xception simpler model by tuning it. Xception model has given us maximum AUC value and a very smooth Roc curve. The reason of xception model effectiveness lies in the depth of the model and also the way the separable convolutions are applied in bit different way than InceptionV3 model. In InceptionV3 model, there is the point-wise convolution first and then the depth wise convolutional operations, but in Xception model there are depth wise convolutional operations take place first and then the point wise convolutions. In Xception model also there is no intermediate activation function while in InceptionV3 there are intermediate activation functions. ResNet skip connections are also incorporated in Xception model all through the network flow which makes it more efficient and deeper. In X-ray dataset we used, there are very thin detailed features that need some extra depth wise deep modeling mechanism which is fulfilled by the Xception model. InceptionV3 without residual connections perform a slightly less than Xception model with residual connections.

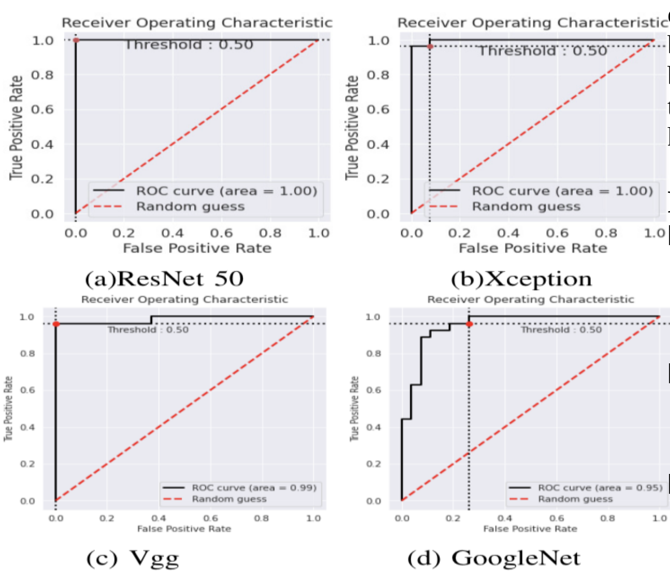

Fig. 8 Comparison of ROC curve

We also compered our models' accuracy with different transfer learning models mentioned in related works as shown in Table 6. Our Inception V3 model compared with 1-fold accuracy obtained by Narin [15]. VGG19 accuracy obtained by Ioannis et al. [2] shows similar accuracy of 98%. we got higher accuracy in both Xception and Resnet 50 models of 99% and 98 % respectively.

Table 6: Comparison of our model accuracy and existing work

Models	Reference	Accuracy	Our Accuracy
VGG19	Ioannis et al. [2]	98%	98%
Xception	Prabira et al. [17]	93%	99%
Resnet50	Prabira et al. [17]	95%	98%
InceptionV3	Ali Narin [15]	85%	90%

6. Conclusion and Future Work

Early detection of COVID-19 cases is an important matter to prevent the diffusion of the disease to other people. In this study, we have shown an automatic approach to classify chest X-rays into either COVID-19 cases or normal/pneumonia cases. We have applied four transfer learning approaches, namely Xception, VGG19, Resnet50, and InceptionV3 pre- trained models. The Xception model provided the highest performance as 99% whereas the accuracy of the VGG19 model and the Resnet50 model was 98%, and the InceptionV3 achieved 90% accuracy on testing data. This study is a good basis to form assumptions that we can also detect patients of the COVID-19 virus using this deep learning method which is effectively less error prone. In future studies, as more data becomes available, we can train more realistic models with better efficiency. Another possible path for future work is to use a dataset of CT imaging for training models of this highly important research topic.

References

[1] Tao Ai, Zhenlu Yang, Hongyan Hou, Chenao Zhan, Chong Chen, Wenzhi Lv, Qian Tao, Ziyong Sun, and Liming Xia. correlation of chest ct and rt-pcr testing in coronavirus disease 2019 (covid-19) in china: a report of 1014 cases. Radiology, page 200642, 02 2020.

[2] Ioannis D. Apostolopoulos and Tzani A. Mpesiana. Covid-19: automatic detection from x-ray images utilizing transfer learning with convolu- tional neural networks. Physical and Engineering Sciences in Medicine, Apr 2020.

[3] Harrison Bai, Ben Hsieh, Zeng Xiong, Kasey Halsey, Ji Choi, Thi Tran, Ian Pan, Lin-Bo Shi, Dong-Cui Wang, Ji Mei, Xiao-Long Jiang, Qiu-Hua Zeng, Thomas Egglin, Ping-Feng Hu, Saurabh Agarwal, Fangfang Xie, Sha Li, Terrance Healey, Michael Atalay, and Wei-Hua Liao. perfor- mance of radiologists in differentiating covid-19

from viral pneumonia on chest ct. radiology, page 200823, 03 2020.
[4] Francois Chollet. xception: deep learning with depthwise separable convolutions. pages 1800–1807, 07 2017.
[5] Dr. Muhammad Chowdhury, Tawsifur Rahman, Amith Khandakar, Rashid Mazhar, Muhammad Kadir, Zaid Mahbub, Khandakar Islam, Muhammad Salman Khan, Atif Iqbal, Nasser Al-Emadi, and Mamun Bin Ibne Reaz. can ai help in screening viral and covid-19 pneumonia? 03 2020.
[6] Michael Chung, Adam Bernheim, xueyan mei, ning zhang, mingqian huang, xianjun zeng, jiufa cui, wenjian xu, yang yang, zahi a fayad, et al. Ct imaging features of 2019 novel coronavirus (2019-ncov). Radiology, 295(1):202–207, 2020.
[7] Joseph Paul Cohen, Paul Morrison, and Lan Dao. Covid-19 image data collection, 2020.
[8] Ahmed Hamimi. mers-cov: middle east respiratory syndrome corona virus: can radiology be of help? initial single center experience. The Egyptian Journal of Radiology and Nuclear Medicine, 47, 11 2015.
[9] Ezz El-Din Hemdan, Marwa A. Shouman, and Mohamed Esmail Karar. COVIDX-Net: A framework of deep learning classifiers to diagnose COVID-19 in x-ray images. arXiv preprint arXiv:2003.11055, 2020.
[10] Keras. InceptionV3, May 2020.
[11] Keras. ResNet and ResNetV2, May 2020.
[12] Keras. VGG16 and VGG19, May 2020.
[13] Keras. Xception, May 2020.
[14] Paul Mooney. Chest x-ray images (pneumonia), 2017.
[15] Ali Narin, Ceren Kaya, and Ziynet Pamuk. automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. 03 2020.
[16] Ming-Yen Ng, Elaine Lee, Jin Yang, Fangfang Yang, Xia Li, Hongxia Wang, Macy Lui, Christine Lo, Barry Siu Ting Leung, Pek-Lan Khong, Christopher Hui, Kwok-yung Yuen, and Mike Kuo. imaging profile of the covid-19 infection: radiologic findings and literature review. Radiology: Cardiothoracic Imaging, 2: e200034, 02 2020.
[17] Prabira Kumar Sethy and Santi Kumari Behera. Detection of coronavirus disease (covid-19) based on deep features. 2020.
[18] Karen Simonyan and Andrew Zisserman. very deep convolutional networks for large-scale image recognition. arXiv 1409.1556, 09 2014.
[19] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2818–2826, 2016.
[20] Sasha Targ, Diogo Almeida, and Kevin Lyman. Resnet in resnet: Generalizing residual architectures. arXiv preprint arXiv:1603.08029, 2016.
[21] Xuanyang Xie, Xi Li, Shouhong Wan, and Yuchang Gong. mining x- ray images of sars patients, page 282–294. Springer-Verlag, Berlin, Heidelberg, 2006.

Sadeem Alharthi received the Degree of Bachelor of Computer Engineering, and Higher Diploma in Education Certificate from Taif University in 2017, and 2018, respectively. She is currently an Artificial Intelligence Master's Student at Umm Al-Qura University. Her research interests include deep learning and Natural language processing.

Shahad Alqurashi had Bachelor’s degree in Computer Science from Taif University in 2019 . Currently, she is a Master’s student in Artificial Intelligence at Umm Al-Qura University . Her research interests include Machine Learning, Natural language processing and security. She has some interests in web design and development.

Manal AlAmir received her Bachelor's Degree in Computer Science from Umm Al-Qura University in 2018. Currently, she is a Master's student in Artificial Intelligence at Umm Al-Qura University. Her research interests include Deep Learning, Computer Vision, and Security.

Manal AlGhamdi received her Ph.D. degree in Computer Vision from University of Sheffield, United Kingdom in 2015. She received her MS. degree in Advanced Computer Science from University of Sheffield, United Kingdom in 2010, and her BS in Computer Science from KAU, Saudi Arabia in 2008. Her study involved video representation and video similarity measurements. From 2016 to 2017, she was appointed as a Deputy head of the Department of Computer Science at Umm Al- Qura University (UQU). Currently, She is an Assistant Professor at the Department of Computer Science, UQU, Saudi Arabia. Manal's research interests include Machine Learning, Computer Vision and Security. She focuses on developing and evaluating video and image processing techniques for various applications including video representation, similarity measurements and crowed analysis. Recently, she developed interest in computer security techniques including steganography and cryptography. In 2019, she was a visiting scholar at the Department of Electrical and Computer Engineering, University of Miami, USA, where she developed interest in deep learning and its application in different areas of computer vision. Her current interest in computer vision involves developing convolution deep learning techniques for HealthCare applications.

Tahani Alsubait is a faculty member of the College of Computer and Information Systems at Umm Al-Qura University. She earned her PhD in AI and instruction from the University of Manchester. She hold a Bachelor’s in Computer Science from King Saud University and a Master’s from King Abdulaziz University. Her research interests include AI, knowledge representation and reasoning, data analytics and HCI.