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Performance Evaluation of Transfer Learning Technique for Automatic Detection of Patients with COVID-19 on X-Ray Images

Oussama EL GANNOUR[(1)], Soufiane HAMIDA[(1)], Bouchaib CHERRADI[(1),(2)], Abdelhadi RAIHANI[(1)] & Hicham MOUJAHID[(1)]

[(1)] SSDIA Laboratory, ENSET of Mohammedia, Hassan II University of Casablanca, 28820, Mohammedia, Morocco.
[(2)] STIE Team, CRMEF Casablanca-Settat, provincial section of El Jadida, 24000, El Jadida, Morocco.

{oussama.elgannour, hamida.93s, bouchaib.cherradi, hicham88moujahid}@gmail.com, abraihani@yahoo.fr

***Abstract*—A new pandemic of coronavirus (COVID19) reported for the first time in Wuhan, China. This new virus has spread rapidly around the world with fever, cough, and difficulty breathing symptoms. In this paper, we propose a Deep Learning based system for the diagnosis of COVID19 disease. This system is based on Transfer Learning technique of six pretrained models. The X-Ray image dataset used contains 2905 images with a resolution of 1024*1024 pixels. A series of preprocessing operations has been applied to this dataset. The performance results obtained in this study confirm that the classification obtained by the Xception network is the most precise for detecting cases infected with COVID19. Our system has achieved accuracy and sensitivity of 98% and 100% respectively.**

Keywords — *COVID19, Machine Learning, Deep Learning, Transfer Learning, CNN, VGG16, VGG19, InceptionV3, Xception, ResNet50V2, MobileNetV2.*

I. INTRODUCTION

Coronaviruses are a large category of viruses that cause various diseases in human's body. MERS-CoV and SARS-CoV are two of the most serious diseases that have affected the world. A new pandemic of coronavirus COVID19 [1], was reported for the first time in Wuhan, China. This virus spread rapidly worldwide with seven million cases infected and more than 400,000 deaths by June 10th, 2020. Symptoms of this new virus are common such as respiratory symptoms, fever, cough, shortness of breath, and difficulty breathing. COVID19 spread between people through respiratory droplets produced by an infected person. These droplets are transmitted on surfaces or by physical way such as greetings. This can transmit the virus to the face then to the respiratory system. The detection of COVID19 cases allows isolating the patients as quickly as possible; in order to reduce the spread of this virus and flatten the infection curve. Indeed, the RT-PCR technique [2] is a nuclear-derived technique, which requires a lot of time to detect the presence of the virus genome in the patient. Therefore, medical imaging [3], modalities such as Chest X-Radiography (CXR) and Computed Tomography (CT) can be used to rapidly diagnosis COVID19 cases and reduce the spread of this pandemic.

New technologies play a vital role in reducing the spread of this pandemic. For this purpose, companies and researchers around the world are focusing their work on ways to meet the challenges of this virus. Especially the development of new systems based on Artificial Intelligence (AI) to reduce interpersonal contact. For example, drones to disinfect public places, facial recognition cameras to track infected people, thermal cameras to detect rising temperatures, and mobile applications to identify contacts of infected people. Indeed, systems based on Machine-Learning (ML) techniques have proven very high accuracy in the medical field [4], [5]. These type of systems allow diagnosis of many human diseases such as: Breast cancer disease [6], Heart disease prediction [7], Parkinson disease [8], Diabetes disease [9]-[10], brain tumor segmentation [11]–[14].

In this paper, Deep Learning (DL) technique was applied to detect cases infected with this virus. The use of the X-Ray or CT medical images can save time and make a diagnosis more quickly and cheaper than with the RT-PCR test. Therefore, using DL techniques, radiologists can diagnose the new COVID19 virus using only medical imaging. We propose an intelligent system based on six CNN based Transfer Learning (TL) models. This system allows diagnosing COVID19 patients in a relevant and efficient way. We used the following six Transfer Learning models: VGG16, VGG19, InceptionV3, Xception, ResNet50V2 and finally MobileNetV2. Then choose the accurate model between them. The dataset used consists of 2905 radiographic images that contains three classes: COVID19, Normal and Viral Pneumonia. These images are used to train and validate the six-transfer learning-based models.

The rest of the paper is organized as follows: Section II presents some related works. Section III describes the dataset and, the CNN based TL used in our study and the methodology followed to build our COVID19 diagnosis system. The performance evaluation measures, and experimental results are described in Section IV. Section V conclude our work and gives some future perspectives.

II. SOME RELATED WORKS

At the beginning of 2020, the world experienced the emergence of a new virus from the coronavirus family. All scientific research around the world are focusing their efforts on vaccines to fight this pandemic. Moreover, researchers interested in methods of diagnosing this pandemic using AI techniques. This section presents some recent studies.

In [15], the authors proposed a system for detecting cases infected with the new coronavirus. This system is based on the *DarkNet* classifier, and it has reached an accuracy of 98.08% for binary classes (COVID19, Normal). For the Multi-classes experiment (COVID19, Normal or Pneumonia) the precision decreases to 87.02%. The image database used in this system is an IEEE database available on GitHub.

The research work in [16] presented a deep convolutional network study based on a comparison between three TL models namely VGG16, VGG19, and MobileNetV2. This study used a database that contains three classes: COVID19, Normal and Pneumonia; collected from five publicly database. They concluded that VGG19 can be considered the best model to detect the COVID19 with an accuracy of 96,97%.

In another study [17], the authors proposed a model of convolutional neural networks, which is based on the technique of transferring Bayes-SqueezeNet learning. This model is based on two multi-class datasets merged together. The classification rate for coronavirus cases in this system is approximately 97.3%.

Another study published in [18], based on the comparison of TL algorithms such as VGG19, MobileNetV2, Inception, Xception and ResNetV2. This study used two datasets. The first dataset is customized for the choice of the best algorithm. The second one is for the evaluation of this algorithm. The MobileNet model was chosen as the accurate model with an accuracy of 94.72%.

In [19], the authors studied the performance of four models for new coronavirus diagnosis such as a Convolutional Neural Network (CNN) system based on differential multi-objective evolution (MODE), CNN, ANN and ANFIS. They conclude that MODE is the best model for the classification of patients infected with COVID19. In Table 1, we present a comparative overview of some relevant work on the diagnosis of patients infected with COVID19 using medical imaging of the lung.

TABLE 1. SUMMARY OF SOME LITERATURE WORK

Authors/year	Predictive Models	Used Database	Accuracy	Sensitivity	Specificity
T. Ozturkal et al. (2020)	DarkNet	IEEE Binary	98.08	95.13	95.3
		IEEE Multi-class	87.02	85.35	92.18
H. Moujahid et al. (2020)	VGG16	Dataset Multi-class	96.22	97	N/A
	VGG19		96.97	99	N/A
	MobileNetV2		95.84	100	N/A
F. Ucar et al. (2020)	Bayes-SqueezeNet	IEEE Multi-class	97.3	N/A	99.1
D. Loannis et al. (2020)	MobileNetV2	IEEE Binary	96.78	98.66	96.46
		Kaggle Multi-class	94.72	98.66	96.46
S. Dilbag et al. (2020)	MODE	Dataset Binary	93	90	90.5
	CNN		92.3	89.8	88.8
	ANN		91.5	89	88.3
	ANFIS		90.5	88.5	88.3

III. MATERIALS AND METHODS

A. Dataset description

The COVID19 Radiography Database used in this study is an open source database available on the Kaggle website. This database developed by a team of researchers from the University of Doha in Qatar and their collaborators. The dataset contains three classes 219 of COVID19 positive images, 1341 Normal images and 1345 Pneumonia images. Figure 1 shows a description of the data samples available in the dataset used. All the images in this database are in PNG format with a resolution of 1024*1024 pixels. Table 2 represents the architecture of the dataset used.

a) b) c)

Fig. 1. Some samples of the images from the X-Ray dataset used. a) COVID19 sample. b) Normal sample. c) Viral Pneumonia sample.

We divided the dataset into two sets 80:20 ratio. The first set of 2324 X-Ray images is reserved for the training process. The second was divided into two sets, 290 X-Ray images for the test and 291 X-Ray images for the validation process.

TABLE 2. DESCRIPTION OF THE DATA SAMPLES AVAILABLE IN THE COVID19 RADIOGRAPHY DATABASE

Dataset	Class	X-ray Images	Training	Validation	Testing
COVID19 Radiography Database	COVID19	219	175	22	22
	Normal	1341	1073	134	134
	Pneumonia	1345	1076	135	134
	Total	2905	2324	291	290

B. Deep learning-based techniques

In this sub-section, we describe the different Deep Learning algorithms such as Deep Neural Networks (DNN), CNN and TL models.

1) Deep neural networks

Neural Networks are much more complex models than all other ML models [20]. They represent mathematical functions with millions of parameters. Most models of neural networks use a deep network between 3 and 10 layers of neurons. Figure 2 shows an example of DNN containing an input layer, three hidden layers and an output layer.

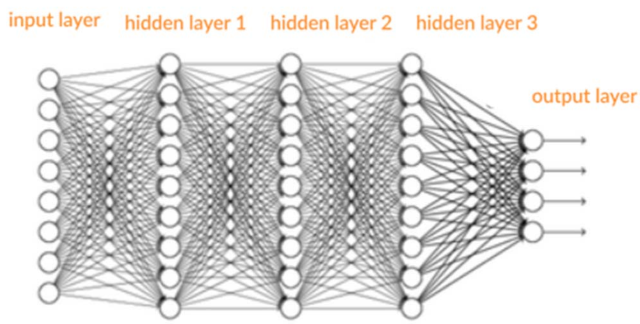

Fig. 2. A deep neural network with three hidden layers.

2) *Convolutional neural networks*

Convolutional neural networks are considered among the most powerful tools for image classification [21]. They allow reducing the image size to facilitate the processing phase. This can be done without losing their features, which are essential to obtain a good prediction. The architecture of a CNN is organized in two steps as shown in Figure 3. In the first, we extract the features of the input image. Then, we traversed the input image from several layers of convolution and pooling. To extract the features matrix of this image. In the second step, we flatten the previous matrix to obtain a features vector. Now, the model is capable to train and distinguish between the different nonlinear combinations of the features of the images.

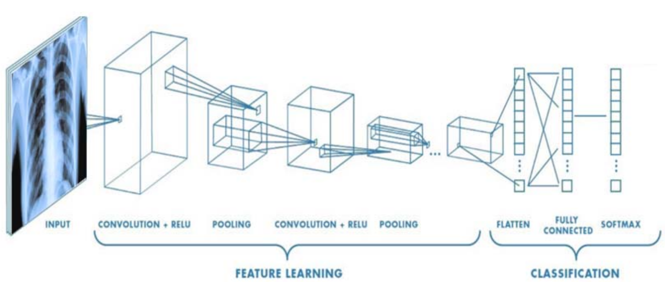

Fig. 3. Example of CNN with several layers for the classification of X-ray images.

3) *Transfer Learning technique*

In deep learning, CNNs play a major role in the classification of images, which takes a long time to train on very large data sets. For this, the use of preformed models remains the best solution to develop more efficient models of ML.

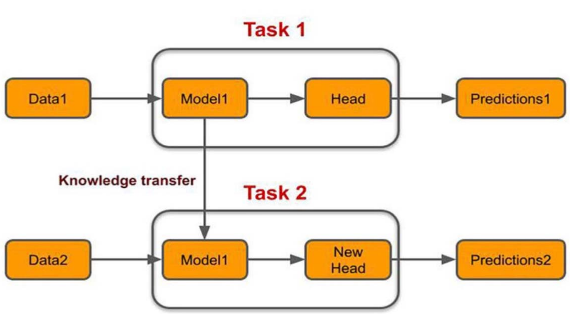

Fig. 4. Architecture of Transfer Learning based models.

Transfer learning is a method of automatic learning that allows the knowledge acquired to be transferred to a source dataset as a starting point for better processing a new dataset [22]. Figure 4 illustrates the architecture of the Transfer Learning model which allows knowledge to be transferred from model 1 to model 2.

C. *CNN models architecture*

1) *VGG16 Network*

The VGG16 is a CNN network model developed in 2015 by two researchers from the University of Oxford [23]. The accuracy of this model is 91.3% on the ImageNet dataset, which contains 14 Million images belonging to 1000 classes. Their architecture is composed of 16 layers distributed between 13 convolutional layers, 2 fully connected and a *SoftMax* layer.

2) *VGG19 Network*

The VGG19 network belong to the CNN family of networks, it was formed on the ImageNet database in 2015 [23]. He reaches an accuracy of 71.3%. The architecture of this network consists of 19 deep layers, 16 of these layers are the convolution type, 2 fully connected and one *SoftMax* layer. In Figure 5, we represent the operating architecture of VGG19 network.

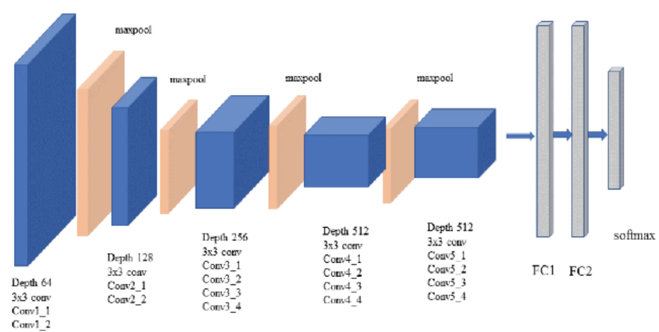

Fig. 5. VGG19 network architecture.

3) *INCEPTIONV3 Network*

The InceptionV3 model was developed in 2016 on the ImageNet database with a depth of 159. The architecture of this model is based on the InceptionV2 network architecture. This model aims to increase the accuracy and reduce the complexity of calculation [24].

4) *XCEPTION Network*

The Xception model is a CNN network created in 2017, it was also developed based on ImageNet images. This Transfer Learning model has an architecture based on 36 deep separable convolution layers [25]. These layers are structured in 14 modules forming the basis for extracting network features.

5) *RESNET50V2 Network*

The ResNet50V2 model was built from the ResNet50V1 model in 2016. This model was trained with different optimizers to improve the accuracy of the ResNet50V1 model [26]. Like the other transfer learning models. This model has been trained on all ImageNet data.

6) *MOBILENETV2 Network*

The MOBILENETV2 model is a CNN of 53 layers and a depth of 88. It was developed on a million images of the

ImageNet database. He reached an accuracy of 71.3% [27]. Table 3 shows an overall comparison between the different TL models compared in this study.

TABLE 3. DESCRIPTION OF THE TRANSFER LEARNING MODELS USED WITH IMAGENET DATASET

Network	Size (MB)	Year	Settings (106)	Depth	Accuracy
VGG16	528	2015	138	23	91.3%
VGG19	549	2015	143	26	91.3%
InceptionV3	92	2016	23	159	77.9%
Xception	88	2017	22	126	79%
ResNet50V2	98	2016	25	-	76%
MobileNetV2	14	2018	3	88	71. 3%

D. *Proposed COVID19 detection methodology*

Firstly, we begin with the preprocessing of our X-Ray images dataset. This phase is very important in the majority of ML task. This consists to clean and normalize the images to facilitate and promote their exploitation.

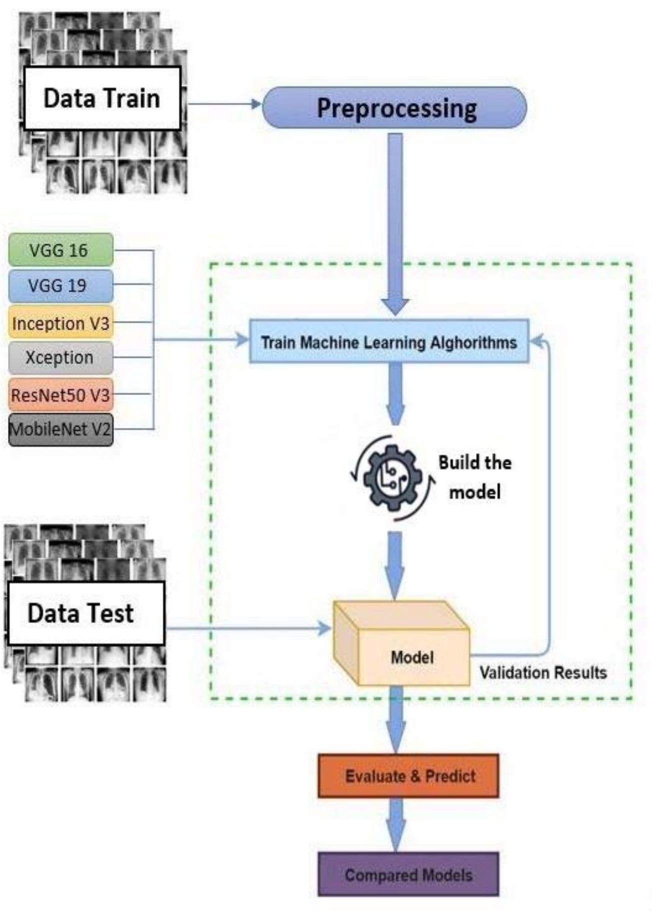

Fig. 6. Proposed model diagram.

This can increase the recognition rate obtained by the model. The images obtained after this phase are used to train and validate the six TL models of our study. The diagram represented in Figure 6 describe the main stages to build our diagnosis system architecture.

In this architecture, we train our six TL models (VGG16, VGG19, InceptionV3, Xception, ResNet50V2 and MobileNetV2) on the X-Ray train dataset. After building the models, we validate the training process with validation dataset to avoid the over-fitting problem. Then, we used the test dataset to evaluate the classification results obtained by each model. The evaluation of the performance models realized by drawing the confusion matrices and calculating some scoring metrics. Finally, we can identify the best performance model.

IV. EXPERIMENTAL RESULTS

A. *Performance evaluation metrics*

In this section, we present the metrics used to assess the performance of CNN models used in our diagnosis system.

Confusion matrix is a tool for measuring the performance of a ML model. In particular, by checking how often its predictions are correct compared to reality in classification problems. To draw the confusion matrix, we used the actual labels extracted from the dataset and the labels predicted by the classification models. To fully understand the confusion matrix process, it's important to understand the four main terminologies: TP, TN, FP and FN. The precise definition of each of these terms presented in Table 4.

TABLE 4. DESCRIPTION OF CONFUSION MATRIX ELEMENTS

Confusion matrix elements	Description
TP (True Positives)	Denotes number of patients that are correctly predicted as COVID19.
TN (True Negatives)	Denotes number of patients that are correctly predicted as not COVID19.
FN (False Negative)	Denotes number of patients that are incorrectly predicted as not COVID19
FP (False Positive)	Denotes number of patients that are incorrectly predicted as COVID19.

To assess the TL models performance chosen in our study, we calculate four evaluation metrics accuracy, specificity, sensitivity and precision. The scoring metrics for each class are given by the following equations

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (1)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{FN} + \text{TP}} \quad (2)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

B. *CNN models best configuration*

In this work, the TL based models used are implemented in the Google Collab environment. It is a cloud service for training and research in ML. The machine environment used Tesla K80 GPU with 12GB of GDDR5 VRAM, Intel Xeon Processor with 2 cores@2.20 GHz and 13 GB RAM. In Table 5, we present the parameters of the learning algorithms that are used to train and evaluate these models. All the images in our database are standardized in size of 300x300 pixels.

TABLE 5. THE CNN MODELS HYPERPARAMETERS

Network	Learning Rate	Batch Size	Optimizer	Loss Function	Epochs
All models	0.0001	16	Adam	Categorical cross entropy	50

C. COVID19 detection performance comparison results

From the results obtained in our study, we can notice that all the models give a good classification of the three classes.

For all classification models, the TP is higher compared to the FP and FN value for all classes. For all the TL models used, the value of FP and FN of COVID19 class is lower compared to the other classes. Moreover, we observed that the VGG16, Xception, ResNet50V2 and the MobileNetV2 model have an FP value equal to zero. This means that the models have a low probability of confusing the cases infected with COVID19.

Indeed, the Xception TL model provided the best classification of radiological images. Figure 7 represents the confusion matrix of this model.

Table 6 represents the evaluation metrics accuracy, precision, sensitivity and specificity for our models. From these results, we can notice that all the transfer learning classification models obtained significant precision between 98% and 97%. The VGG19, Xception, ResNet50V2 and MobileNetV2 models reached a precision of 100% concerning COVID19 class. However, the Xception model is the only model, which has a sensitivity of 100% concerning COVID19 class. For the Normal class, we noticed that these models have a precision of 99% except the InceptionV3 model obtained 100%. For all these models, the sensitivity values of this Normal class vary between 96% and 98%.

The specificity metric varies between 95% and 100% for all classes. All results presented in Table 6 confirmed that the best classification is given by the Xception network.

TABLE 6. PERFORMANCE EVALUATION OF OUR SIX TRANSFER LEARNING MODELS BASED ON SCORING METRICS: ACCURACY, PRECISION, SENSITIVITY AND SPECIFICITY

Models	Accuracy	COVID19 Precision	Normal Precision	Viral Pn Precision	COVID19 Sensitivity	Normal Sensitivity	Viral Pn Sensitivity	COVID19 Specificity	Normal Specificity	Viral Pn Specificity
VGG16	97%	100%	99%	95%	92%	96%	99%	100%	99%	95%
VGG19	97%	91%	99%	96%	95%	97%	97%	99%	98%	96%
InceptionV3	98%	95%	100%	96%	95%	96%	100%	99%	100%	96%
Xception	98%	100%	99%	96%	100%	96%	98%	100%	98%	96%
ResNet50V2	97%	100%	99%	96%	96%	96%	98%	100%	98%	96%
MobileNetV2	97%	100%	99%	95%	85%	98%	99%	100%	99%	95%

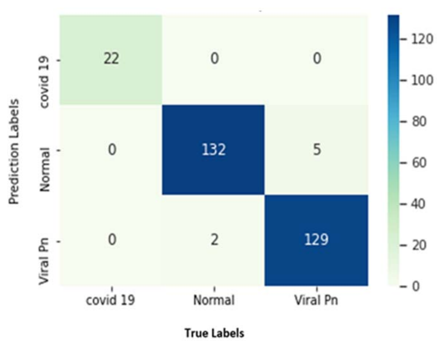

Fig. 7. Confusion matrix of Xception model.

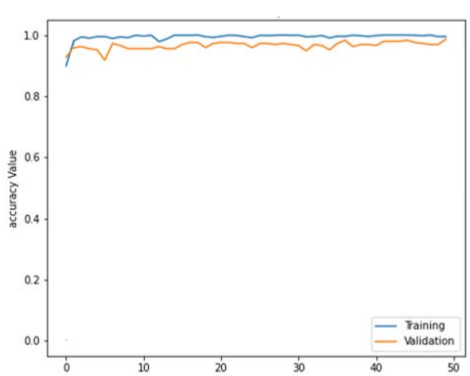

Fig. 8. Xception model performance.

Figure 7 and Figure 8 represent the Xception confusion matrix test results and the performance curve during the training and validation process.

D. Discussion

In this research, we proposed a classification system based on the performance of the six TL models (VGG16, VGG19, InceptionV3, Xception, ResNet50V2 and MobileNetV2). on a set of radiographic image data. This dataset contains 219 COVID19 images, 1341 Normal images and 1345 pneumonia images. We draw the confusion matrix and then calculated the statistical evaluation metrics (precision, sensitivity, specificity). After analyzing the results obtained in Table 6, we noticed that the Xception model provided a very important classification compared to other models. In general, all models achieve high precision between 97% and 98%. In our work, we find that the accuracy rate obtained exceed the other previous research. In [18] the authors obtained an accuracy rate of 94.72% by classifying three classes and using the MobileNetV2 model.

V. CONCLUSION AND PERSPECTIVES

In summary, we propose a COVID19 detection system based on X-Ray images dataset. In this study, the six Transfer Learning models trained and validated on a data set of X-Ray images available on Kaggle. The Xception model obtains the best classification. We have achieved an accuracy and sensitivity of 98% and 100% respectively. In future work, we will focus on the development of a model, based on the concatenation of two Transfer Learning models to improve performance. This makes it possible to diagnose COVID19 patients in a relevant and effective manner.

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