Automatic Diagnosis of Pneumonia and COVID-19 Using Convolutional Neural Networks and Transfer Learning

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Abstract- Several studies are currently exploring the diagnosis of lung disorders using deep learning analysis of medical images. Deep learning is also considered to be a valuable aid to experts in the interpretation of medical images. Heuristics such as transfer learning are becoming more common; these methods (based on pretrained models) are utilized as the basis for computer vision tasks and can significantly improve various issues. This work proposes models built on Convolutional Neural Networks (CNNs) that incorporate transfer learning to identify various pneumonia infections in X-ray images. The experiments show that the model based on Xception network outperforms many existing state-of-the-art methods and several recent backbones.

Keywords- Convolutional neural networks, COVID-19 detection, Deep learning, Transfer learning, Pneumonia diagnosis, XceptionNet, Inception modules, Residual networks.

I. Introduction

Pneumonia diseases are among the most common and severe infectious diseases that exhibit high morbidity and mortality, particularly in the elderly and immunocompromised. The diagnosis of several pulmonary illnesses, including COVID-19, lung opacity, viral pneumonia, and bacterial pneumonia, could greatly benefit from recent Al-based technologies, when integrated into the medical field. In general, the problem of diagnosing depends on the symptoms, mostly through physical examinations and other tests such as chest X-ray images.

The implementation of an automatic diagnosing system based on the latest algorithms will constitute a great assistance for doctors. The challenge for AI (Artificial Intelligence) in the healthcare field is how to execute tasks that require the highest level of cognitive functions, and how to ensure the reduction of bias during the learning process. In addition, what matters the most is data, which represent the fuel of any AI algorithm. The utilized data should be of high quality and homogeneity degree and must be relevant to the actual subject. In this paper, we focus on the automatic diagnosis of pulmonary diseases (and especially COVID-19) using chest X-ray images from "COVID-19 Radiography Dataset" while improving the accuracy. In this context, we propose and compare six types of CNNs (Convectional Neural Network) that use transfer learning and customized dense layers to detect the presence of COVID-19 and other pneumonia in X-ray images. Our proposed models can be summarized as follows:

- A backbone based on MobileNet_V2 plus a single dense layers.
- A backbone based on Inception_V2 plus three dense layers.
- A backbone based on ResNet50_V2 plus three dense layers.
- A backbone based on Xception plus a single dense layers.
- A backbone based on Inception_ResNet_V2 plus three dense layers.
- A backbone based on DenseNet plus a single dense layers.

The remainder of the paper is structured as follows. The state-of-art with different sub-classes of COVID-19 diagnosis approaches is presented in Section II. The proposed method with the different used backbones is described in Section III. The results are shown and discussed in Section IV. In the final section V., we present conclusions and future directions.

II. State of Art

To face the COVID-19 outspread, many researchers have implemented deep learning models to rapidly diagnose and determine the severity of the disease. In general, most researchers have used three types of clinical images, namely computed tomography (CT) scans, X-rays, and lung ultrasounds (LUS). In addition, the works have leveraged multiple architectures, including feed-forward networks and recurrent networks, [1],[2], to boost the effectiveness and the reliability of the diagnosis. In this section, we will explore two main classes of deep learning methods for diagnosing lung disorders. First class is based on CNN trained from scratch, and the second one represents the models based on transfer learning.

A. Models based on Convolutional Neural Networks

Behera B et al., [3], proposed a deep convolutional neural network based on VGGNet. The used dataset consisted of 9438 chest X-ray images divided into two categories: Covid cases and normal cases. The results reached 96.82% for training accuracy and 92.63% for validation accuracy; Table 1 shows more details about the performance.

Measure	Value	Derivations
Sensivity	0.9187	TPR=TP/(TP+FN)
Specifity	0.9378	SPC=TN /(FP+TN)
Precision	0.9576	PPV=TP/(TP+FP)
Negative predictive	0.8829	NPV=TN/(TN+FN)
False positive rate	0.0622	FPR=FP/(FP+TN)
False discovery rate	0.0424	FDR=FP/(FP+TP)
False Negative rate	0.0813	FNR=FN/(FN+TP)
Accurancy	0.9263	ACC=(TP+TN)/(P+N)
F1 Score	0.9378	F1=2TP/(2TP+FP+FN)

Table 1: Performance VGG 16 based model [3]

El Asnaoui et al., [4], compared different fine-tuned architectures(VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, ResNet50, and MobileNet_V2). The dataset included 6087 images (2780 images represented the bacterial pneumonia class, 1493 represented the coronavirus class, and 1583 the normal class). The results confirmed the superiority of Inception_ResNet_V2 and DensNet201 with respect to the other models (the accuracy of Inception_ResNet_V2 is equal to 92.18 % and that of DenseNet201 is equal to 88.09%).

Four different classes (COVID-19, normal, viral pneumonia, and bacterial pneumonia) along with three distinct binary classifications were used by Kaya et al., [5]. Their model's performance was evaluated through the fivefold cross-validation technique with five different previously trained models (Inception_v3, ResNet50, ResNet101, ResNet152 and Inception_ResNet_V2). The data were organized in three separate sets, with 80% used for the training and 20% used for testing including 2800 normal chest X-ray images, 2772 bacterial pneumonia, 1493 viral pneumonia, and 1023 COVID-19. The ResNet50 pre-trained model demonstrated the highest accuracy: 96.1%, 99.5% and 99.7% .

Ozturk et al., [6], introduced a model for COVID-19 detection based on X-ray images called the DarkCovidNet model inspired by the Darknet-19 model; instead of initiating deep models from scratch, a more rational approach is to construct a model using already proven models. For evaluation, they used a five-fold cross-validation procedure and trained the model for 100 epochs; for the dataset, they constructed a collection using 127 COVID-19-diagnosed cases, 500 normal cases, and 500 several pneumonia cases. Furthermore, 80% of the dataset was used for training and 20% was used for validation. The authors performed two separate training sessions; in the first one, they used a multi-class classification model and the accuracy was equal to 87.02 (on average). For the second training, they designed a binary classification model, and the accuracy was equal to 98.02.

Aras and Sengur, [7], proposed three variants of CNN models to classify X-ray images into COVID- 19 and normal cases. The dataset contained 180 COVID-19 and 200 healthy chest X-rays, it is randomly split into 75% for training and 25% for testing. For experiments, the authors proposed a framework with 03 variants: (1) end-to-end CNN models that were trained from scratch, (2) pre-trained models with parameter fine-tuning, and (3) pre-trained models coupled with SVM as a classifier head. The pre-trained models included VGG16, ResNet18, ResNet50, ResNet101, and VGG19. The results were 91,58% for the end-to-end approach, 92.63% for fine-tuned pre-trained models (especially ResNet50), and for SVM it reaches the highest accuracy, especially for the linear kernel. The results are shown in the next three Tables.

Fine-tuned	Accurancy
VGG16	85.26
ResNet18	88.42
ResNet50	92.63
Resnet101	87.37
VGG19	89.47

Table 2: Accuracy of pre-trained models with fine-tuning [7]

Ouchicha et al., [8], proposed to enhance the ResNet to more reliably discriminate COVID-19 cases from

Method: SVM	ResNet18	ResNet50
Linear Kernel	86.3	94.7
Quadratic Kernel	87.4	91.6
Cubic Kernel	89.5	90.5
Gaussian Kernel	86.3	93.7
Average	87.4	92.6

Table 3: Accuracy of ResNet-based models with SVM kernels [7]

Method: SVM	VGG16	VGG19
Linear Kernel	88.4	89.5
Quadratic Kernel	87.4	89.1
Cubic Kernel	89.5	90.3
Gaussian Kernel	87.4	89.1
Average	89.8	88.1

Table 4: Accuracy of VGG-based models with SVM kernels [7]

normal and viral pneumonia cases using chest X-ray images. Ouchicha et al., [8], suggested CVDNet, a designed CNN with two parallel columns. The only difference between the two columns is the size of the filters. The chest X-ray image dataset used for the ULNet model proposed by Rahman et al., [9], was Kaggle's COVID-19 Radiography Dataset, which is the same one used by Ouchicha et al., [8]. This dataset comprises 2905 chest X-ray images, comprising 1341 normal images, 1345 viral pneumonia images, and 219 COVID-19 images. Researchers from Qatar University and Tampere University generated another dataset, the QaTa-COV19 dataset. To test our model, Rahman et al., [9], chose 300 chest X-ray images at random (100 COVID-19 images, 100 normal images, and 100 viral pneumonia images). It is worth mentioning that the COVID-19 Radiography Dataset does not include these 300 images from the QaTa-COV19 Dataset.

The goal of the Wang et al., [10], study was to assess the computational efficiency and performance of several deep neural network architectures quantitatively. They compared the performance of two deep neural network architectures to accomplish this analysis: VGG-19 and ResNet50. These two deep neural network architectures were chosen because they lack COVID Net's main distinguishing characteristics. Wang et al., [10], generated the COVIDX dataset, which has combined and modified five different publicly available data repositories: (1) the COVID-19 Image Data Collection, (2) the COVID-19 Chest X-ray Dataset Initiative, (3)the ActualMed COVID-19 Chest X-ray Dataset Initiative, (4) the RSNA Pneumonia Detection Challenge dataset, and (5) the COVID-19 radiography database, whith a total of 13,975 CXR images across 13,870 patient cases. The best results achieved were 93.3% for the accurency.

Jain et al., [11], the primary aim of their paper was to conduct a systematic review and meta-analysis, aggregating all available data from published studies, of symptoms and comorbidities predictive for severe disease and ICU admission with COVID-19. Jain et al., [11], created a model using Inception_V3, Xception, and ResNet which was the highest accuracy 97.97%.

Gouda et al., [12], have built the COV-PEN dataset, which combines two publicly available data repositories: (1) COVID-19 Image Data Processing and (2) CXR Images (Pneumonia). The COV-PEN dataset includes 2790 CXR images taken randomly from these two sources. The primary architecture of Gouda et al., [12], in the proposed system is based on the ResNet50 model. For CXR picture identification, they investigated two modified versions of the ResNet50 model. The results were 99.63% accurate with 100% precision.

Li et al., [13], proposed to develop a fully automatic framework to detect COVID-19 using chest CT and evaluate its performance. The used COVID-19 detection neural network (COVNet) was developed to extract visual features from volumetric chest CT exams with 95% confidence.

B. Models Based on Transfer Learning

Mpesiana et al., [14], aimed to evaluate the performance of convolutional neural network architectures that use transfer learning for the automatic detection of coronavirus disease. They used datasets consisting of 224 confirmed COVID-19, 700 confirmed common bacterial pneumonia images, and 504 normal images, which add up to 1428 images of X-ray chest radiography.

For their experiment, they used five pre-trained models (VGG19, MobileNet_V2, Inception, Xception, and Inception_Resnet_v2) that achieved 96.78% accuracy, 98.66% sensitivity, 96.46% for specificity, VGG19 and MobileNet have demonstrated the highest classification accuracy.

Minaee et al., [15], trained four state-of-the-art convolutional networks for COVID-19 detection using transfer learning. The used dataset combined 5000 chest X-rays, split into 2000 for training and 3000 for testing. For their experiment, they used four famous pre-trained models (ResNet18, ResNet50, SqueezeNet, and DenseNet161), they trained them using 100 epochs with 20 batch sizes and adam optimizer. The best performance achieved was 98% for sensitivity and 92% for specificity achieved by SqueezeNet.

Horry et al., [16], presented a comparative study in order to select a suitable deep learning model among VGG16, VGG19, ResNet50, Inception_V3, Xception, Inception_ResNet, DenseNet and NASNetLarge. They reported on the effectiveness of transfer learning in

COVID-19 diagnosis from medical imaging technologies including X-Rays, Ultrasounds, and CT scans. The present research focuses on X-ray images only. The dataset used was constructed with 140 COVID images, 322 pneumonia images, and 60361 normal images of Chest X-rays. The best results were gained by VGG19, which achieved an F1-score evaluation value of 0,87.

Chowdhury et al., [17], created a Kaggale database from six different sub-databases to create their database, for the COVID-19 database, the data was collected from several sources available online. Chowdhury et al., [17], reported transfer learning approach for classifying a dataset of 3487 X-ray eight different pre-trained CNN models (MobileNet_v2, SqueezeNet, ResNet18, ResNet101 and DenseNet201) were trained to classify two different schemes the first was normal and COVID-19 pneumonia and the second normal, viral and COVID-19 pneumonia. The classification accuracy, precision, sensitivity, and specificity of normal and COVID-19 images, and normal, COVID-19 and viral pneumonia for DenseNet201 were (99.7%, 99.7%, 99.7% and 99.55%), and (97.9%, 97.95%, 97.9%, and 98.8%) respectively.

Rahman et al., [9], have compiled a large X-ray dataset (COVQU) consisting of 18,479 CXR images with the application of transfer learning. In this research, six different pre-trained Convolutional Neural Networks (CNNs) (ResNet18, ResNet50, ResNet101, Inception_V3, DenseNet201, and ChexNet) and a shallow CNN model were trained. Rahman et al., [9], constructed a dataset under the name COVQU. It combined the Radiological Society of North America (RSNA) CXR dataset and the COVID-19 dataset. They have used 8851 normal and 6012 non-COVID X-ray images from the RSNA dataset, and the COVID-19 dataset was developed by modifying the collected and publicly available databases including the BIMCV-COVID19+ dataset, GitHub, Kaggle and Twitter. They got the highest accuracy with 96.29% and 96.28% for the precision.

In Aggarwal et al., [18], study, the performance of eight pre-trained models was assessed: MobileNet_v2, VGG16, ResNet50_v2, Inception_v3, NASNet Mobile, DenseNet121, Inception_ReNet50_v2 and Xception. The dataset developed for Aggarwal et al., [18], work is made up of two independent datasets that are both publicly available open-source Git Hub was used to create the COVID-19 images. Images of persons with COVID-19, pneumonia, Middle East respiratory syndrome (MERS), acute respiratory distress syndrome (ARDS), chest X-rays, and CT scans are commonly seen in the archive. 209 photos with confirmed COVID-19 and posterior-anterior (PA) views of chest X-rays were chosen from 625 images accessible in this source. The best Accuracy for the first dataset was 97% and for the second dataset was 81%.

Souid et al., [19], proposed a transfer learning approach to solve this problem of classifying and predicting lung diseases in chest X-rays using MobileNet_V2 model; they used 112120 images of 30805 unique patients. Its best results were of 95% for training and 91.3% for validation.

In Haghanifar et al., [20], numerous chest x-ray images from several sources are collected, and one of the largest publicly accessible datasets is prepared. Finally, using the transfer learning paradigm, the well-Known CHeXNet model is utilized to develop COVID-CXNet. The dataset consists of 1326 chest X-rays COVID positive. The best accuracy was 96.72% on the test-set within 100 epochs.

Panwar et al., [21], proposed a deep transfer learning algorithm that accelerates the detection of COVID-19 cases using X-ray and CT-Scan images of the chest. The model used in this work is based on VGG19. The dataset is comprised of 673 X-ray images; the authors used 03 experiments (Exp-1: Covid-19 vs Normal, Exp-2: Pneumonia vs Covid-19, Exp-3: Covid vs non-Covid). The best accuracy for the model is equal to 95.61%.

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III. Proposed Approach

In this section, we present the configuration of the five proposed architectures (e.g., the number of dense layers, and the size of each dense layer). In addition, we show the loss variation as well as the accuracy score for both training and validation.

A. *Dataset*

The dataset used in our experiment is an open source collection downloaded from kaggle [1] [17] [9]. It was constructed by a team of researchers from Qatar university, Doha, Qatar, with collaborators from university of Dhaka Bangladesh and radiologist doctors from Pakistan and Malaysia with radiologist doctors. The dataset consists of chest X-ray images of four different classes: COVID-19 positive cases, normal viral-pneumonia cases along with lung opacity. Collecting images was done in stages. The latest update and the version used in our experiment contains 21165 total images; among which, we distinguish 3616 images for COVID-19, 6012 for lung opacity, 1345 for viral-pneumonia, and 10192 for normal cases.

B. *General Architecture*

In this section, we specify the used models and their architectures. As said before, we are using transfer learning which consists of getting pre-trained models (with frozen representation layers and new dense layers that are well adapted to our needs, that is, the prediction of four classes that represent the normal case, COVID-19, viral-pneumonia, and lung opacity). We used six models with transfer learning, including: MobileNet_V2, Inception_V2, ResNet50_V2, Xception, Inception_Resnet_V2, and DenseNet121; the general architecture is summarized in Figure 1.

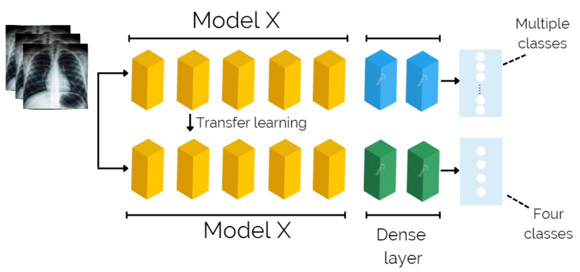

Fig. 1: General Architecture of the proposed models

C. *Used Backbones*

As we previously stated, we are using transfer learning which consists of getting pre-trained models and freezing the fully connected layers, then creating a new one with the specific needs of our experiment. In particular, we aim to predict four classes (COVID-19, viral-pneumonia, lung opacity, and normal class) which are inspired from our dataset. We developed six models based on the transfer learning of the following backbones: MobileNet_V2, Inception_V2, ResNet50_V2, Xception, Inception_Resnet_V2, and DenseNet121.

In Tables 5 and 6, we present the detailed characteristics of the used backbones (Input Size and Number of convolutional layers (up to the last representation layer); number of pooling layers; number of parameters; number of channels of the last feature map).

The used operators vary from one backbone to another: MobileNet mainly uses bottleneck, depthwise, convolutions, pointwise convolutions; Xception mainly uses depthwise and pointwise convolutions; for Inception_V2 we principally use factorized convolutions and pointwise convolutions; the Inception_ResNet_V2 uses the pointwise convolutions and the depthwise convolutions.

Backbone	Input size	Conv	Pooling
Mobile Net	224*244*3	54	01
Xception	299*299*3	40	05
Inception V2	299×299×3	95	12
InceptionResNetV2	299*299*3	233	06

Table 5: Characteristics of the used backbones [22], [23], [24], [25]

Backbone	Parameters	Last feature map
Mobile Net	1.7M - 6.9M	-
Xception	22.855.952	2048
Inception V2	-	2048
InceptionResNetV2	-	1792

Table 6: Characteristics of the used backbones [22],[23], [24], [25]

IV. Experimental study

A. *MobileNet_V2*

It was the first implemented model and the most trained compared to others (86 times), with an average training time of four hours. The best accuracy of training is equal to 0,9523, and the validation accuracy is equal to 0.8962; all the other details are shown in Figure 2. As displayed in the same figure, the best validation accuracy is obtained around the 7th epoch; after that, the validation accuracy shows a zigzagging behavior and it is almost always under the training accuracy curve.

[1]https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database

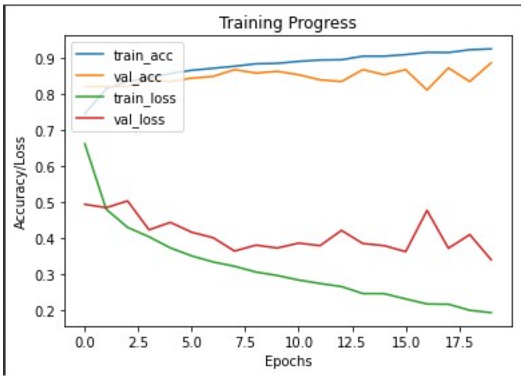

Fig. 2: Mobilenet_V2 accuracy/loss with respect to epochs

B. Inception_V2

Inception_V2 model had an accuracy of 0,8645 for training and 0,8596 for validation; the other details are shown in Figure 3. We observe that the best validation accuracy is obtained in the 8th epoch; in addition, we notice that the curve of training accuracy is almost above the curve of validation accuracy.

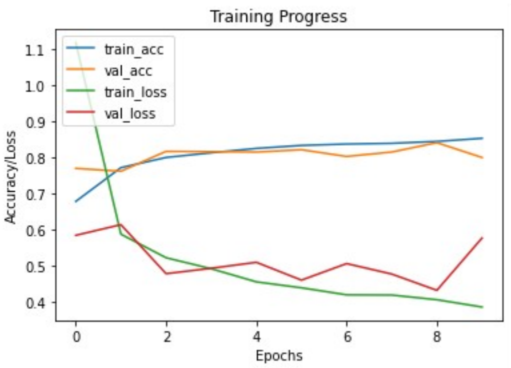

Fig. 3: Inception_V2 accuracy/loss with respect to epochs

C. ResNet50_V2

This model has shown a good result in terms of training and validation accuracy (which are equal to 0.9408 and 0.8868, respectively), it took an average of six hours for training. We notice that this model had the highest precision for the normal class and higher recalls for the other classes (see Figure 4).

D. Xception

The Xception model reaches 0,972 for training and 0,9387 for validation; additionally, Xception had a good result for all the four classes; the accuracy related to the validation curve (Figure 5) is always under the training one, but it converges to the same levels. Furthermore, we observe that the curve of loss-validation gets higher

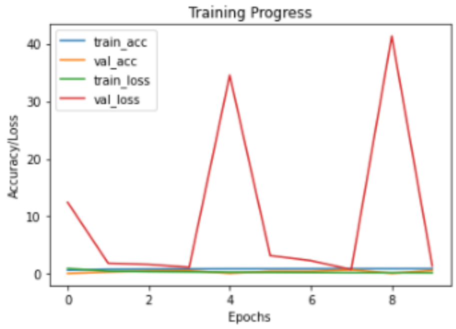

Fig. 4: ResNet50_v2 accuracy/loss with respect to epochs

values in the beginning, but decreases with time and gets closer to the training loss.

	Precision	Recall	F1-Score
Covid	0.90	0.82	0.86
Normal	0.87	0.93	0.90
Lung Opacity	0.90	0.73	0.81
Viral Pneumonia	0.78	1.00	0.88

Table 7: Confusion matrix for Xception model

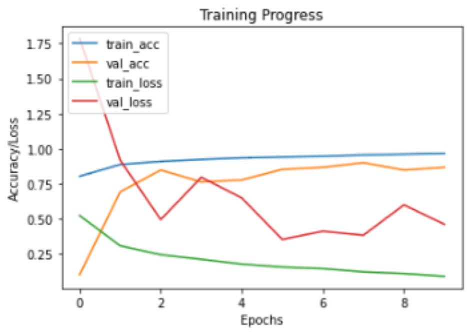

Fig. 5: Xception accuracy/loss with respect to epochs

E. Inception_ResNet_V2

Inception_ResNet_V2 also shows a good result with 0,9245 for validation and 0,9583 for training; we observe that the best validation accuracy is obtained around the fourth epoch and the curve of validation accuracy is always under the training accuracy curve. Besides, the experiment shows interesting rates in terms of the F1-score and recall (see Figure 6).

	Precision	Recall	F1-Score
Covid	0.59	1.00	0.75
Normal	0.94	0.78	0.85
Lung Opacity	0.81	0.85	0.83
Viral Pneumonia	0.91	0.95	0.93

Table 8: Confusion matrix for InceptionResNet V2 model

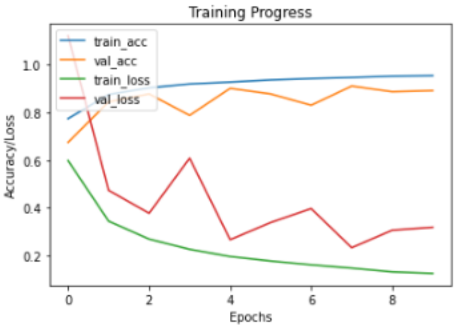

Fig. 6: Inception_resnet_V2 accuracy/loss with respect to epochs

F. DenseNet121

Among DenseNet network variants, we worked with DensNet121. This network had the worst performance over all the previous models with a training accuracy equal to 0,9 and a validation accuracy equal to 0.63. Besides, it gets the highest value of the loss-validation curve (see Figure 7).

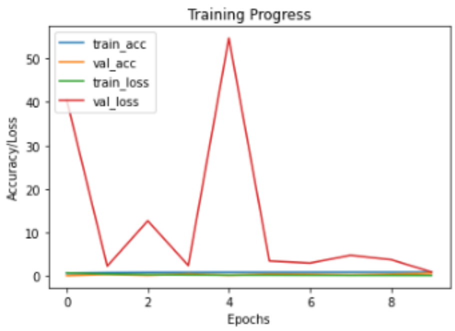

Fig. 7: DenseNet121 accuracy/loss with respect to epochs

G. Discussion

We notice that the performance is different from one model to another, and depends on a set of parameters. It is worth noting that the Xception and Inception_Resnet_V2 models have gained the best results (see Tables 9 and 10). According to Tables 5 and 6, we observe that these two backbones contain a higher number of convolutional layers concerning the other alternatives; in addition, they provide a higher resolution of the last feature map; these characteristics give more advantages for these two models to get promising performances on the types of pneumonia diagnosis challenge. As for the changes made to the Xception model, we added one dense layer with 512 units (see Table 9) and Elu-based activation function (with 10 epochs of training). Moreover, the Inception_Resnet_V2-based model is changed by adding three dense layers (see Table 9); each of them has 512 units with an Elu activation function. Finally, we notice that the denseNet model has given the worst performance as compared with the remaining five models, and this confirms the fact that the re-utilization of the early features in the subsequent layers does not bring any gain. Concerning the Xception model performance, we notice that the validation accuracy curve is smoother than the curves of the majority of the remaining methods. Furthermore, we observe that the validation accuracy is reaching the highest value concerning all experiments, despite the relative high value of the validation loss observed at the end of training. When we analyze the results presented in Table 7, we deduce that the performance of the Xception-based model is highly effective on all types of pneumonia, but it is somewhat poor on the lung opacity class. This is mainly due to the fact that lung opacity involves several diseases (e.g., cancers, bronchitis.) that exhibit overlapping patterns with other classes, and the grouping of these unlabeled images in the same class makes the prediction more challenging. According to Table 8, we observe that the Inception_ResNet_ V2 model has an acceptable performance in all classes except the COVID19 category. In particular, the low precision performance of the COVID19 class is due to the high number of mislabeled images coming from the lung opacity and the normal classes. This means that this model can perform better if we further augment the images of the aforementioned classes.

Model	Dense layers	Layer size	Val-Acc
MobileNetV2	1	256	0,8962
InceptionV2	3	512	0,8596
ResNet50V2	3	1024	0,8868
Xception	1	256	0,9387
InceptionResNetV2	3	512	0,9245
DenseNet121	1	256	0,62267

Table 9: Validation accuracy for all methods (a)

Model	train-Acc
MobileNetV2	0,9523
InceptionV2	0,8645
ResNet50V2	0,9408
Xception	0,972
InceptionResNetV2	0,9583
DenseNet121	0,9033

Table 10: Training accuracy for all methods (b)

V. Conclusion

In this work, we have presented six transfer-learning CNN-based models for the diagnosis of pulmonary illnesses using data from x-ray radiography. The results demonstrate a significant improvement in the Xception model as compared to other models and the existing state-of-arts techniques.

We notice that the Xception-based model is effective on all types of pneumonia, but it is less successful on the opacity lung class since this category contains several diseases that exhibit multiple types of textures and shapes that may overlap with patterns encountered in the first classes.

In future works, we will concentrate on extending the models for managing multi-model data, like CTScan and CBC data (count of blood cells) for a higher rate of accurate diagnosis of various types of pneumonia. Additionally, we intend to offer visual justifications for the decisions made by CNN's.

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