Advanced Deep Transfer Learning Using Ensemble Models for COVID-19 Detection from X-ray Images

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Abstract: The pandemic of Coronavirus disease (COVID-19) has become one of the main causes of mortality over the world. In this paper, we employ a transfer learning-based method using five pre-trained deep convolutional neural networks (CNN) architectures fine-tuned with an X-ray image dataset to detect COVID-19. Hence, we use VGG-16, ResNet50, InceptionV3, ResNet101 and Inception-ResNetV2 models in order to classify the input images into three classes (COVID-19 / Healthy / Other viral pneumonia). The results of each model are presented in detail using 10-fold cross-validation and comparative analysis has been given among these models by taking into account different elements in order to find the more suitable model. To further enhance the performance of single models, we propose to combine the obtained predictions of these models using the majority vote strategy. The proposed method has been validated on a publicly available chest X-ray image database that contains more than one thousand images per class. Evaluation measures of the classification performance have been reported and discussed in detail. Promising results have been achieved compared to state-of-the-art methods where the proposed ensemble model achieved higher performance than using any single model. This study gives more insights to researchers for choosing the best models to accurately detect the COVID-19 virus.

1 INTRODUCTION

Since the spread of COVID-19, the real-time polymerase chain reaction (RT-PCR) was the most popular technique applied to detect this virus. Despite the good performance achieved by this technique, it still has many problems like time-consuming, false negative results, and its expensive price (Altan and Karasu, 2020). Since the mortality cases with COVID-19 is constantly increasing, the aforementioned drawbacks of RT-PCR test could further complicate the situation. Recently, deep learning techniques to detect and diagnose the COVID-19 have become an active research area using X-ray images or (Computerized Tomography) CT scans (Luz et al., 2022; Hariri and Narin, 2021). Their high performance achieved to detect other diseases such as Alzheimer using transfer learning has motivated the researchers to adopt this novel technique to prevent against the COVID-19 pandemic (Zaabi et al., 2020). Besides the high performance, deep learning-based techniques are very fast compared to RT-PCR test (Huang and Liao, 2022). Therefore, we propose in this paper various deep learning based-strategies to deal with the COVID-19 detection and diagnosis using publicly available dataset of X-ray images. The remainder of the paper is structured as follows: in Section II, we present the related works. Section III explains the contribution of the paper. The proposed method is presented in detail in Section IV. Experimental results and comparative study are reported in Section V. Conclusions end the paper.

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2 RELATED WORKS

Few weeks after the propagation of COVID-19 pneumonia, many works to detect the virus from radiography imaging are carried out using deep learning-based techniques (Ali et al., 2022). Among these techniques we can find ***"traditional deep learning methods"*** that aim to train deep models from scratch using a specified labeled dataset. Since the appearance of the COVID-19 pandemic, some datasets have been introduced to allow researchers to test their models. For example, (Zheng et al., 2020) trained a supervised deep learning model. The segmentation of the lung region is applied using Unet model from CT-scans.

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Other methods are based on ***"deep features extraction"*** where the deep pre-trained models have been widely used as feature extractors, in which the last convolutional layers or the fully connected layers are used to feed a machine learning classifier. For example, (Ismael and Şengür, 2021) applied five pre-trained models including VGG-16, ResNet18, ResNet50, ResNet101, and VGG19 to train an SVM classifier. Different kernel functions are then used in the SVM classification stage such as Linear, Quadratic, Cubic, and Gaussian kernels. An other method used AlexNet-based features to feed an SVM classifier is introduced in (Turkoglu, 2021). In this work, the deep features are extracted from the fully-connected and convolution layers. Another method proposed by (Rahimzadeh and Attar, 2020) aims to combine the deep extracted features from Xception (Chollet, 2017) and ResNet50V2 (He et al., 2016b) networks. A global feature vector is then generated to train a classifier. From another point of view, to be able to make a real time detection of COVID-19, training a deep model from scratch has many problems, especially the insufficiency of representative data and also it is time-consuming and requires high performance machines. In this case ***"transfer learning (TL)"*** were the most useful technique to figure out train time and data troubles. TL is one of the deep learning approaches that consists of reusing a pre-trained model for one job to accomplish another one in the same domain of missions. By way of example, (Vaid et al., 2020) applied a transfer learning method using VGG-16 pre-trained model. They used a labeled frontal X-ray images dataset of patients from different countries around the word. The particularity of the used dataset lies in the additional information of each patient such as location, old and gender. (Das et al., 2020), however, used the extreme version of Inception (Xception) model, in order to develop an automated deep transfer learning to detect COVID-19 pneumonia in X-ray images. Transfer learning has also been used to classify the CT scans of lungs into COVID-19 or NORMAL cases as presented in (Ahuja et al., 2021). Four pre-trained models are then used including ResNet18, ResNet50, ResNet101, and SqueezeNet. A different transfer learning-based method using the DetRaC model is presented in (Abbas et al., 2021). The combination of TL and the DetRaC model makes the proposed method able to deal with any irregularities in the image dataset by investigating its class boundaries using a class decomposition mechanism. Authors in (Nayak et al., 2020) used eight pre-trained models namely, AlexNet, VGG-16, GoogleNet, MobileNet-V2, Squeezenet, ResNet34, ResNet50 and InceptionV3. They evaluated the pre-trained models with X-ray illustration taken from covid-chestxray-dataset (Cohen et al., 2020). Similar method has been proposed in (Kumar and Mallik, 2022). After fine-tuning several CNN models, the authors proposed to train the output each models using another deep neural network to enhance the performance. To deal with the lack of grand amount of labeled datasets, ***"generative models"*** have been widely used to generate new images using the existing ones. Many strategies have been carried out such as flipping the image horizontally of vertically, zooming in or out. For example, (Loey et al., 2020) proposed a model of two axes, the first one about the data augmentation using common techniques across Conditional generative adversarial network (CGAN), the second axe is about deep TL model, which is formed of five model, named as following: AlexNet, VGG-16, VGG-19, GoogleNet and ResNet50. All of these models are fine-tuned with COVID-19 CT-image dataset. Another data-augmentation-based method using X-ray and CT Chest Images has been proposed in (Bargshady et al., 2022). It consists of coupling GANs with with trained, semi-supervised CycleGAN. Inception V3 is then fine-tuned to detect COVID-19.

3 CONTRIBUTION OF THE PAPER

A transfer learning-based technique is applied in this paper to detect COVID-19 virus using labeled datasets of X-ray images. To avoid training a deep CNN from scratch on a limited labeled dataset, we propose in this paper to carry out a transfer learning technique using five pre-trained models and acquired data only to fine-tune them. This is very useful when the data is abound for an auxiliary domain, but very limited labeled data is available for the domain of experiment. Figure 1 presents our proposal overview.

We opted for the following pre-trained models: VGG-16, ResNet50, InceptionV3, ResNet101 and Inception-ResNetV2. This choice is based on the diversity of these models, the difference of their architecture as well as their structure. A comparative study is then conducted between these models in terms of training accuracy, loss accuracy, validation accuracy and validation loss during the training stage. A confusion matrix is then generated after the classification of test samples. Other performance measures are computed to show the efficiency of each model (e.g. recall, precision, F-score). The difference between the applied models can be useful in our sec-

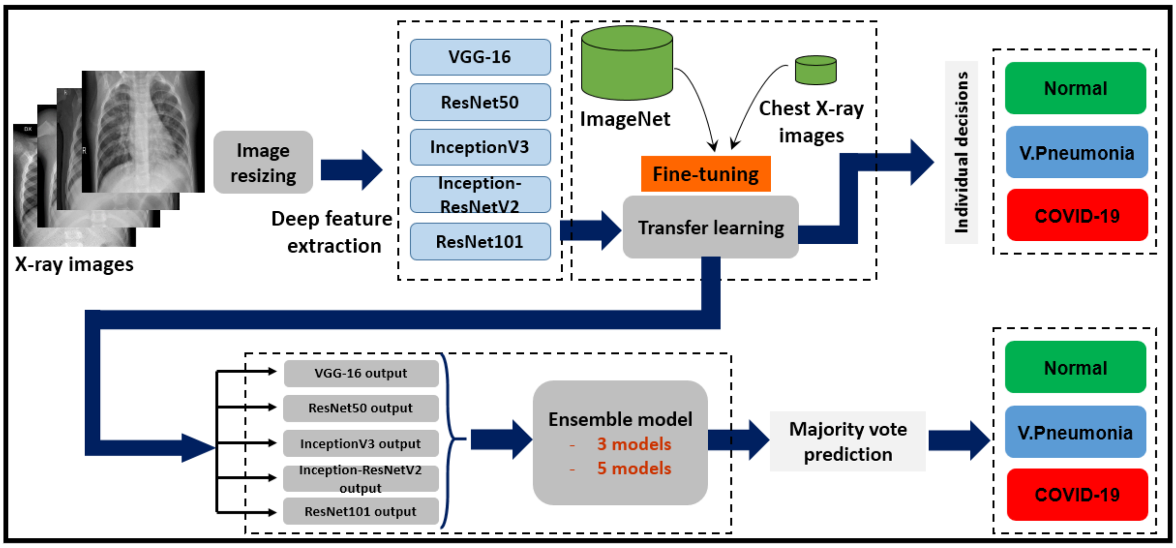


Figure 1: Overview of the different steps of our proposal.

ond step where their outputs will be combined using an ensemble learning technique (also called ensemble model) using the majority vote strategy. This combination enhances the classification performance of the non-learned samples compared to the obtained rates using each pre-trained model separately.

4 THE PROPOSED METHOD

4.1 Pre-Trained Models

In this Section, we present the architecture of the five models that we used in our TL system. These models are pre-trained on ImageNet database (Krizhevsky et al., 2012).

- **VGG-16:** (Simonyan and Zisserman, 2014) is trained on the very large ImageNet dataset which has over 14 million images and 1000 classes. It contains 16 layers including 13 convolutional layers, 3 dense layers and 5 Max Pooling layers. Each convolutional layer is 3×3 layer with a stride size of 1 and the same padding. The pooling layers of VGG-16 are all 2×2 pooling layers with a stride size of 2. Figure 2 presents modified VGG-16 architecture as an example of TL.
- **ResNet50:** ResNet50 is a variant of ResNet pre-trained model on ImageNet dataset which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has 3.8×10^9 Floating points operations (He et al., 2016a).
- **ResNet101:** Anther variant of ResNet deep neural network series, trained on more than a million images from the ImageNet database (Dai et al., 2016). It consists of 101 deep layers with identity connection between them.
- **Inception-ResNetV2:** A CNN that builds on the Inception family of architectures (Szegedy et al., 2017). Its architecture combines the Inception architecture with residual connections. This CNN contains 164 deep layers trained on ImageNet dataset and is able to classify images into 1000 classes.
- **InceptionV3:** presented by google is the third version of Inception DL convolution architectures, with 42 deep layers contain Convolution layer, AvgPool, MaxPool, Concat, Dropout, Fully Connected layer and Softmax activation function (Szegedy et al., 2016). The input layer size of this model is different from the other models ($299 \times 299 \times 3$ instead of $224 \times 224 \times 3$).

4.2 Transfer Learning

We aim to transfer the acquired information from the CNN models pre-trained on ImageNet dataset to our specific task. The issue that needs to be addressed is the highly dependance of these models on the initial dataset, whereas our Chest X-ray images are different. Consequently, the generalization of the network will be poor since the extracted features from the large amount of data are not inadequate to represent our target images (to feed a classifier or softmax function). The solution consists of fine-tuning the pre-trained models on our Chest X-ray images dataset that is a very small dataset compared to the ImageNet. In

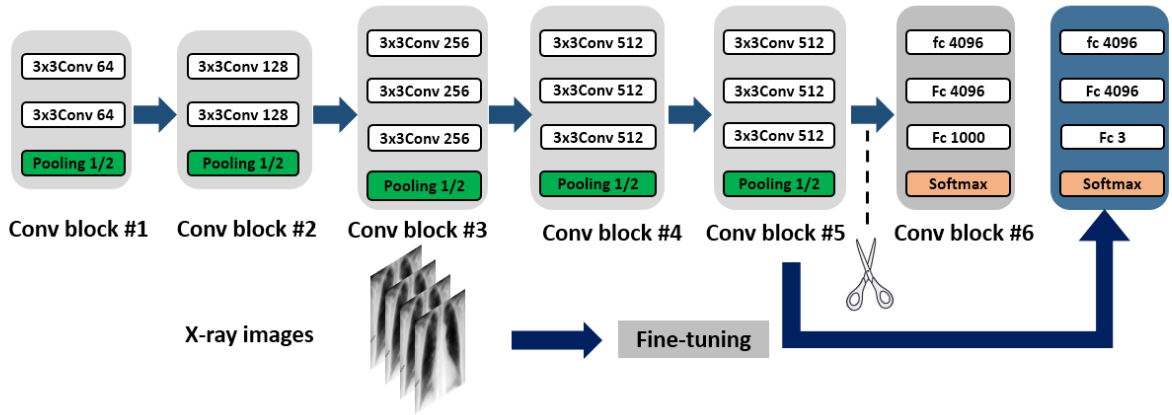


Figure 2: The modified VGG-16 network architecture.

other words, pre-trained CNN structures are updated to suit our classification task. This strategy is generally much faster than the traditional training of the CNN model from scratch with arbitrary weights. For example, using VGG-16, the total number of parameters after training is 14,789,955. The number of trainable parameters is 75,267 which is very small compared to 14,714,688 of non-trainable parameters.

4.3 Deep Ensemble Learning

To enhance the classification performance, we exploit the different architectures of the five pre-trained models and we fuse their outputs to make a global decision. Thus, we propose to apply a majority voting strategy as an ensemble learning stage. We then use the combination of 5 and 3 models, respectively using the output of the last epoch (30) of the 10^{th} training fold. The obtained results are presented and discussed in detail in the following section.

5 EXPERIMENTAL RESULTS

All the experiments were performed on Windows 7 operating system 64 bits the TensorFlow/Keras framework of python language. The implementation of our proposal is provided by Google Colaboratory Notebooks. The obtained results by each pre-trained model, and using the deep ensemble model strategy are presented in the following.

5.1 Database Description

COVID19 Radiography Database (Rahman, 2020)**:** contains 3616 COVID-19 positive cases along with 10,192 Healthy, 6012 Lung Opacity (Non-COVID lung infection), and 1345 Viral Pneumonia images. In this work, we carry out 3 class classification (COVID-19, Healthy and Viral pneumonia). Some scans from this database are shown in Figure 3.

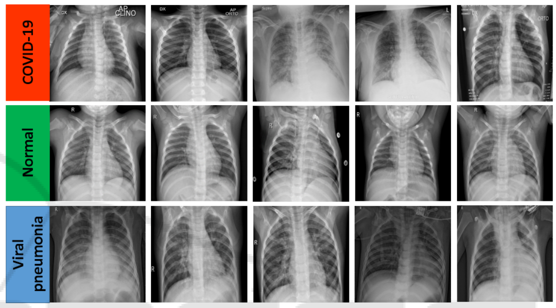


Figure 3: X-ray images from COVID19 Radiography Database (Rahman, 2020).

5.2 Method Performance

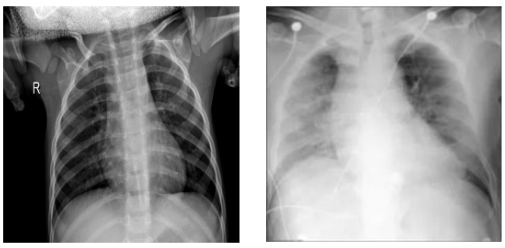
The 10 fold-cross validation setting is applied using the 4^{th} version of COVID19 Radiography Database. It is randomly split into training and test datasets. The initial learning rate is of 0.0003 and cross entropy loss. The models are trained for 30 epochs where the batch size is 32.

In the following, we show the training performances (accuracy and loss) as well as the validation performances using the three best models including Inception-ResNetV2, VGG-16 and InceptionV3, respectively. The performance during the fold 1, 6 and 10 are displayed in detail in Figure 7. These curves show that using VGG-16 architecture, the highest training accuracy is observed 98.85% in epoch 7 where the highest validation accuracy is 99.65% in epoch 24. The loss is 0.0324 and 0.024 at epoch 30 of training and validation respectively. All the reported results are put out from fold 10.

On the contrary, Inception-ResNetV2 achieved higher training accuracy compared to VGG-16 by 99.46% in epoch 29. The highest validation accuracy is 100%. Training and validation loss are respectively 0.026 and 0.005 (See Figure 8). Although the initial loss value of Inception-ResNetV2 is very high compared to that of VGG-16 (1.00 vs 0.2), the previous values show that Inception-ResNetV2 is more efficient during the training and validation stages compared to VGG-16 over all the epochs of the 10^{th} fold. InceptionV3, however, is the third best model among the five models (See Figure 9).

More details about the performance measures of the best three models as well as the two remaining ones (ResNet50 and ResNet101) are shown in Table 1. According to the displayed values of precision, recall, and F-score, ResNet101 is slightly better than ResNet50. This performance can be clearly seen in the confusion matrix of these models. Figure 5 shows that ResNet101 has less false classifications. From the same Figure, we can also notice that false classified samples of VGG-16 and Inception-ResNetV2 are very limited compared to the two previous models. This explains the very high rates registered as recall, precision and F-score. Figure 4 presents two challenging samples of false positive and false negative cases.

The use of ensemble learning, however, enhances all the previous performances using the combination of the three and five models' outputs as shown in the Table 1. Using this strategy, we achieve 1.00 of precision, recall and F-score when dealing with the COVID-19 classes. Compared to recent state-of-the-art methods, our proposed methods achieved higher classification rate of the test set by 0.96 using the ensemble model of the combination (VGG-16+ResNet50+ResNet101).

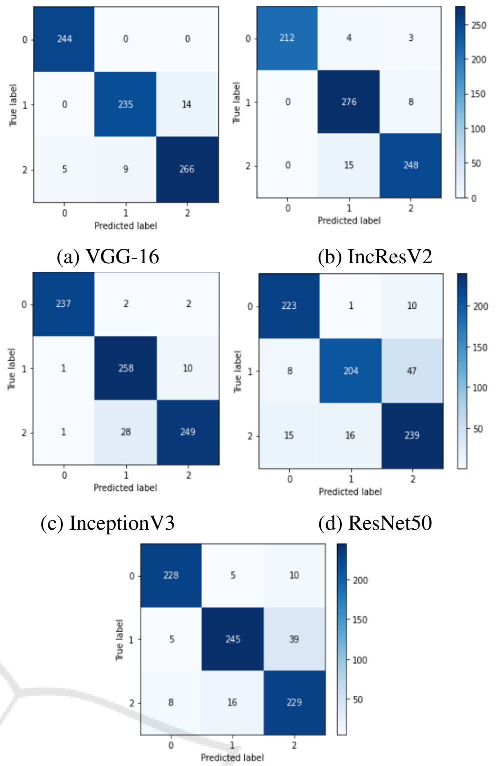


(a) (b)

Figure 4: (a): False positive case, (b): false negative case.

5.3 Discussions

The experimental study proves that the TL is one of the best deep learning techniques to efficiently detect the COVID-19 using X-ray images.

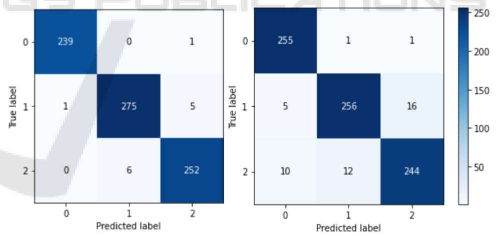


(a) VGG-16 (b) IncResV2

(c) InceptionV3 (d) ResNet50

(e) ResNet101

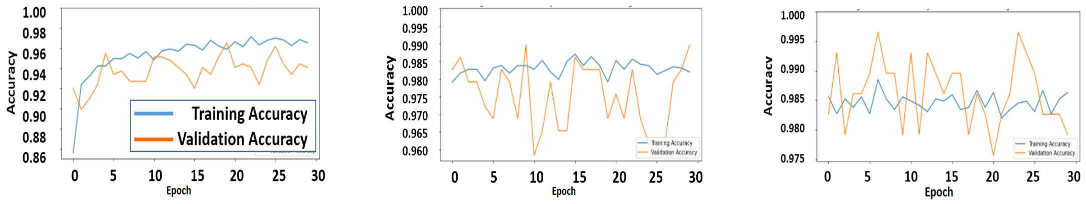
Figure 5: Confusion matrix of the pre-trained models. **Label 0** refers to COVID-19 class, **label 1** refers to Healthy class, and **label 2** refers to the VP.



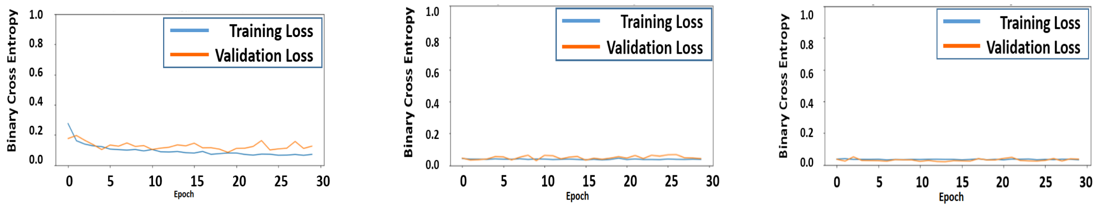
(a) 5 models (b) 3 models

Figure 6: Confusion matrix of the majority vote prediction. (a) refers to all the five models. (b) refers to the following three models: VGG-16, ResNet50 and ResNet101.

The obtained results show that the ensemble models enhance the classification performance of the fine-tuned CNNs. This paper proposes five pre-trained models that give promising results which are still competitive to those of the state-of-the-art method. The TL strategy using the combination of the best models outperforms the other methods and gives 0.98 accuracy of test images. The high performances achieved are explained by the fact that TL is suitable since the first CNN layers learn low-level features. These features and mostly invariable from a classi-

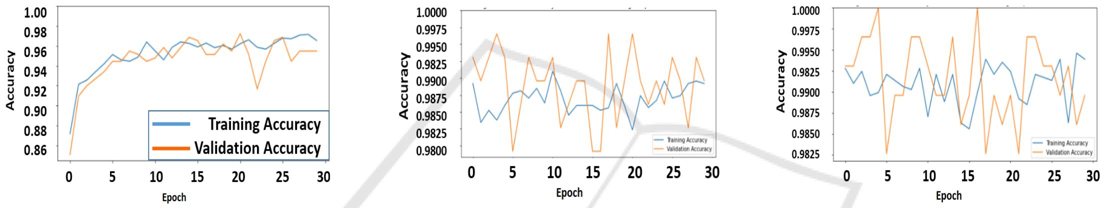


(a) Fold 1 acc (b) Fold 6 acc (c) Fold 10 acc

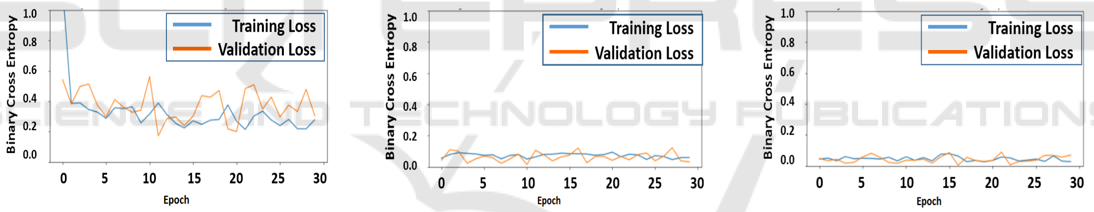


(d) Fold 1 loss (e) Fold 6 loss (f) Fold 10 loss

Figure 7: Training and validation accuracy / loss using VGG-16.

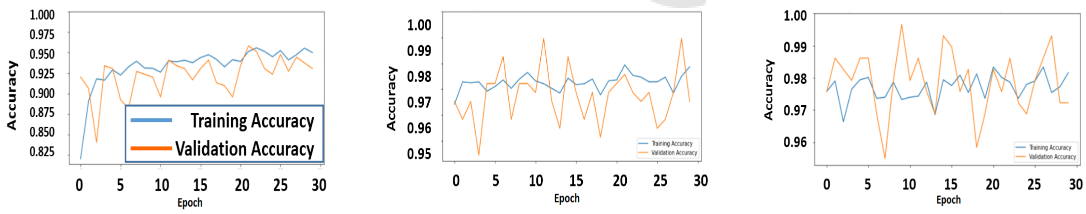


(a) Fold 1 acc (b) Fold 6 acc (c) Fold 10 acc

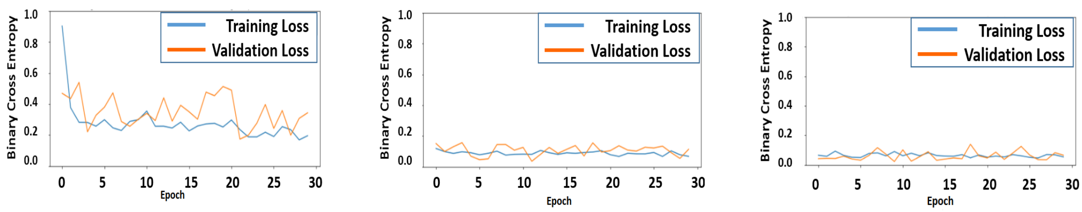


(d) Fold 1 loss (e) Fold 6 loss (f) Fold 10 loss

Figure 8: Training and validation accuracy / loss using Inception-ResNetV2.



(a) Fold 1 acc (b) Fold 6 acc (c) Fold 10 acc



(d) Fold 1 loss (e) Fold 6 loss (f) Fold 10 loss

Figure 9: Training and validation accuracy / loss using InceptionV3.

Table 1: Performance of 5 fine-tuned CNNs and ensemble learning with X-ray images of COVID-19, Healthy and VP cases.

Model / measure	**Precision**			**Recall**			**F-score**			**Accuracy**
Class	COVID	Healthy	VP	COVID	Healthy	VP	COVID	Healthy	VP	Test set
VGG-16	0.98	**0.96**	0.95	**1.00**	0.94	**0.95**	**0.99**	**0.95**	**0.95**	0.96
ResNet50	0.91	0.92	0.81	0.95	0.79	0.89	0.93	0.85	0.84	0.88
ResNet101	0.95	0.92	0.82	0.94	0.85	0.91	0.94	0.88	0.86	0.90
Inception-ResNetV2	**1.00**	0.94	**0.96**	0.97	**0.97**	0.94	0.98	**0.95**	**0.95**	0.96
InceptionV3	0.99	0.90	0.95	0.98	0.96	0.90	**0.99**	0.93	0.92	0.95
All five models	0.94	0.95	0.93	0.99	0.92	0.93	0.97	0.94	0.93	0.94
VGG-16+ResNet50+ResNet101	**1.00**	**0.98**	**0.98**	**1.00**	**0.98**	**0.98**	**1.00**	**0.98**	**0.98**	**0.98**
Pham et al. (Pham, 2021)	/	/	/	/	/	/	/	/	/	0.96
Cavallo et al. (Cavallo et al., 2020)	/	/	/	/	/	/	/	/	/	0.91
Rajpal et al. (Rajpal et al., 2020)	0.99	0.91	0.94	0.96	0.96	0.92	0.97	0.93	0.93	0.94

fication task to another (i.e. edges). The fine-tuning provides specific features of the target domain such as COVID-19 detection. It is worth noting that the proposed method can be improved using class weight algorithm to deal with the data imbalance issue which is a common challenge in medical image diagnosis. This is an important perspective since the majority of medical datasets contains majority class of healthy cases compared to positive cases.

6 CONCLUSION

Since the epidemic is still fast-spreading, the proposed method seems to be a good solution to early diagnose the virus. We fine-tuned five pre-trained CNN models to our COVID-19 dataset of X-ray images. High classification performances have been achieved especially with VGG-16 and Inception-ResNetV2. Slightly lower performances have been achieved using the other models. This transfer learning technique reduces considerably the training cost compared to learning from scratch that becomes an amassed technique. To exploit the different features extracted by each model, we proposed to combine their outputs to find a global decision through a majority voting strategy. This strategy further enhances the performance of the proposed transfer learning-based method. In future work, we look at the application of Graph neural network along with CNNs to improve the performance and reduce the computation time. Also, the visualisation using Grad-Cam technique can be made to highlight the attention map of the classification.

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