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# Convolutional Neural Networks Model for Medical Radiographic Image Recognition COVID-19 Cases of Madagascar

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## ABSTRACT

**The symptoms related to COVID-19 are diverse depending on the severity of the disease. COVID-19 is responsible for a clinical picture called the coronavirus, named SARS-CoV-2 by the who, which involves multiple organ systems, including the lungs. To determine if the lungs are affected, the doctor relies on radiographic images and its interpretation requires a specialist physician. Our research work proposes an artificial intelligence-based system toreplace the specialist doctor in order to provide an interpretation of the obtained image and address the problems of a shortage of qualified doctors (radiologists). Indeed, a convolutional neural network has been proposed to train data from real images for casesof patients diagnosed with COVID or not, based on real data COVID-19 in Madagascar. Various parameters of the network were adjusted to obtain an efficient neural network model. Due to a shortage of image data and the limited computing resources (CPU and memory) of our machine, and in order to achieve sufficient performance, we used the transfer learning technic, which involves reusing a pretrained model capable to classify and adapte images to our own model. Our validation shows that the obtained model provides better classification.**

**Keywords:** Transfer learning, VGG16, keras, Radiographic image, COVID-19, Convolutional neural networks, classification.

## INTRODUCTION

The global COVID-19 pandemic, caused by the SARS-CoV-2 virus, has wreaked havoc on humanity. COVID-19 infection and its severe form require radiographic analysis. There is a shortage of specialist doctors in pulmonology and radiology, moreover, healthcare systems have limitations. Artificial intelligence advancement has enabled the development of highly

accurate diagnostic assistance applications. This is why the analysis and evaluation related to the medical radiographic image recognition system using artificial intelligence are paramount importance.

Various studies like [KAMJW 2021] has proposed robotics and intelligent systems against a pandemic. Then, [HAZMC 2017] has presented the model of convolutional neural networks, and two pretrained MobileNet models. [SKZ 2015], [G 2019], [AMPPM 2019], [SFWJS 2021] have explored VGG16, generalized research, and the use of artificial intelligence in medicine, which reviewing artificial intelligence techniques in imaging, data acquisition, segmentation, and diagnosis for COVID-19. This is why researchers are encouraged to analyze and evaluate medical radiographic images related to the recognition system using artificial intelligence.

The problem involves classifying radiographic images into two classes: infected images and healthy images. The radiographic images used for training and validation are obtained from real data provided by multidisciplinary labs from hostpitals in Madagascar. We used dedicated convolutional neural networks for image classification. The modeling process involves finding the architecture and parameters of the network that provide better classification after training. After several trials with different architectures and parameters of convolutional neural networks, we were able to achieve higher accuracy: 0.998. Transfer learning was used to improve the quality of the obtained accuracy.

We achieved an accuracy of 0.998 with transfer learning compared to an accuracy of 0.7 without transfer learning. As a result, we obtained a positive or negative classification for a new radiographic image.

## METHODOLOGY

To detect COVID-19 cases, we have radiographic images as training data from real-world data in Madagascar. We generated radiographic images for different positions (rotation at various angles, 2D rotation), variations in brightness, contrast, sharpness, and inclinations using Python code in a Jupyter notebook on Google Colab to obtain 2380 images as training data.

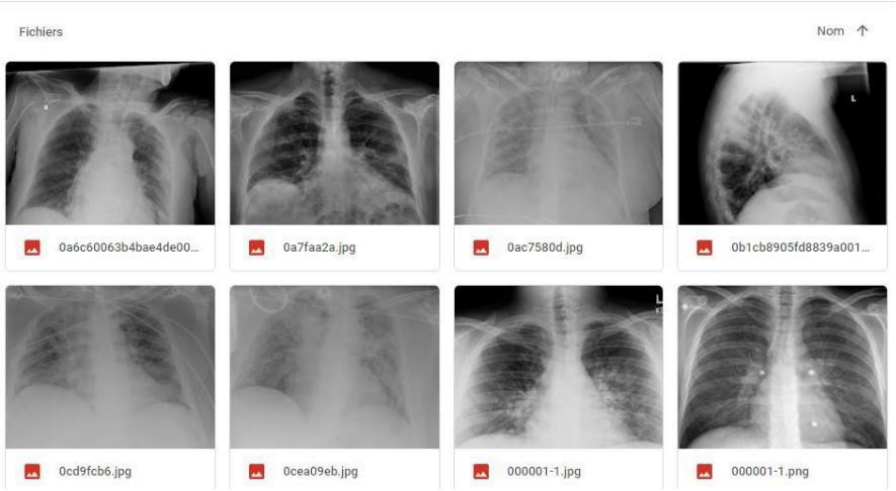



**Figure 1: Extract from radiographic image**

Most of current studies use radiographic images to classify between COVID-19 and healthy subjects. Image segmentation plays a significant role in COVID-19 applications, namely in lung delineation and lesion measurement. It facilitates the accurate identification of lung infection by radiologists and encourages quantitative analysis.

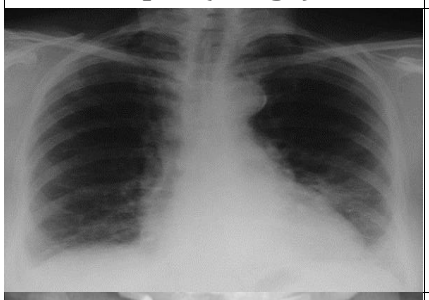
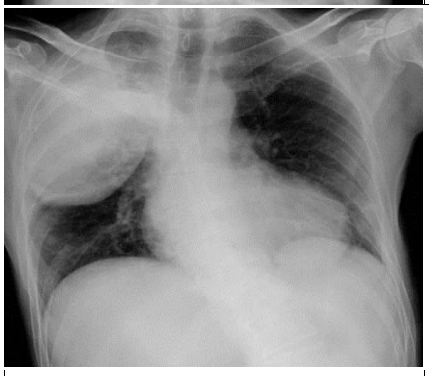
| Input (Image) | Output (Classification) |
|---|---|
|  | Positive |
|  | Negative |
|  | Positive |

**Figure 2: Input and Output Image**

The dataset is divided into two folders: the folder /covid contains 1643 confirmed COVID-19 radiographic images, and the folder /normal contains 438 confirmed healthy radiographic images.

**Table 1: Details of Data Split**

| Classes | Data | | |
|---|---|---|---|
| | Training | Validation | Total |
| COVID-19 | 1643 | 247 | 1890 |
| Normal | 438 | 52 | 490 |
| Total | 2081 | 299 | 2380 |

There are a number of studies aimed at differentiating COVID-19 patients from non-COVID-19 subjects (including common pneumonia subjects and non-pneumonia subjects). The Keras sequential model and the pre-trained convolutional neural network model VGG16 are responsible for segmenting COVID-19-related lesions. The final label (COVID-19 or non-COVID-19) is determined based on the segmented lesions. The evaluation results for COVID-19 classification using the proposed models are as follows:

- TPR = TP / P = TP / (TP + FN), called sensitivity, corresponding to thetrue positive rate.
- ACC = (TP + TN) / (P + N), called precision or accuracy.
- SPC = TN / N = TN / (FP + TN) = 1 - FPR, called specificity or truenegative rate.
- TP: true positive TN: true negative FP: false positive FN: false negative

**Table 2: Comparison of Performance Measures**

| Sensitivity | Accuracy | Specificity |
|---|---|---|
| 99,71 % | 99,80 % | 99,72 % |

## Convolutional Neural Networks Model

In this study, we created two models. First, we created our own model using the Keras sequential model. Keras is an open-source library written in Python that allows interaction with deep neural network and machine learning algorithms. Then, we used the pre-trained VGG16 model and combined it with our own model. Additionally, we employed Conv2D layers from Keras, which are 2D convolution layers. We used convolutional neural networks dedicated to image classification. The complexity of creating convolutional neural networks can be avoided by adapting publicly available pre-trained networks. These techniques are called transfer learning because we examine the leverage knowledge gained from a general classification problem to apply it with a new specific problem.

Modeling involves finding the architecture and parameters of the network that provide better classification after training.

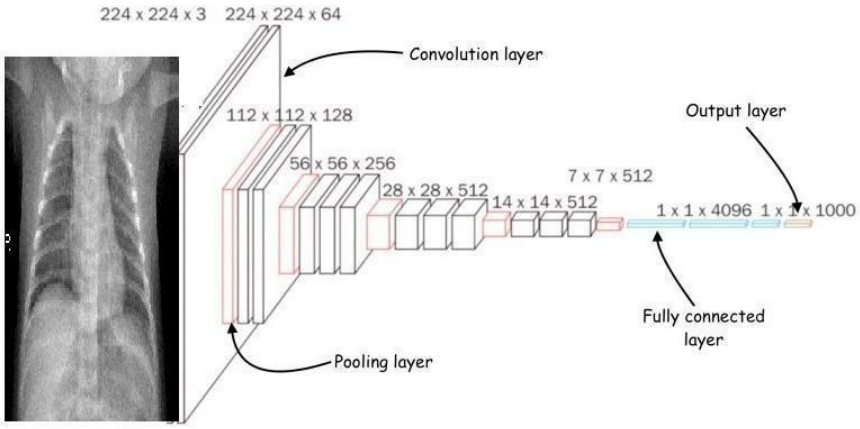



**Figure 3: Architecture of Convolutional Neural Networks**

This figure includes radiographic images as input. It has several convolution layers of different sizes. Then there are the Pooling layers, which are a form of image subsampling. Fully

connected layers connect each neuron in one layer to each neuron in another layer. And finally, there is the output layer.

VGG16 is a convolutional neural network (CNN) architecture. It is considered one of the best vision model architectures to date. The most unique thing about VGG16 is that instead of having a large number of hyperparameters, they focused on 3x3 filter convolution layers with a stride of 1 and consistently used the same padding and a 2x2 stride 2 max-pooling layers.

It follows this consistent arrangement of convolution and max-pooling layers throughout the architecture. In the end, it has 2 fully connected layers. (Fully connected layers) followed by a softmax for the output. The '16' in VGG16 refers to the 16 layers that have weights. This network is a fairly large network and has approximately 138 million (approximately) parameters.

**Learning**

After several trials with different architectures and parameters of convolutional neural networks, we were able to achieve better accuracy of 0.998.

Below is an excerpt from the code of our training program
model_final = Model (inputs=vggmodel. input, outputs=predictions) model_final. compile (loss = "categorical_crossentropy", optimizer
= 'adam', metrics=["accuracy"]) model_final. summary () epoch= 10
history=model_final.fit (traindata, steps_per_epoch=len(traindata), epochs=epoch, validation_data=testdata, validation_steps=len(testdata))

Deep learning enables the development of end-to-end models that learn and discover patterns and classification features using multiple layers of processing.

**Transfer Learning**

Transfer learning allows as to improve the quality of accuracy,especially in cases where:

- There is a shortage of traning data.
- CPU and memory resources are limited, especially whenthe machine does not have a GPU.
- It involves a model obtained from very large datasets (millions of images) with thousands of classifications and was executed on powerful machines, which can then be made to enhance the performance of another model significantly with small datasets and limited resources.

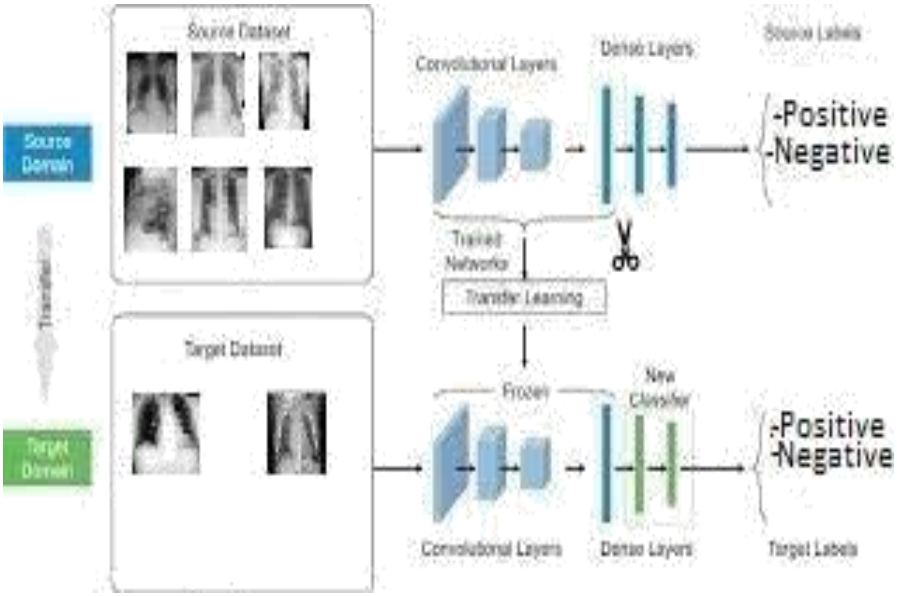



**Figure 4: Transfer Learning Architecture**

The technique of transfer learning was used in this work because of the limited amount of data. Transfer learning and model optimization were conducted on a personal computer. It is advantageous to use pretrained architectures to improve the training speed and accuracy of the new proposed model since the key image features that have already been learned can be transferred to the new task. Transfer learning provides a higher learning rate during training. Therefore, with a higher learning rate, transfer learning converges neural networks to higher performance more quickly, with better accurate results.

## RESULTS

80% of the data is used for training, and 20% is reserved for validation. The learning curves are plotted on 2081 radiographic images as the training dataset and 299 radiographic images as the validation dataset. Details of the training and validation datasets are provided in Table 1. With Transfer Learning, the accuracy reaches a result of 0.998.

The training performance of the studied models was evaluated in terms of important metrics, including training accuracy, validation accuracy, training loss, and validation loss at different epochs. Details of the training and validation data are found in Table 1. The training and validation curves across epochs during training are shown in Figure 5.

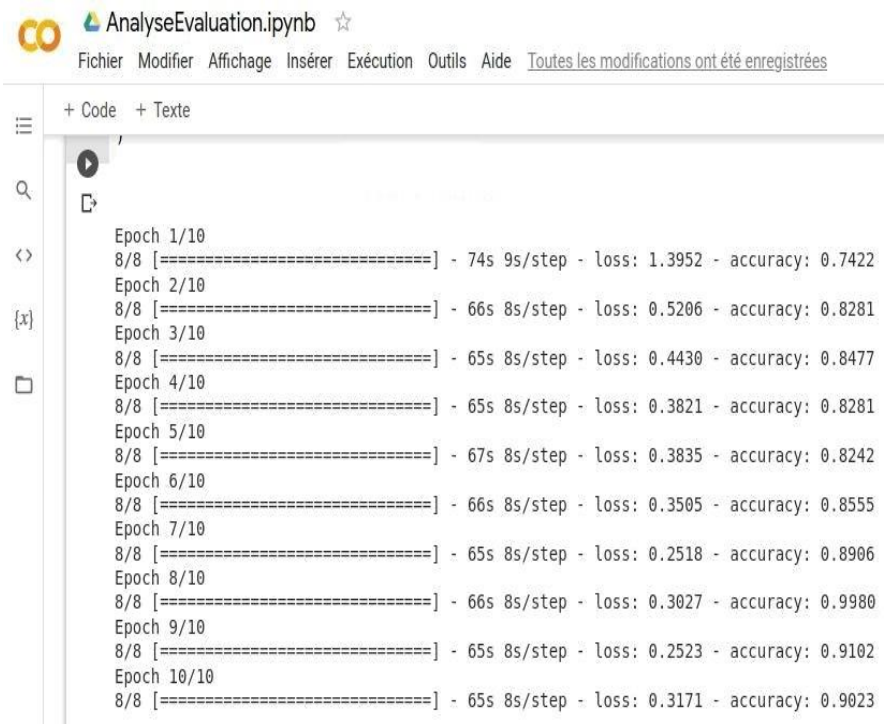



**Figure 5: Training Data Details**

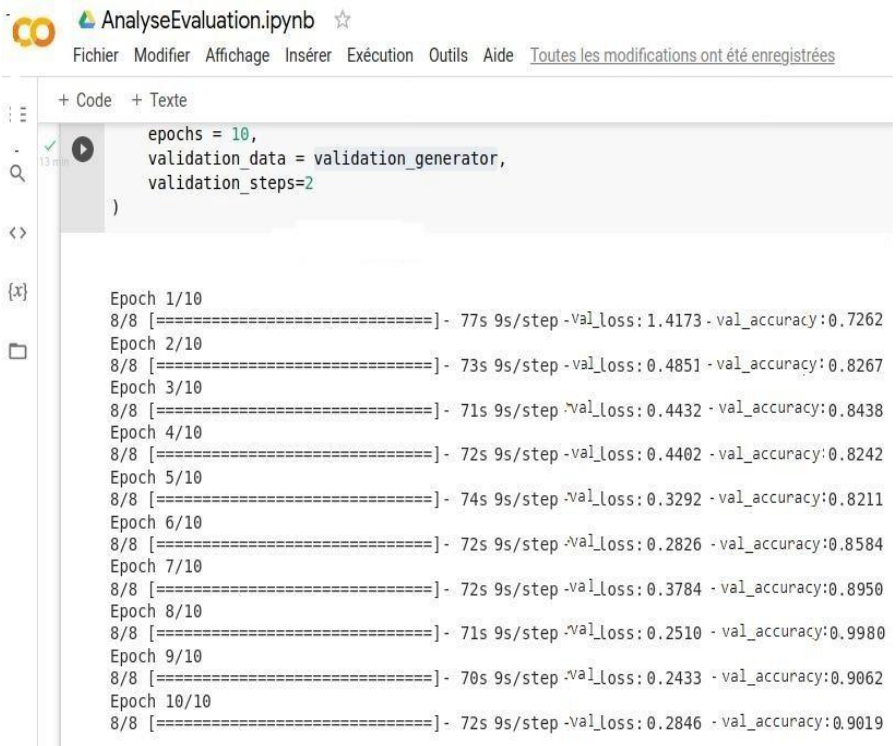



**Figure 6: Validation Data Details**

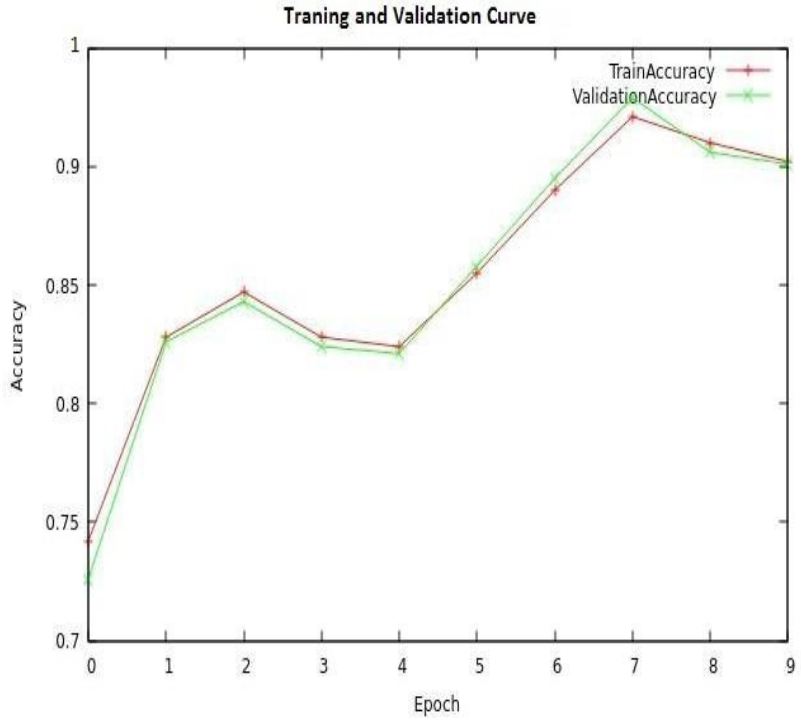



**Figure 7: Training and Validation Curve**

The training and validation curves depict accuracy rates as a function of epochs. In the time interval [0; 9], the accuracy rates are nearly the same for both training and validation, indicating that the model is performing well.

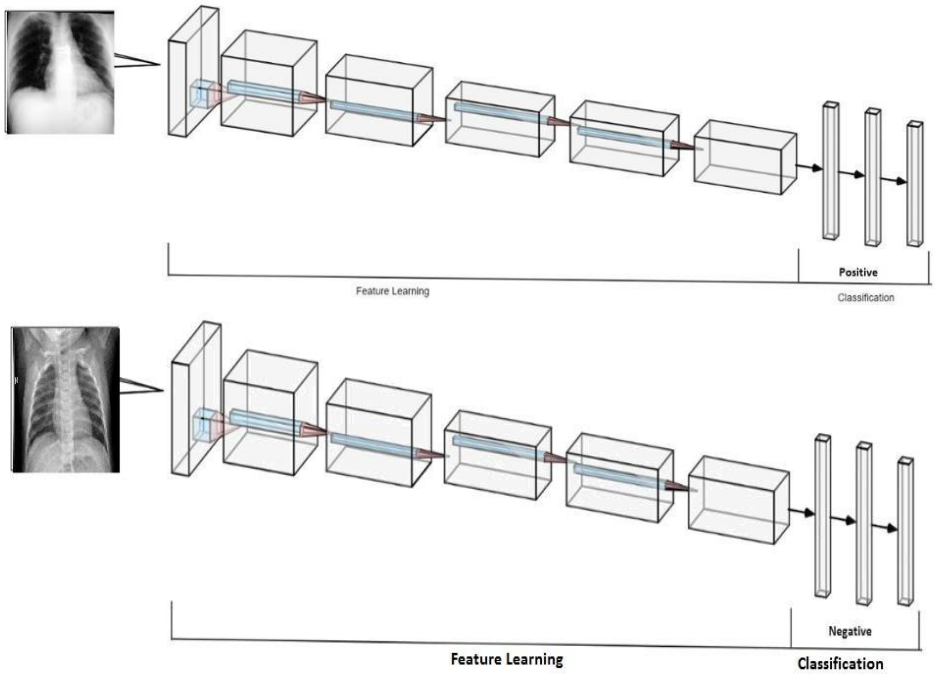



**Figure 8: Results after transfer learning and classification**

We used our own model trained on 2380 images from two different classes, which are positive and negative, with radiographic images as inputs. Then, we used the pretrained VGG16 model. After classification, we obtained the results as either positive or negative

## CONCLUSION

Fast diagnosis and triage are crucial for controlling infectious diseases, especially COVID-19. There is an urgent need for effective and timely alternative diagnostic methods that can be used by frontline healthcare staff for rapid and accurate COVID-19 diagnosis. The use of artificial intelligence-based models is becoming important in screening COVID- 19-infected patients from radiological images. Many studies have utilized similar datasets with models to differentiate COVID-19 pneumonia from healthy individuals. For example, in a study conducted by Hemdan et al., the COVIDX-Net model with an accuracy rate of 90% was developed to screen COVID-19 from radiographic images [EMM 2020]. In another study reported by Wang and Wong, a deep learning-based model called COVID-NET with an accuracy rate of 92.4% was suggested for COVID-19 detection using 16,756 chest X- ray images collected from various open-access sources [LA 2020]. Ioannis et al. proposed a transfer learning model with a high accuracy rate of 98.75% for detecting COVID-19 cases from radiographic images [IT 2020]. Singh et al. presented the performance of their proposed model by dividing the dataset into various training and testing ratios, reporting the highest accuracy as 94.65% at a 70% training and 30% testing ratio [DVM 2020]. For the same purpose, we obtained 99.71 % for detecting COVID-19 cases in Madagascar. Using transfer Learning improves the training performance which was trained by sequential model combined with VGG-16 model. Then, our classification accuracy reaches 99.80 %.

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