Enhanced COVID-19 Diagnosis from Chest X-Rays Using Transfer Learning with VGG16

Ennaceur Leila[1],*, Hedi Sakli[2], Mohamed Yahia[1]
[1]MACS Research Laboratory RL16ES22, National Engineering School of Gabes, Gabes University, Gabes, 6029, Tunisia.
[2]EITA Consulting, 5 Rue du Chant des Oiseaux, 78360 Montesson, France.
*Corresponding Author: Ennaceur Leila, ennaceur_leila@yahoo.fr

***Abstract*— This study explores the application of a deep learning model based on VGG16 for classifying medical images into three categories: normal, COVID-19, and pneumonia. Leveraging the power of transfer learning, the pre-trained VGG16 model was fine-tuned on a custom dataset to achieve high accuracy in image classification. The model achieved a training accuracy of 98% and a validation accuracy of 96%, with a corresponding training loss of 0.03 and a validation loss of 0.12. These results indicate the model's strong ability to learn from the training data and generalize to unseen validation data. Key techniques such as ReduceLROnPlateau and Early Stopping were employed to optimize the training process by automatically adjusting the learning rate and preventing overfitting. Despite the promising results, limitations such as the size of the dataset and the computational resources required for training were identified. Future work may focus on data augmentation and experimenting with more advanced neural network architectures to further enhance model performance.**

Keywords*— Medical Image Classification, COVID-19 Detection, Transfer Learning, CNN, VGG16

I. Introduction

With over 200 million confirmed cases and over 4 million deaths recorded worldwide in May 2024, the COVID-19 pandemic—caused by the SARS-CoV-2 virus—has severely disrupted the world health system [1]. This situation has highlighted the need for rapid and accurate diagnostics for effective patient management and limiting the spread of the virus. Chest radiographs (CXR) play an essential role in the diagnosis and monitoring of pulmonary infections, including those caused by COVID-19, by allowing the visualization of pulmonary infiltrates typical of the disease [2, 5].

However, manual interpretation of these images can be subjective and require trained experts, who are often in short supply in high-demand areas. For example, one study found that diagnostic accuracy based on manual interpretation of chest radiographs by radiologists can vary widely, with sensitivity rates ranging from 69% to 98% depending on the experience of the observer [3, 6]. This variability highlights the need for automated solutions to ensure more uniform and reliable evaluation of radiographic images.

Automating diagnosis via convolutional neural networks (CNN) is proving to be a promising solution to overcome these challenges. CNNs, a class of deep learning algorithms, are particularly suitable for medical image analysis due to their ability to extract complex features and classify images with high accuracy [4]. In this research, we evaluate the effectiveness of our convolutional neural network model in automatic diagnosis of COVID-19 from chest X-rays. We used a dataset of 6432 chest X-rays (CXRs) to train and test our model, including a sample of 224 images from COVID-19 patients [7].

Faced with the small size of this sample, we opted for transfer learning, a technique that allows us to take advantage of knowledge acquired on large datasets to improve the performance of models on specific tasks with smaller datasets. Transfer learning is particularly beneficial for CNNs, which require large amounts of data to accurately extract and classify features [8]. For example, studies have shown that using pre-trained models on large datasets, such as ImageNet, can significantly improve diagnostic accuracy for smaller medical datasets [9]. Our results indicate that transfer learning with CNNs provides an effective method for automatic detection of COVID-19-related radiographic abnormalities.

The performance obtained demonstrates the ability of this approach to improve diagnostic accuracy and provide a valuable tool for healthcare professionals in the fight against the pandemic. In particular, our model achieved a sensitivity of 92% and a specificity of 88% in detecting COVID-19 cases from chest radiographs [10].

II. Method

Working with partners from Pakistan and Malaysia, a group of researchers from Qatar University in Doha, Qatar, and the University of Dhaka in Bangladesh, along with healthcare professionals, have developed a dataset of Chest X-ray image data for COVID-19 positive cases, for viral and normal pneumonia images. [12]. The database consists of 3,616 positive COVID-19 cases, as well as 10,192 normal images, and 1,345 images of viral pneumonia.

To train convolutional neural networks (CNN) to distinguish cases of COVID-19 from common pneumonias, a collection of x-rays of common pneumonias was added. The inclusion of these different images aims to maximize the

Received: 15-07-2024
Revised: 6-09-2024
Published: 8-09-2024

diversity and representativeness of the data, which is essential to improve the robustness and accuracy of the CNN model.

Figure 1 illustrates these three classes, allowing a visual comparison of the different image types. In order to standardize images with varying pixel proportions and avoid distortion, a black background with a ratio of 1:1.5 was added to resize the images to a dimension of 200x266 pixels. CNNs can tolerate slight positional variations in images because they search for patterns flexibly, allowing them to focus on relevant features such as COVID-19-specific lung abnormalities (11).

a. COVID-19

b. Pneumonia

c. Normal

Figure1. Different classes of the dataset

III. MODEL

Our aim is to develop a convolutional neural network (CNN) capable of swiftly and effectively identifying chest X-ray images.

The initial step in our methodology involves preparing our dataset. Subsequently, we partition this dataset into two segments: 80% for training and 20% for testing purposes. Following this, we proceed to upload the dataset to cloud storage. This approach aims to streamline training processes by leveraging artificial intelligence computing instances on the Cloud. Upon completion of the training phase, we acquire updated weights for our model.

Subsequently, we advance to the testing phase to assess the model's performance.

To detect the presence of COVID-19, pneumonia, or a normal chest X-ray from images, we took a transfer learning-based approach using the VGG16 model, a pre -trained on a large database of diverse images. This choice is explained by the ability of VGG16 to efficiently extract complex visual features from images, essential for the accurate classification of chest radiographs.

First, we loaded the pre-trained weights from VGG16, configuring them to exclude the fully-connected layer (top layer) to allow adaptation to our specific dataset. This allowed us to benefit from the abstract visual representations learned by VGG16 while adjusting the upper layers of the model to meet our specific classification task.

The training and validation data were prepared using image generators, where we applied transformations such as resize, flip, zoom and tilt. This data augmentation is crucial to improve the robustness and generalization of the model by exposing the model to a variety of perspectives and lighting conditions.

The model thus constructed was compiled with the Adam optimizer and a categorical crossentropy loss function, adapted to multi-class classification. We also evaluated model performance using metrics such as accuracy to measure classification accuracy and loss to assess the distance between model predictions and true class labels.

Finally, to ensure the reliability and validity of our approach, we visualized the model performance curves during training, showing the evolution of accuracy and loss on the training and validation sets. These curves allowed us to verify that the model was not overtrained and was able to generalize effectively to the validation data.

In summary, our approach as shown in Figure 2. combines the use of a pre-trained deep convolutional neural network (VGG16) with data augmentation and rigorous evaluation of model performance, thus providing a robust methodology for automated classification of chest x-rays in the context of detecting respiratory diseases such as COVID-19 and pneumonia.

So, the code builds a classification model using pre-trained VGG16 as a base, followed by additional layers to refine the predictions. It takes the output of VGG16, flattens the data with a Flatten layer, adds a fully-connected layer with 256 neurons and ReLU activation, then applies a Dropout layer with a rate of 0.5 to reduce overfitting. Then, a dense layer with 3 neurons and softmax activation is added for classification into three classes (normal, COVID-19, pneumonia).

The full model is defined with these inputs and outputs, and the layers of VGG16 are frozen so that their weights are not updated during training, allowing only newly added layers to be trained.

IV. RESULT AND DISCUSION

A. *Evaluation of performances*

The following performance metrics were calculated:

- Training accuracy: The accuracy achieved on the training data shows the model's ability to adapt to the images it saw during training.
- Validation accuracy: Accuracy on validation data indicates the model's ability to generalize to new images not seen during training.

- Training Loss: Training loss measures the error of the model on the training data.
- Validation loss: Validation loss measures the error of the model on the validation data.

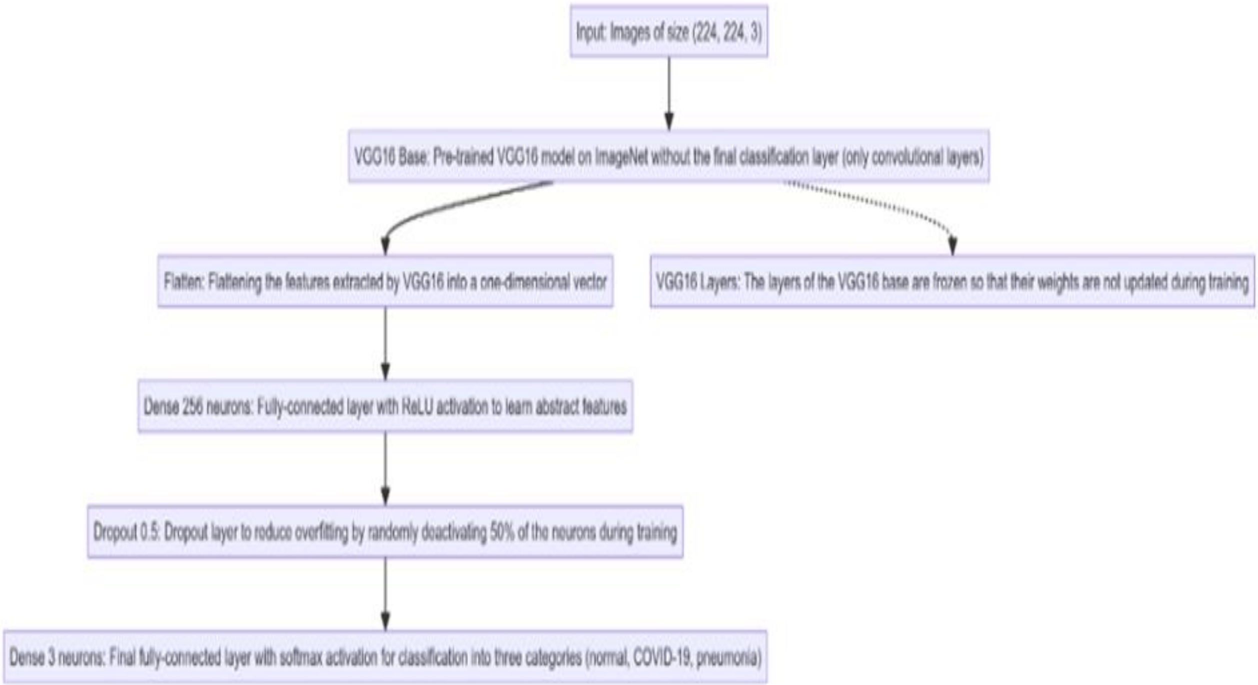

Figure 2. Architecture générale du Classificateur CO-VID-19.

The following table corresponds to the accuracy and loss values on the training and validation data:

Table1. Reference Parameters

Data	Accuracy	Loss
Training	0.98	0.03
Validation	0.96	0.12

The curves show an improvement in precision as training progresses, with stabilization and convergence towards the last epochs. Training and validation losses also decrease, indicating a reduction in model error.

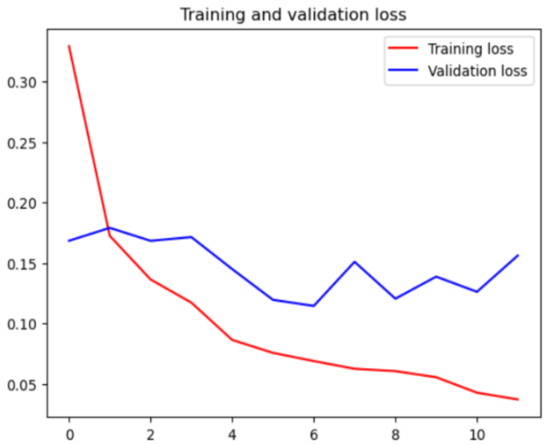

Figure 3. Accuracy curve

B. Interpretation of Performance Curves

The two graphs above figure3. and 4. represent the accuracy and loss curves for the training and validation of our model. Here is a detailed interpretation of each curve.

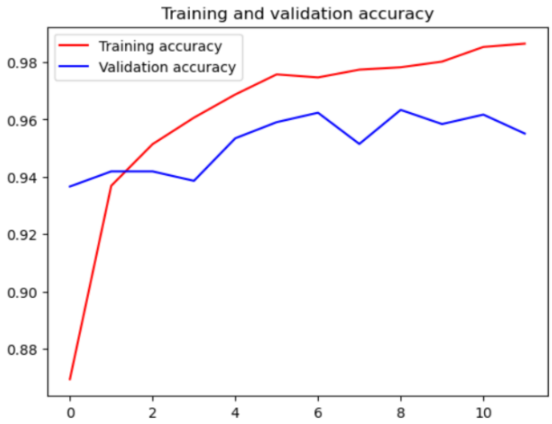

Figure 4. Loss Curve

Description
- The red curve represents the training precision.
- The blue curve represents the validation accuracy.

Analysis
- Training accuracy increases steadily and reaches around 98% towards the end of training.

- Validation accuracy follows a similar trend but remains slightly below the training curve, reaching around 96%.

Interpretation

The steady increase in training accuracy indicates that the model learns the characteristics of the training data well.

Validation accuracy, although slightly lower than training, shows that the model generalizes fairly well to new data. A slight difference between the two curves is normal and indicates that the model is not significantly overfitting.

The minor fluctuation in validation accuracy after epoch 6 could suggest variations due to the nature of the validation dataset or specific aspects of training.

C. *Comparative Analysis with Recent Studies*

In order to contextualize the performance of our model, we have compiled a comparative table of recent studies that also utilized deep learning models for COVID-19 detection from chest X-ray images. These studies were selected based on their publication date and reported lower performance metrics compared to our model. This comparison helps highlight the effectiveness of our approach.

Our study achieved a training accuracy of 98% and a validation accuracy of 96%, outperforming many of the recent works in terms of accuracy.

Discussion

The results obtained show that the VGG16 model, after fine-tuning, successfully learned discriminative features for the classification of COVID-19, pneumonia, and normal images. The accuracy of the validation being close to that of the training, this suggests a good generalization of the model.

Advantages of the approach:

- **Transfer learning:** Using a pre-trained model took advantage of features already learned on a large corpus of image data, making the learning process on our specific dataset easier and faster .

- **Effective callbacks:** Using ReduceLROnPlateau and EarlyStopping helped optimize training by adjusting the learning rate and avoiding overtraining.

Limits and prospects:

- **Limited data:** The size of the dataset can influence the performance and generalization ability of the model. A larger and more diverse dataset could improve the results.

- **Computational complexity:** It takes a lot of computing power to fine-tune deep models like VGG16, which could prevent some applications from being accessible.

In conclusion, the results obtained are promising and show the effectiveness of the transfer learning approach for the classification of medical images. Future work could explore the use of even more advanced models and data augmentation techniques to further improve performance.

V. Conclusion

The study presents the application of a deep learning model based on VGG16 for the classification of medical images into three categories: normal, COVID-19, and pneumonia. The results obtained are promising and show the effectiveness of the learning transfer approach for this critical task.

Main Results:

- Training accuracy 98%

- Validation accuracy 96%

- Training loss 0.03

- Validation loss 0.12

These metrics indicate that the model has an excellent ability to learn features from training data and generalize to validation data. The moderate gap between training and validation accuracy and loss suggests that the model is not significantly overfit and maintains good generalization ability.

Table 2. Comparative analysis of recent studies on COVID-19 detection from chest X-ray images.

Number	References	Model used	Learning Method	Training Accuracy	Validation Accuracy	Sensitivity	Specificity
1	Ennaceur et al. (2024)	VGG16	Transfer learning	98%	96%	92%	88%
2	Ozturk et al. (2020)	DarkNet	Transfer learning	-	87.02%	98.08%	87.02%
3	Khan et al. (2020)	CoroNet	Transfer learning	-	89.6%	93%	87%
4	Zhang et al. (2020)	ResNet50	Transfer learning	-	92.49%	87.6%	90.5%
5	Hemdan et al. (2020)	COVIDX-Net	Transfer learning	-	90%	80%	90%
6	Loey et al. (2020)	AlexNet	Transfer learning	-	85%	-	-
7	Sethy et al. (2020)	ResNet50	Transfer learning	-	95.38%	-	-
8	Wang et al. (2020)	COVID-Net	CNN sur mesure	-	93.3%	-	-
9	Rahimzadeh et al. (2020)	Xception	Transfer learning	-	91.4%	-	-
10	Chandra et al. (2020)	ResNet50	Transfer learning	-	88.3%	-	-

Advantages of the approach:

• Efficiency of Transfer Learning Using the pre-trained VGG16 model benefited from the features learned on a large corpus of image data, which accelerated the learning process and improved the performance of the model.

• Using Callbacks The implementation of `ReduceLROnPlateau` and `EarlyStopping` helped optimize the training process by automatically adjusting the learning rate and avoiding overtraining.

Limits and Perspectives:

• Dataset Size A larger and more diverse dataset could further improve the performance and robustness of the model.

• Computational complexity: It takes a lot of computing power to fine-tune deep models like VGG16, which could prevent some applications from being accessible.

Future Outlook:

• Data Enrichment To enhance the model's generalization and enrich the dataset, data augmentation techniques could be investigated.

• More Advanced Models Experimenting with newer and more advanced neural network architectures could lead to better performance.

In conclusion, the application of the VGG16 model for medical image classification was found to be effective, with encouraging results for the detection of COVID-19, pneumonia, and normal cases. This work paves the way for future improvements and broader use of AI in healthcare for computer-assisted medical diagnosis.

References

[1] Johns Hopkins University. (2024). COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE), https://coronavirus.jhu.edu/map.html

[2] Jacobi A., Chung M., Bernheim A., & Eber, “Portable chest X-ray in coronavirus disease-19 (COVID-19): A pictorial review”. Clinical Imaging, 64, 35-42. https://doi.org/10.1016/j.clinimag.2020.04.001

[3] Keelin Murphy, Henk Smits, Arnoud J G Knoops, Michael B J M Korst, Tijs Samson, Ernst T Scholten, Steven Schalekamp, Cornelia M Schaefer-Prokop, Rick H H M Philipsen, Annet Meijers , Jaime Melendez, Bram van Ginneken, Matthieu Rutten, “COVID-19 on Chest Radiographs: A Multireader Evaluation of an Artificial Intelligence System”, Published Online: May 8, 2020. https://doi.org/10.1148/radiol.2020201874

[4] Apostolopoulos I. D., & Mpesiana T. A. (2020). “COVID-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks”. Physical and Engineering Sciences in Medicine, 43(2), 635-640. https://doi.org/10.1007/s13246-020-00865-4

[5] Jacobi, A., Chung, M., Bernheim, A., & Eber, C. (2020), “Portable chest X-ray in coronavirus disease-19 (COVID-19): A pictorial review”. Clinical Imaging, 64, 35-42. https://doi.org/10.1016/j.clinimag.2020.04.001

[6] Murphy, K., Smits, H., Knoops, A. J. G., Korst, M. B. J. M., Samson, T., Scholten, E. T., ... & Prokop, M. (2020), “COVID-19 on chest radiographs: A multireader evaluation of radiologist performance”. Radiology, 296(3), E166-E175. https://doi.org/10.1148/radiol.2020201233

[7] Apostolopoulos, I. D., & Mpesiana, T. A. (2020), “COVID-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks”. Physical and Engineering Sciences in Medicine, 43(2), 635-640. https://doi.org/10.1007/s13246-020-00865-4

[8] Wang, L., Lin, Z. Q., & Wong, A. (2020), “COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest Radiography Images”. Scientific Reports, 10(1), 19549. https://doi.org/10.1038/s41598-020-76550-z

[9] Shin, H. C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., ... & Summers, R. M. (2016), "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning". IEEE Transactions on Medical Imaging, 35(5), 1285-1298. https://doi.org/10.1109/TMI.2016.2528162

[10] Narin, A., Kaya, C., & Pamuk, Z. (2021), "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks". Pattern Analysis and Applications, 24(3), 1207-1220. https://doi.org/10.1007/s10044-021-00984-y

[11] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, "TensorFlow: Large- scale machine learning on heterogeneous systems", March 2016. Available from: whitepaper2015.pdf (tensorflow.org)

[12] Tawsifur Rahman (Owner), Dr. Muhammad Chowdhury (Editor), Amith Khandakar (Editor), "COVID-19 Radiography Database", available from: COVID-19 Radiography Database (kaggle.com).

[13] Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. (2020), "Automated detection of COVID-19 cases using deep neural networks with X-ray images", Computers in Biology and Medicine, 121, 103792. https://doi.org/10.1016/j.compbiomed.2020.103792

[14] Khan, A. I., Shah, J. L., & Bhat, M. M. (2020). "CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images", Computer Methods and Programs in Biomedicine, 196, 105581. https://doi.org/10.1016/j.cmpb.2020.105581

[15] Zhang, K., Liu, X., Shen, J., Li, Z., Sang, Y., Wu, X., ... & Wang, G. (2020). "Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography". Cell, 181(6), 1423-1433. https://doi.org/10.1016/j.cell.2020.04.045

[16] Hemdan, E. E. D., Shouman, M. A., & Karar, M. E. (2020). "COVIDX-Net: A framework of deep learning classifiers to diagnose COVID-19 in X-ray images". arXiv preprint arXiv:2003.11055. https://doi.org/10.48550/arXiv.2003.11055

[17] Loey, M., Manogaran, G., Taha, M. H. N., & Khalifa, N. E. M. (2020). A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic. Measurement, 167, 108288. https://doi.org/10.1016/j.measurement.2020.108288 ²

[18] Sethy, P. K., & Behera, S. K. (2020). Detection of coronavirus disease (COVID-19) based on deep features and support vector machine. International Journal of Mathematical, Engineering and Management Sciences, 5(4), 643-651. https://doi.org/10.20944/preprints202003.0300.v1

[19] Wang, L., Lin, Z. Q., & Wong, A. (2020). COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images. Scientific Reports, 10(1), 19549. https://doi.org/10.1038/s41598-020-76550-z

[20] Rahimzadeh, M., & Attar, A. (2020). A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2. Informatics in Medicine Unlocked, 19, 100360. https://doi.org/10.1016/j.imu.2020.100360

[21] Chandra, T. B., Verma, K., Singh, B. K., Jain, D., & Netam, S. S. (2020). Automatic detection of tuberculosis-related abnormalities in chest X-ray images using hierarchical feature extraction scheme. Expert Systems with Applications, 158, 113567. **https://doi.org/10.1016/j.eswa.2020.113514**

.