African Journal of
Management Engineering
and Technology

Afr. J. Manag. Engin. Technol., 2024, Vol. 2, N° 2, 100-108

Copyright © 2024,
SupMoTI Rabat
Morocco

Advancements in Transfer Learning Models: A Robust Framework for Precise COVID-19 Detection in X-Ray Images

El-Gannour O. [1, 2]***, Hamida S.** [3, 4]**, Cherradi B.** [2, 5]

[1] *LIASSE Laboratory, ENSA of Fez, Sidi Mohamed Ben Abdellah University, Fez, Morocco.*

[2] *EEIS Laboratory, ENSET of Mohammedia, Hassan II University of Casablanca, Mohammedia, Morocco.*

[3] *GENIUS Laboratory, SupMTI of Rabat Rabat, Morocco.*

[4] *2IACS Laboratory, ENSET of Mohammedia, Hassan II University of Casablanca, Mohammedia, Morocco.*

[5] *CRMEF Casablanca-Settat, provincial section of El Jadida, 24000, El Jadida, Morocco*

**Corresponding author, Email address: oussama.elgannour@gmail.com*

Received *18 Aug 2023,*
Revised *02 Sept 2023,*
Accepted *03 Sept 2023*

Citation*: El-Gannour O., Hamida S., Cherradi B. (2024) Advancements in Transfer Learning Models: A Robust Framework for Precise COVID-19 Detection in X-Ray Images, Afr. J. Manag. Engg. Technol., 2(2), 100-108.*

Abstract: A new coronavirus pandemic, known as COVID-19, first appeared in Wuhan, China, and caused a worldwide health emergency. The virus spread quickly and was characterised by common symptoms like fever, coughing, and respiratory discomfort. To address the urgent demand for effective diagnostic instruments, this research study presents a Deep Learning-based system designed for COVID-19 illness detection. Using six pre-trained models, the suggested diagnostic system makes use of the Transfer Learning technique to maximise performance by utilising experience. The Deep Learning system's performance evaluation confirms the Xception neural network's superior accuracy in identifying COVID-19 cases in the studied dataset. Notably, the system achieves commendable metrics, with an accuracy rate of 98% and a sensitivity rate of 100%.

Keywords: *Transfer Learning; Detection of COVID-19; X-Ray Imaging; Machine Learning; Medical Image Analysis*

1. Introduction

A broad class of viruses known as coronaviruses causes a range of diseases in humans. MERS-CoV and SARS-CoV have become particularly serious worldwide health issues among them (Aleebrahim-Dehkordi *et al.*, 2021; Diass *et al.*, 2023). Wuhan, China, was the first place to report on the COVID-19 pandemic (Kang *et al.*, 2020), which was brought on by a new coronavirus. It spread quickly around the world, infecting seven million people, and killing over 400,000 by June 10th, 2020. Breathing difficulties, fever, coughing, shortness of breath, and respiratory signs are among the clinical symptoms linked to COVID-19. The virus is mainly propagated by respiratory droplets that are transferred by surfaces or direct physical contact; therefore, early discovery is essential for efficient isolation and containment.

To speed up diagnosis and stop the pandemic's spread, medical imaging technologies, including computed tomography (CT) and chest X-Rays (CXR), were investigated in addition to traditional detection techniques like the laborious RT-PCR methodology (La Marca *et al.*, 2020). New technologies are essential to reducing the pandemic's effects, especially those that use artificial intelligence (AI). Drone-based disinfection, facial recognition to track afflicted individuals, thermal cameras to detect high temperatures, and smartphone applications to track contacts are some of the innovations. In a variety of medical applications (Terrada, Cherradi, Raihani, *et al.*, 2020; Terrada, Hamida, *et al.*, 2020), such as brain tumour segmentation (Ait Ali *et al.*, 2018; Ali *et al.*, 2019; Bouattane *et al.*, 2011), heart disease prediction (Terrada, Cherradi, Hamida, *et al.*, 2020), and breast cancer diagnosis (Laghmati *et al.*, 2020), machine learning (ML) methods have proven to be highly accurate.

In this research, we use medical pictures from X-Rays and CT scans to quickly diagnose COVID-19 using Deep Learning (DL), more specifically Transfer Learning (TL). For effective and precise diagnosis, an intelligent system using six Convolutional Neural Network (CNN)-based TL models (VGG16, VGG19, InceptionV3, Xception, ResNet50V2, and MobileNetV2) is suggested. The dataset, which includes 2905 radiography pictures classified into classes for COVID-19, Normal, and Viral Pneumonia, makes it easier to train and validate the TL models.

Section III of the paper elaborates on the dataset, CNN-based TL models, and the technique underlying the COVID-19 diagnosis system. The following sections of the paper outline similar works in Section II. Metrics for performance evaluation and experimental findings are covered in detail in Section IV. Section V offers insights into potential future directions as the article comes to a close.

2. Literature Review

The COVID-19 pandemic has sparked a wave of research projects aimed at using artificial intelligence (AI) to automatically identify COVID-19 patients from X-Ray pictures (Jemioło *et al.*, 2022). An extensive summary of recent research in this field is given in the section that follows, together with insights into various approaches and their corresponding successes.

- ***DarkNet classifier System***

Researchers unveiled a detection approach for COVID-19 identification in (Ozturk *et al.*, 2020) that uses the DarkNet classifier. This work used an IEEE database that is accessible on GitHub to achieve an accuracy of 98.08% for binary classes (COVID-19, Normal), demonstrating the potential of non-traditional classifiers.

- ***Comparison of TL Models***

For COVID-19 detection, a study described in (Moujahid *et al.*, 2020) compared three Transfer Learning (TL) models: VGG16, VGG19, and MobileNetV2. Focusing on a database with three classifications (COVID-19, Normal, and Pneumonia), VGG19 showed itself to be the most promising model, with a 96.97% accuracy rate.

- ***Bayes-SqueezeNet-Based Convolutional Neural Networks***

A convolutional neural network model with Bayes-SqueezeNet transfer learning was presented in (Ucar & Korkmaz, 2020). This method, which was based on two combined multi-class datasets, demonstrated the effectiveness of hybrid neural network architectures with an impressive classification rate of almost 97.3%.

- ***Comparing TL Algorithms***

As reported in (Apostolopoulos & Mpesiana, 2020), a notable study also conducted a thorough comparison of TL algorithms, encompassing VGG19, MobileNetV2, Inception, Xception, and ResNetV2. The best option turned out to be the MobileNet model, which achieved an accuracy of 94.72% on two carefully chosen datasets.

- ***Evaluation of Four Models' Performance***

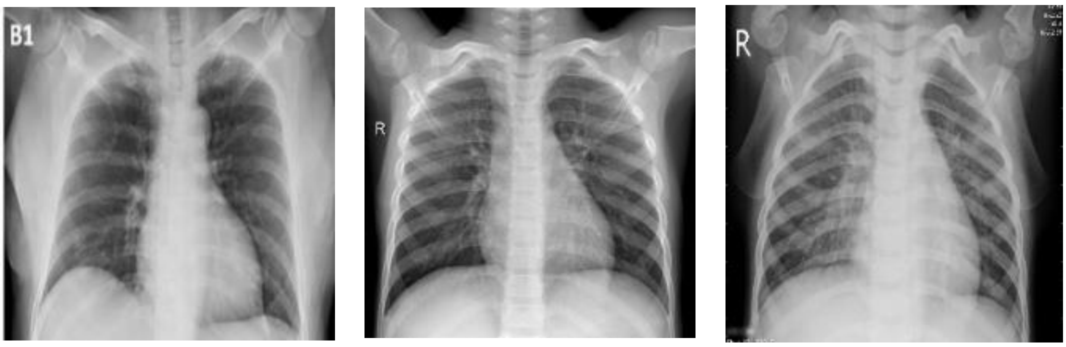
Four models—Convolutional Neural Network (CNN) with MODE, CNN, Artificial Neural Network (ANN), and Adaptive Neuro-Fuzzy Inference System (ANFIS)—were evaluated for COVID-19 diagnosis in (Singh *et al.*, 2020). According to their research, the MODE model performed better than other models in identifying COVID-19-positive patients.

The combined knowledge gained from these research projects served as the foundation for our study of the effectiveness of a Transfer Learning method for automatically identifying COVID-19 patients from X-Ray pictures. Our suggested method seeks to advance precise and quick diagnostic solutions in the midst of the ongoing global health crisis by building on the advantages and resolving the drawbacks noted in the body of current literature.

3. Materials and Methods

3.1 Data Collection and Preprocessing

The COVID-19 Radiography Database, a freely accessible repository accessible through the Kaggle platform, is the source of the dataset used in this study. This database was created through teamwork under the direction of a research team from the University of Doha in Qatar. The dataset is a tripartite classification that includes 219 photos that are positive for COVID-19, 1341 images that are normal, and 1345 images that are pneumonia. **Figure 1** shows a graphic depiction of the data samples that clarifies the distribution within the designated classes. Interestingly, every image in this database is in PNG format and has a consistent 1024 × 1024-pixel dimension. **Table 1** provides an explanation of the architectural attributes of the dataset, providing a thorough understanding of its features and organisational structure. This carefully selected dataset is the basis of our research, enabling thorough examination and evaluation within the framework of COVID-19 automatic detection from X-Ray pictures.



a) b) c)

Figure 1. Some samples of the images from the X-Ray dataset used. a) COVID-19 sample. b) Normal sample. c) Viral Pneumonia sample.

Table 1. Description of the data samples available in the COVID-19 radiography database

Dataset	Class	X-Ray Images	Training	Validation	Testing
COVID-19 Radiography Database	COVID-19	219	175	22	22
	Normal	1341	1073	134	134
	Pneumonia	1345	1076	135	134
	Total	2905	2324	291	290

3.2 Deep neural networks

Neural networks are among the most sophisticated models in machine learning; their complexity exceeds that of other traditional models (Schmidhuber, 2015). These networks are distinguished by the way they express complex mathematical functions—many of which have millions of parameters. A deep network, which consists of three to ten layers of coupled neurons, is often included in neural network architectures. An illustration of a Deep Neural Network (DNN) configuration is shown in **Figure 2**. There are three hidden layers, an output layer, and an input layer in this DNN instantiation. Neural networks are especially good at performing complicated tasks and identifying complex dependencies because of their multilayered structure, which enables them to capture complex patterns and interactions within the data.

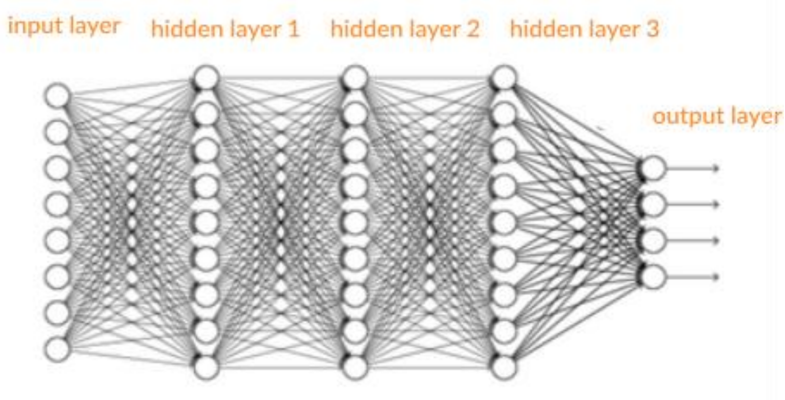


Figure 2. A deep neural network with three hidden layers.

3.3 Transfer Learning Models Selection

Transfer learning is an automated learning approach that makes it easier to transfer learned information from one source dataset to another, providing a starting point for more advanced processing of a new dataset (Tan *et al.*, 2018). **Figure 3** provides an architectural representation of the Transfer Learning model and illustrates the process by which information is moved from the first model (called Model 1) to the second model (called Model 2). By utilising the knowledge obtained from the original dataset, this method maximises the new model's ability to handle a different dataset. By strategically utilising prior information, the transfer of knowledge from Model 1 to Model 2 promotes more effective learning and adaptability to novel data patterns and characteristics.

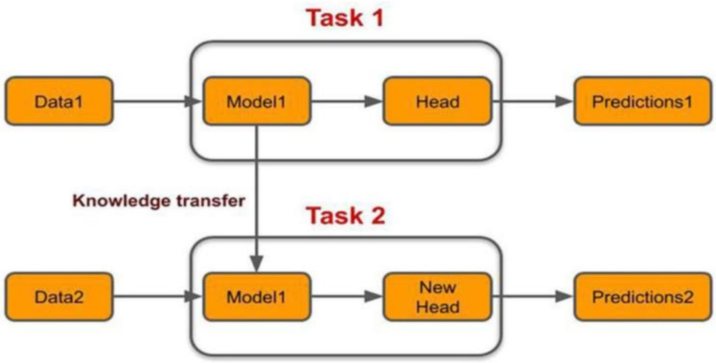


Figure 3. Architecture of Transfer Learning based models.

3.4 Experimental Design

Commencing our study, we must first preprocess our dataset of X-Ray images, which is an essential first step for most machine learning activities. Image cleaning and normalisation are included in this preprocessing to maximise and facilitate the use of the images in further analysis. Improving the recognition rate that the machine learning model achieves is the primary goal. The final pictures obtained from this preprocessing stage are then utilised in the training and validation procedures for the six Transfer Learning (TL) models that are being examined. The architectural workflow that is shown in **Figure 4** outlines the important phases that go into building our diagnostic system.

The X-Ray training dataset is used to train the six TL models (VGG16, VGG19, InceptionV3, Xception, ResNet50V2, and MobileNetV2) in this architectural framework. To reduce the possibility of overfitting, the training procedure is verified using a different validation dataset after the model is constructed. During the assessment step, each model's classification performance is evaluated using a specific test dataset. Confusion matrix development and the calculation of pertinent score metrics are included in performance evaluation. By means of this thorough examination, the best-performing model is identified, resulting in an efficient and well-designed diagnostic system architecture for the automated detection of COVID-19 in X-Ray pictures.

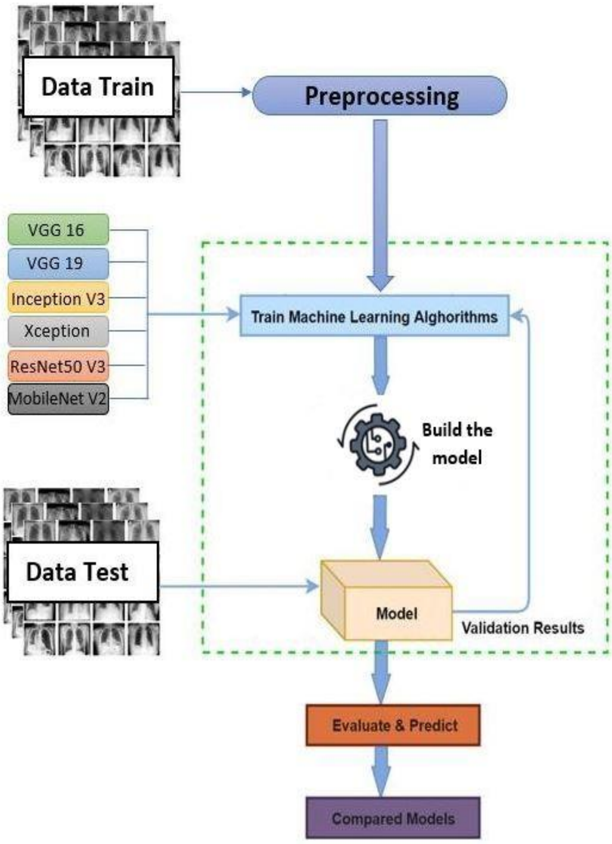


Figure 4. Proposed model diagram.

4. Experimental Results

4.1 Performance Metrics and Evaluation

In this section, we explicate the metrics utilised in the thorough assessment of the CNN models that comprise our diagnostic framework. An essential tool for assessing the effectiveness of machine learning models is the confusion matrix, especially when it comes to categorization issues. This matrix carefully evaluates how often the actual labels in the dataset match the predictions made by the model. Using both the actual labels from the dataset and the labels the classification models predicted, the confusion matrix is constructed. A complete knowledge of the confusion matrix process requires a detailed awareness of four essential terminologies: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The precise definitions and interpretations of these terms are meticulously outlined in **Table 2**, contributing to a meticulous and standardised assessment of the CNN model's performance within our diagnostic framework.

Table 2. Description of confusion matrix elements

Confusion matrix elements	Description
TP (True Positives)	Denotes number of patients that are correctly predicted as COVID-19.
TN (True Negatives)	Denotes number of patients that are correctly predicted as not COVID-19.
FN (False Negative)	Denotes number of patients that are incorrectly predicted as not COVID-19.
FP (False Positive)	Denotes number of patients that are incorrectly predicted as COVID-19.

To evaluate the performance of the chosen Transfer Learning (TL) models in our study, we computed four assessment metrics: accuracy, specificity, sensitivity, and precision.

4.2 Implementation Environment

This work integrates models based on Transfer Learning (TL) that are implemented in the Google Colab environment, a cloud service intended for training and research in machine learning (ML). The computational infrastructure consists of an Intel Xeon Processor with two 2.20 GHz cores, 13 GB of RAM, and a Tesla K80 GPU with 12GB of GDDR5 VRAM. **Table 3** presents the parameters of the learning algorithms that were used to train and evaluate these models in a methodical manner. Interestingly, every photograph in the database has a common size of 300 by 300 pixels. In the context of automatic COVID-19 identification in X-Ray pictures, this infrastructure design guarantees a stable and standardised computational environment for the thorough investigation and evaluation of the TL-based models.

Table 3. The CNN models hyperparameters

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

4.3 Comparative Analysis of Transfer Learning Models

The classification performance of all models in our investigation is quite good, as evidenced by the balanced distribution of True Positives (TP) in relation to False Positives (FP) and False Negatives (FN) for every class. Interestingly, compared to other classes, the Transfer Learning (TL) models consistently show lower FP and FN values for the COVID-19 class, indicating a lesser probability of misclassifying COVID-19 cases. In addition, the models VGG16, Xception, ResNet50V2, and MobileNetV2 demonstrate a significant lack of False Positives (FP=0), indicating a high degree of dependability in identifying COVID-19 cases. The confusion matrix of the Xception TL model illustrates its superior classification performance for radiological pictures, making it the most effective model.

A wide range of evaluation criteria, such as the models' sensitivity, specificity, accuracy, and precision, are shown in Table 6. Surprisingly, all TL classification models obtain significant precision levels of 98% to 97%; for the COVID-19 class, VGG19, Xception, ResNet50V2, and MobileNetV2 attain 100% precision. One further way that the Xception model sets itself apart is that it achieves 100% sensitivity for the COVID-19 class. For the majority of models in the Normal class, precision values are around 99%; the exception is InceptionV3, which achieves 100%. For all models, the

Normal class's sensitivity levels vary from 96% to 98%. For every class, the specificity metric is consistently high, ranging from 95% to 100%. Within the parameters of this investigation, the extensive results shown in **Table 4** confirm the effectiveness of the Xception network in automatically detecting COVID-19 in X-Ray pictures by highlighting its exceptional classification ability.

Table 4. The CNN models hyperparameters: Accuracy, Precision, Sensitivity and Specificity

Models	Accuracy	CD-19 Prec.	Normal Prec.	Viral Pn Prec.	CD-19 Sens.	Normal Sens.	Viral Pn Sens.	CD-19 Spec.	Normal Spec.	Viral Pn Spec.
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%

Key insights into the assessment and performance dynamics of the Xception model are summarised in **Figures 5 and 6**. In particular, **Figure 5** illustrates the confusion matrix that was created based on the test results and offers a thorough summary of how well the model performed in terms of categorization in various categories. This matrix provides a comprehensive insight of the model's performance by allowing a thorough analysis into True Positives, True Negatives, False Positives, and False Negatives.

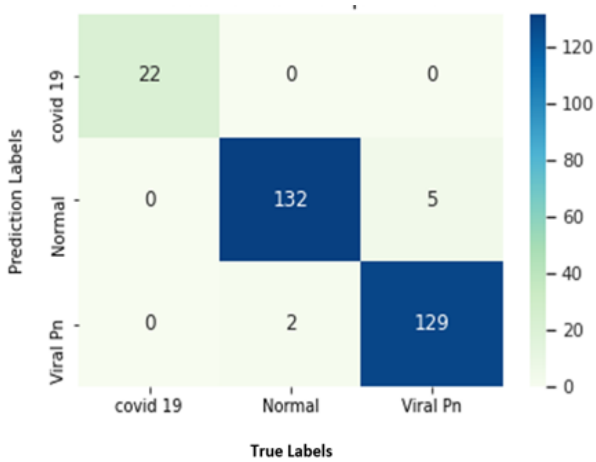


Figure 5. Confusion matrix of Xception model.

Simultaneously, **Figure 6** presents the performance curve, which depicts the course of the model's effectiveness during the training and validation stages. The curve allows for a visual evaluation of the convergence and generalisation abilities of the model by encapsulating important metrics and their progression across subsequent iterations. When taken as a whole, these figures provide a thorough and visual depiction of the training dynamics and classification performance of the Xception model, which is essential for a full examination within the framework of our study's science.

4.4 Discussion of Findings

Throughout this study, we present a classification model based on the performance assessment of six Transfer Learning (TL) models: VGG16, VGG19, InceptionV3, Xception, ResNet50V2, and MobileNetV2. We methodically create confusion matrices and then calculate important statistical assessment metrics including accuracy, sensitivity, and specificity by using a dataset that includes 219 COVID-19 images, 1341 Normal images, and 1345 pneumonia images. Examining the results, which are shown in Table 6, shows that the Xception model is especially good at classification—it can do so much better than the other models. Remarkably, all models routinely attain high levels of precision, ranging from 97% to 98%. Surprisingly, our research achieves a higher accuracy rate than previous studies.

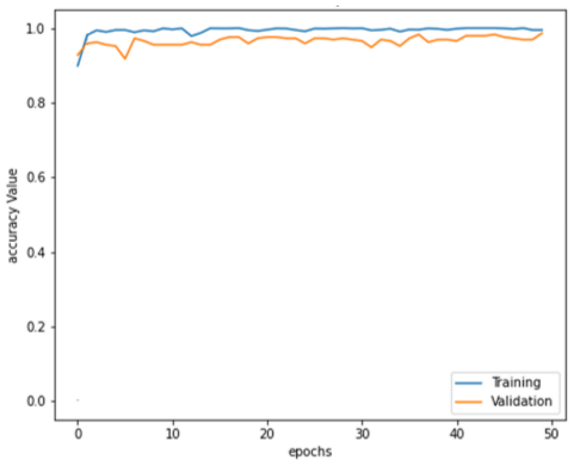


Figure 6. Xception model performance.

Conclusion and perspectives

In synthesis, our study introduces a COVID-19 detection system grounded in the analysis of X-Ray image datasets. Employing six Transfer Learning models, the investigation entails training and validation procedures conducted on a Kaggle-acquired dataset of X-Ray images. The Xception model emerges as the most proficient classifier within this framework, yielding accuracy and sensitivity rates of 98% and 100%, respectively. Our future research trajectory will pivot towards the development of an enhanced model, capitalising on the concatenation of two Transfer Learning models with the overarching goal of augmenting diagnostic precision. This strategic augmentation aims to further refine the system's efficacy, ensuring a more discerning and efficient diagnosis of COVID-19 cases.

References

Ait Ali, N., Cherradi, B., El Abbassi, A., Bouattane, O., & Youssfi, M. (2018). GPU fuzzy c-means algorithm implementations : Performance analysis on medical image segmentation. *Multimedia Tools and Applications*, 77(16), Article 16. https://doi.org/10.1007/s11042-017-5589-6

Aleebrahim-Dehkordi E, Soveyzi F, Deravi N, Rabbani Z, Saghazadeh A, Rezaei N. (2021) Human Coronaviruses SARS-CoV, MERS-CoV, and SARS-CoV-2 in Children. *J. Pediatr. Nurs.*, 56, 70-79. https://doi.org/10.1016/j.pedn.2020.10.020

Ali, N. A., Cherradi, B., El Abbassi, A., Bouattane, O., & Youssfi, M. (2019). Parallel Implementation and Performance Evaluation of some Supervised Clustering Algorithms for MRI Images Segmentation. *Proceedings of the 4th International Conference on Big Data and Internet of Things*, 1-7. https://doi.org/10.1145/3372938.3373007

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

Bouattane, O., Cherradi, B., Youssfi, M., & Bensalah, M. O. (2011). Parallel c-means algorithm for image segmentation on a reconfigurable mesh computer. *Parallel Computing*, 37(4), Article 4. https://doi.org/10.1016/j.parco.2011.03.001

Diass K., Oualdi I., Dalli M., Azizi S.-Ed, *et al*. (2023) Artemisia herba alba Essential Oil: GC/MS analysis, antioxidant activities with molecular docking on S protein of SARS-CoV-2, *Indonesian Journal of Science & Technology*, 8(1), 1-18, https://doi.org/10.17509/ijost.v8i1.50737

Jemioło P, Storman D, Orzechowski P. Artificial Intelligence for COVID-19 Detection in Medical Imaging-Diagnostic Measures and Wasting-A Systematic Umbrella Review. *J. Clin. Med.*, 11(7), 2054. https://doi.org/10.3390/jcm11072054

Kang, D., Choi, H., Kim, J.-H., Choi, J. (2020). Spatial epidemic dynamics of the COVID-19 outbreak in China. *International Journal of Infectious Diseases*, 94, 96-102. https://doi.org/10.1016/j.ijid.2020.03.076

La Marca, A., Capuzzo, M., Paglia, T., *et al*. (2020). Testing for SARS-CoV-2 (COVID-19) : A systematic review and clinical guide to molecular and serological in-vitro diagnostic assays. *Reproductive BioMedicine Online*, S1472648320303187. https://doi.org/10.1016/j.rbmo.2020.06.001

Laghmati, S., Cherradi, B., Tmiri, A., Daanouni, O., & Hamida, S. (2020). Classification of Patients with Breast Cancer using Neighbourhood Component Analysis and Supervised Machine Learning Techniques. 2020 3rd International Conference on Advanced Communication Technologies and Networking (CommNet), Marrakech, Morocco. https://doi.org/10.1109/CommNet49926.2020.9199633

Moujahid, H., Cherradi, B., Bahatti, L., Terrada, O., Hamida, S. (2020). Convolutional Neural Network Based Classification of Patients with Pneumonia using X-ray Lung Images. *Advances in Science, Technology and Engineering Systems Journal*, 167-175.

Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Rajendra Acharya, U. (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

Schmidhuber, J. (2015). Deep learning in neural networks : An overview. *Neural Networks*, 61, 85-117. https://doi.org/10.1016/j.neunet.2014.09.003

Singh, D., Kumar, V., Vaishali, & Kaur, M. (2020). Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks. *European Journal of Clinical Microbiology & Infectious Diseases*. https://doi.org/10.1007/s10096-020-03901-z

Tan, C., Sun, F., Kong, T., Zhang, W., Yang, C., & Liu, C. (2018). A Survey on Deep Transfer Learning. *arXiv*:1808.01974 [cs, stat]. http://arxiv.org/abs/1808.01974

Terrada, O., Cherradi, B., Hamida, S., Raihani, A., Moujahid, H., & Bouattane, O. (2020). Prediction of Patients with Heart Disease using Artificial Neural Network and Adaptive Boosting techniques. 2020 3rd International Conference on Advanced Communication Technologies and Networking (CommNet). https://doi.org/10.1109/CommNet49926.2020.9199620

Terrada, O., Cherradi, B., Raihani, A., Bouattane, O. (2020). Atherosclerosis disease prediction using Supervised Machine Learning Techniques. *2020 1st International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, 1-5. https://doi.org/10.1109/IRASET48871.2020.9092082

Terrada, O., Hamida, S., Cherradi, B., Raihani, A., & Bouattane, O. (2020). Supervised Machine Learning Based Medical Diagnosis Support System for Prediction of Patients with Heart Disease. *Advances in Science, Technology and Engineering Systems Journal*, 269-277.

Ucar, F., & Korkmaz, D. (2020). COVIDiagnosis-Net : Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images. *Medical Hypotheses*, 140, 109761. https://doi.org/10.1016/j.mehy.2020.109761

(2024) ; https://revues.imist.ma/index.php/ajmet/index