COVID-19 Detection on X-Ray Images using a Combining Mechanism of Pre-trained CNNs

Oussama El Gannour[1], Soufiane Hamida[2], Shawki Saleh[3], Yasser Lamalem[4], Bouchaib Cherradi[5], Abdelhadi Raihani[6]
EEIS Laboratory, ENSET of Mohammedia, Hassan II University of Casablanca, Mohammedia, Morocco[1,2,3,5,6]
Computer research laboratory (L@RI), Ibn Tofail University of Kenitra, Kenitra, Morocco[4]
STIE Team, CRMEF Casablanca-Settat, El Jadida, Morocco[5]

***Abstract*—The COVID-19 infection was sparked by the severe acute respiratory syndrome SARS-CoV-2, as mentioned by the World Health Organization, and originated in Wuhan, Republic of China, eventually extending to every nation worldwide in 2020. This research aims to establish an efficient Medical Diagnosis Support System (MDSS) for recognizing COVID-19 in chest radiography with X-ray data. To build an ever more efficient classifier, this MDSS employs the concatenation mechanism to merge pretrained convolutional neural networks (CNNs) predicated on Transfer Learning (TL) classifiers. In the feature extraction phase, this proposed classifier employs a parallel deep feature extraction approach based on Deep Learning (DL). As a result, this approach increases the accuracy of our proposed model, thus identifying COVID-19 cases with higher accuracy. The suggested concatenation classifier was trained and validated using a Chest Radiography image database with four categories: COVID-19, Normal, Pneumonia, and Tuberculosis during this research. Furthermore, we integrated four separate public X-Ray imaging datasets to construct this dataset. In contrast, our mentioned concatenation classifier achieved 99.66% accuracy and 99.48% sensitivity respectively.**

Keywords—COVID-19; deep learning; transfer learning; feature extraction; concatenation technique

I. INTRODUCTION

A group of viruses named Coronaviruses, which includes MERS-CoV, SARS-CoV, and finally SARS-CoV-2, are likely reasons for mild to severe respiratory illnesses [1]. As reported in the report from the World Health Organization, the COVID-19 infection was espoused by the severe acute respiratory syndrome SARS-CoV-2 and originated in Wuhan, Republic of China, before spreading to every country and territory throughout the world in 2020 [2]–[4]. Furthermore, in the preliminary days of SARS-CoV-2, various respiratory symptoms including hyperthermia, cough, shortness of breath, exhaustion, and finally pneumonia are frequent [5], [6]. COVID-19 influences the cardiovascular and respiratory systems, and in extreme situations, it might result in multiple organ dysfunction syndrome or acute respiratory distress.

As a necessary consequence, COVID-19 diseases have become a major health concern that has spread globally. As a result, emerging innovations are important in preventing the outbreak of the epidemic. For these reasons, researchers throughout the world collaborate and work on strategies to overcome the virus's obstacles. In particular, new Artificial Intelligence (AI)-based methods can eliminate interpersonal physical-contact [7]–[11]. Drones, for instance, might be used to sterilize public areas and thermal cameras could be used to detect rising temperatures.

In reality, the two subsets of AI are employed to health data analysis: the first subset is Machine Learning (ML) and the second is Deep Learning (DL) approaches, including radiography images or computed tomography scans, have been shown to be useful on detection of illness and monitoring [12]–[14], [15]–[17]. As a result, various types of human maladies, like as Parkinson's disease [18]–[21], brain tumor segmentation [22], [23], breast cancer [24], diabetes [25], medical image segmentation [26], and heart disease prediction [27]–[30], atherosclerosis diseases [31], could be identified using such techniques. AI advancements have also contributed in the development of a wide range of other scientific fields [32]–[34], [35]–[39].

This research focuses to establish a consistent MDSS [40] for monitoring COVID-19 in Chest Radiography data from a variety of virus diseases and pulmonary infections [41]–[44]. The essential innovation of this MDSS is the employment of the concatenation mechanism to merge pretrained convolutional neural networks (CNNs) predicated on Transfer Learning (TL) techniques to generate an efficient classifier. As a result, we integrated four separate X-Ray image databases in this work to introduce a further dataset, containing four categories: COVID-19, Viral Pneumonia, Normal, and finally Tuberculosis. Our suggested classifier was trained and validated using this novel dataset.

The remainder of this paper is organized as follows: The materials and methods are presented in Section II. The experimental results and discussion are presented in Section III. Finally, in Section IV, we conclude our work with some future research prospects.

II. MATERIALS AND METHODS

A. Schematic of the Planned COVID-19 Monitoring MDSS

We present, in this research, an automated method for classifying COVID-19 cases predicated on different TL classifiers (Fig. 1). This automated approach proposed is founded on the concatenation mechanism among two pretrained classifiers of the TL approach. This approach integrates the information taken from both Base-Models to construct the final classification result, which improves performance. To begin, we use the Keras library to choose two pre-trained classifiers (VGG16 and VGG19). The training and testing datasets of chest X-Ray images were produced using four main public databases. COVID-19, Normal, Pneumonia, and Tuberculosis cases are included in this dataset. The pictures in the produced database are subjected to a series of preprocessing operations. By using the default channel of the network's input structure, all the Chest Radiography images were standardized to similarly input sizes (224×224×3).

In this architecture, the X-Ray training dataset is used to train our proposed concatenation classifier. We employ a cross-validation approach to validate the training phase after we have constructed the classifier to prevent the over-fitting problem. Our proposed classifiers' classification results were then evaluated using the testing dataset. Finally, the suggested concatenation classifier's performance was assessed using confusion matrices and a variety of score measures.

B. Dataset Description

This subsection gives a summary of the datasets used during this research. This work was focused on the gathering and analysis of four public databases separated into four classifications: "COVID-19", "Tuberculosis", "Normal", and finally "Viral Pneumonia". The final dataset employed is mentioned in Table I. We exhibit different exemplary instances of the obtained dataset in Fig. 2.

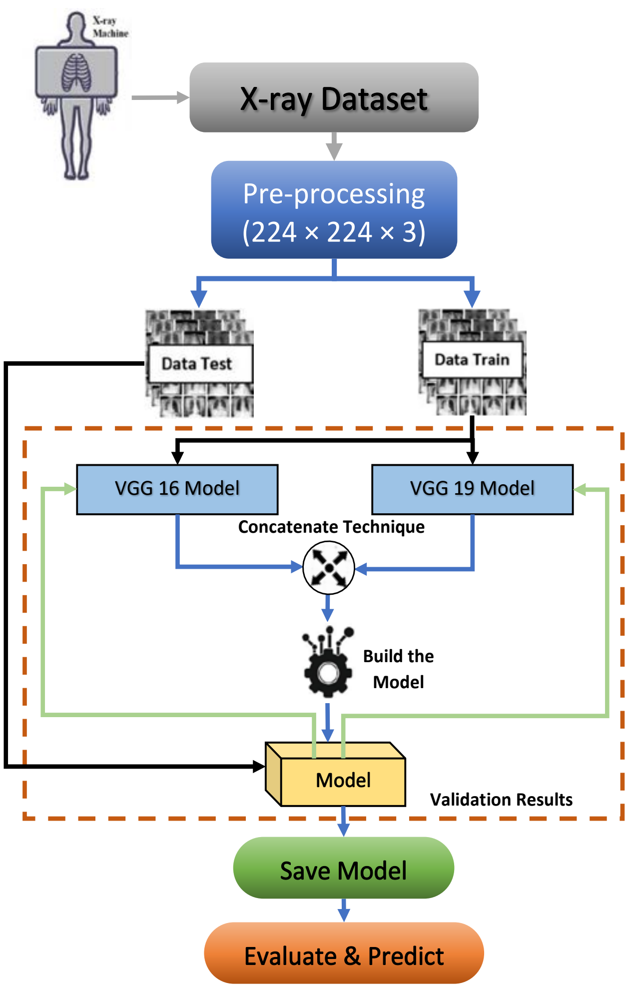
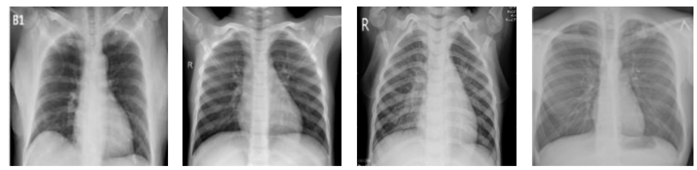


Fig. 1. Schematic Depicting the Planned Classification MDSS Design.

TABLE I. OVERVIEW OF THE MEDICAL X-RAY IMAGES DATABASE SAMPLES

Dataset	Class	Training (90%)	Testing (10%)	Total (100%)
Ref. Dataset[a,b,c,d]	COVID-19	1206	134	**1340**
	Viral Pneumonia	1581	176	**1757**
	Tuberculosis	3150	350	**3500**
	Normal	2024	225	**2249**
Total		**7961**	**885**	**8846**

a. "COVID-19 Radiography Database"
b. "COVID-19 Detection X-Ray Dataset"
c. "COVID-19 Patients Lungs X-Ray Images"
d. "Tuberculosis (TB) Chest X-Ray Database"



(a) (b) (c) (d)

Fig. 2. Specimens of Chest Radiography Images from the Four Categories: (a) COVID-19 Specimen; (b) Normal Specimen; (c) Viral Pneumonia Specimen; (d) Tuberculosis Specimen.

C. Background on TL Algorithms

Instead of developing and learning a CNN from scratch, the TF technique can be used. This technique is a paradigm of machine learning and as such, it is concerned with the knowledge and expertise gained while performing a task. In deep learning, this strategy is applied where the beginning points are saved as pretrained classifiers. This makes it easier for training and accurate efficiency. VGG16 and VGG19 are two pre-trained CNN classifiers that are shareable, and available. They had already been trained on a number of databases, including ImageNet. On a vast scale, it's a massive hierarchical image database. The technical structure of the TL classifiers is depicted in Fig. 3.

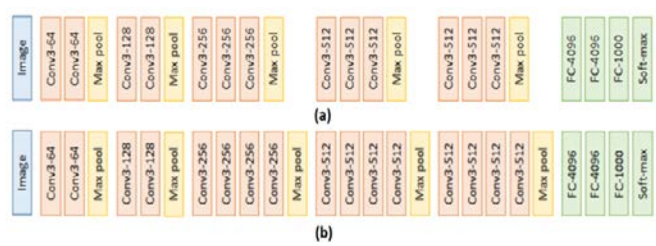


Fig. 3. The Detailed Structure of the TL Classifiers: (a) VGG16 Classifier; (b) VGG19 Classifier.

D. Planned Concatenation Classifier Depending on TL Technique

This subsection explains the technical structure of our classifier, which is shown in Fig. 1. In fact, we used two modified pre-trained TL classifiers, VGG16 and VGG19, both having an identical configuration input dimension, to build our recommended classifier with an initial input size of 3 channels, and 224×224 dimension (224×224×3). The entire flowchart of this classifier is shown in Fig. 4.

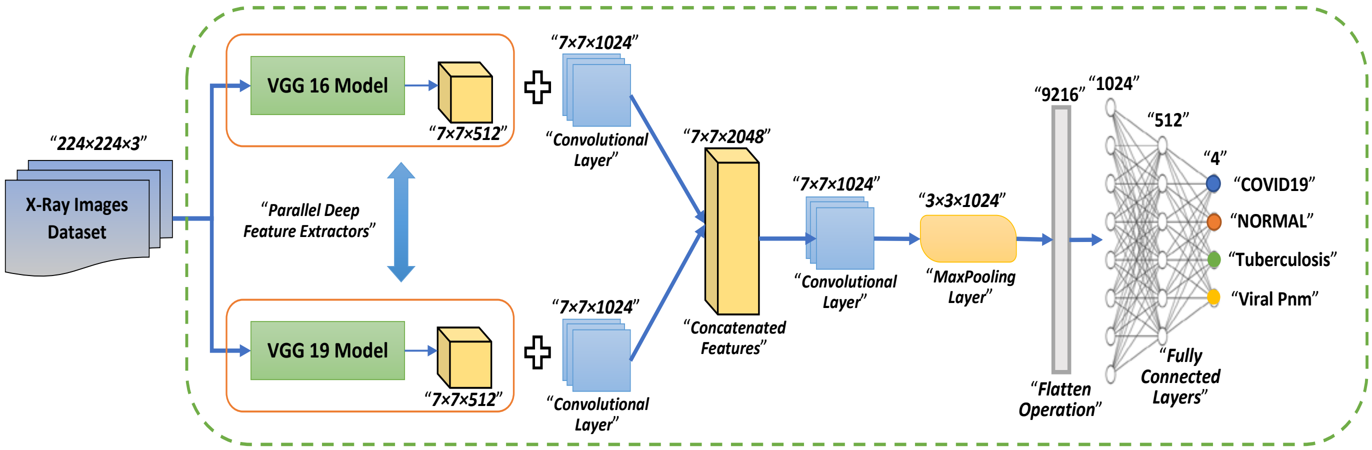


Fig. 4. The Suggested Concatenated Classifier's Design.

III. Results and Discussion

A. Classifier Performance Evaluation

1) Confusion matrix and evaluation metrics: The confusion matrix gives additional feedback about the performance of a classification algorithm, including properly predicted classes, incorrect classes, and the types of errors made. This will help to gather four critical factors for calculating the accuracy of the proposed classifier. TP (True Positive), TN (True Negative), FP (False Positive), and finally FN (False Negative) are the four elements. Expressions below give the confusion factors for the "COVID-19" class as depicted in Table II.

The five indicators employed in this work to evaluate our proposed classifier: Precision, Specificity, Sensitivity, Negative Predictive Value (NPV), and the last indicator is Accuracy.

2) Cross-validation technique: In the ML challenge, the Cross-Validation (CV) technique employs the K-Fold CV method. In fact, we begin by separating the data into training and testing sets. Folds have been generated from our training set, which have been divided into K subsets. Thereafter, we repeatedly fit the model K times, training the data on folds K-1 and assessing fold K each time. At the completion of the training, we average the performance on each of the folds to determine the classifier's final validation metrics. Fig. 5 provides a CV method implementation example.

TABLE II. Definition of Confusion Matrix Factors

Confusion Factors	Definition
TP	The number of Chest Radiography images that are forecast exactly as COVID-19.
TN	The number of Chest Radiography images that are forecast exactly as not COVID-19.
FN	The number of Chest Radiography images that are forecast erroneously as not COVID-19.
FP	The number of Chest Radiography images that are forecast erroneously as COVID-19.

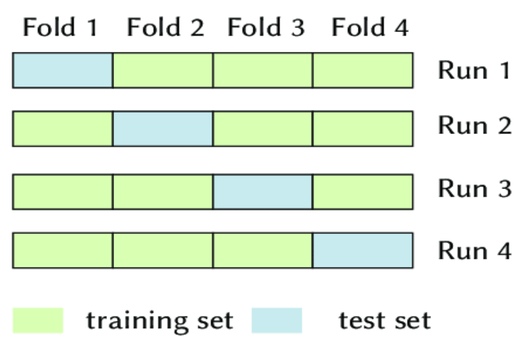
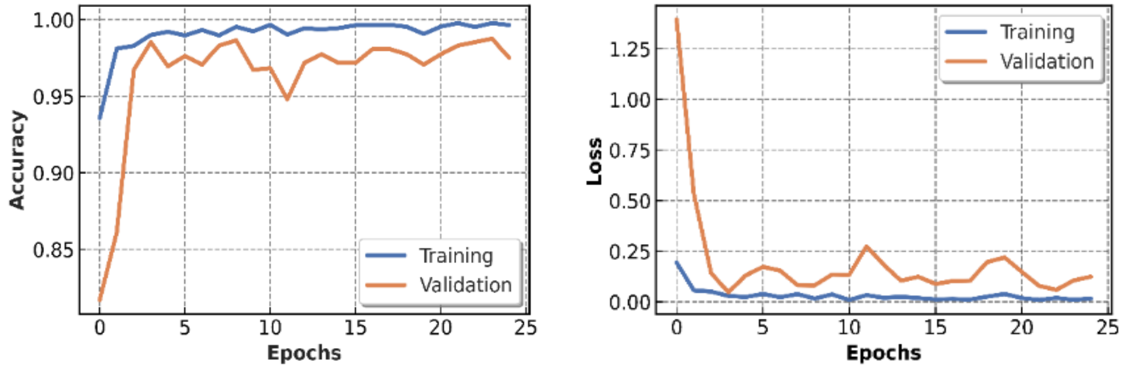


Fig. 5. Example of the Cross-validation Method Implementation with a K-Fold Equal to 4.

B. Experimental Results

1) Results of the planned classifier training: The planned concatenation classifier was built on the Google Collab platform, in this work. It's an AI virtualization technology (Cloud Computer Service) for AI research. An Intel Xeon Processor with 2 cores running at 2.20 GHz, 13GB of RAM, and finally a Tesla K80 GPU with 12GB of GDDR5 VRAM were used in this workstation. To validate this work, we used 4-fold cross-validation to build our planned concatenation classifier over 25 epochs to assure similar results. The charts for our Chest Radiography image datasets training and validation for fold 4 are described in Fig. 6.

2) Results of the planned classifier testing: We may infer that our suggested classifier gives a robust classification of the four classes based on the results of our research. For all classification k-fold classifiers, the TP value for all categories, is higher than either the FP and FN numbers. In all k-fold classifiers, the COVID-19 class of FP and FN values is lower than the other classes. This indicates that our concatenation classifier has a low risk of confusing COVID-19 infected instances. The confusion matrix of the concatenated classifier for all folds is shown in Fig. 7.



(a) (b)

Fig. 6. Curves Produced in Fold 4: (a) Accuracy; (b) Loss.

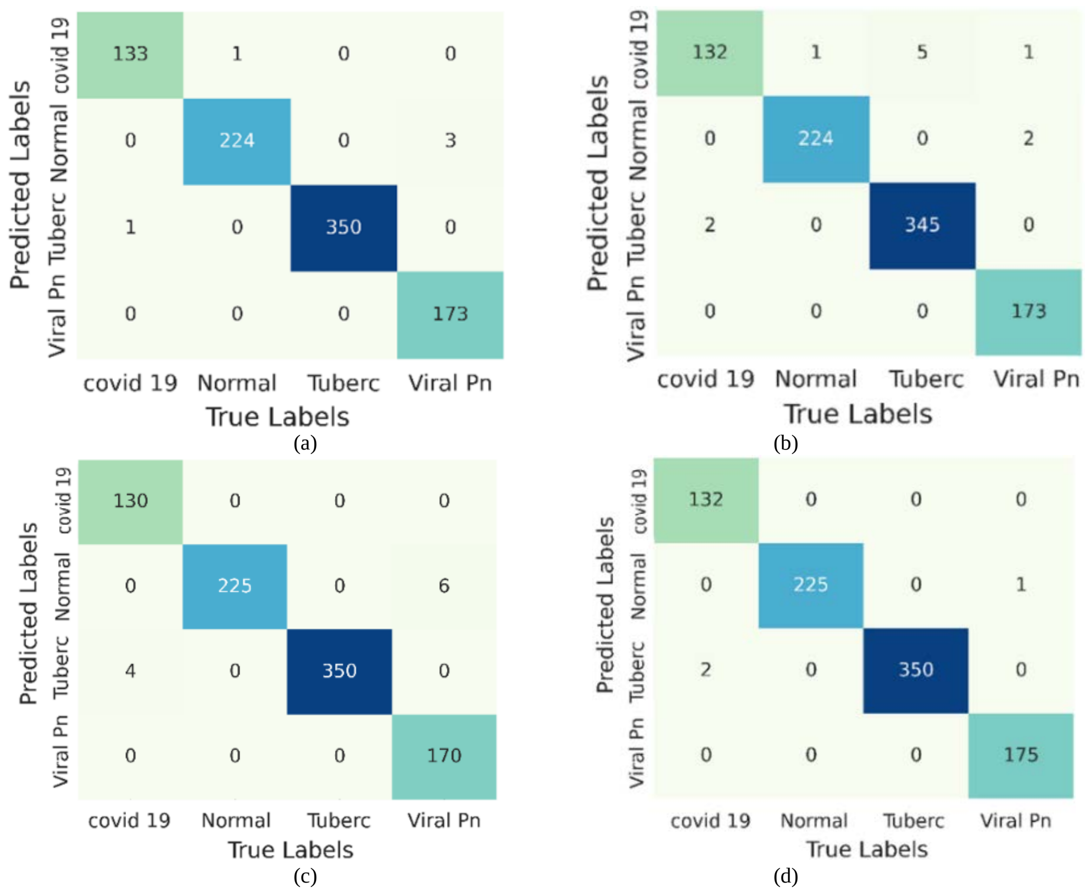


Fig. 7. The Confusion Matrix of the Concatenated Classifier: (a) 1-Fold CM, (b) 2-Fold CM, (c) 3-Fold CM and (d) 4-Fold CM.

A ROC curve could be used to examine these results. This diagnostic test depicts the ratio of False Positive Rate against True Positive Rate as represented by this curve. A ROC curve, in general, helps to compare several classifiers based on the AUC variable's value. The ROC curve for our concatenation classifier in fold four is shown in Fig. 8.

Table III presents the performance evaluation scores of our proposed concatenation classifier for each fold to help elucidate these results.

C. Discussion

In this paper, we developed an innovative COVID-19 diagnostic classifier based on a concatenation mechanism and two pre-trained TL classifiers. The goal of this proposed classifier is to provide the best algorithm possible for the detection of COVID-19 cases. This classifier was built and tested applying a dataset of produced Chest Radiography images from four different databases. Tuberculosis, Pneumonia, Normal and COVID-19 are the four classes in this dataset. In fact, we noticed in the experimental results section that our proposed classifier had a 99% accuracy for all folds. Furthermore, this classifier has a loss value of less than 3%.

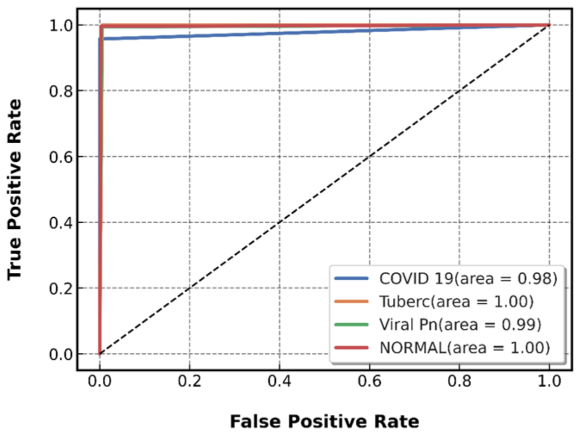


Fig. 8. ROC Curves Findings for the Concatenated Classifier in Fold 4.

Many specialists from around the world have written and published articles on the coronavirus that causes COVID-19 disease in the previous two years. In recently published findings, AI Algorithms have been utilized to examine X-Ray images and assist in the diagnosis of infected cases. DL algorithms are the most frequent in image categorization because they produce better results than classical ML methods. In this subsection, we will examine the research published that applies DL approaches to detect COVID-19 by employing innovative methodologies.

COVIDetection-Net is a classifier used in the categorization of Chest Radiography images proposed by the authors in [45]. To extract the features, this classifier uses ShuffleNet and SqueezeNet networks, as well as Multiclass SVM to classify them. The suggested classifier had a 99.44% accuracy using a multi-class database (COVID-19, normal, Bacterial pneumonia, and Viral pneumonia).

Another paper published in [46], proposed a classifier called SARS-Net, by combining Graph CNN and CNN. X-Ray pictures from five different datasets were used to create this classifier, which had a classification accuracy of 97.6%.

A concatenation classifier was suggested in the scientific paper [47], to merge features retrieved employing the CNN with two pretrained models based on TL approaches like as ResNet-18 and GoogleNet. The two datasets used in this study: X-Ray images, and CT scans, contained binary classes: COVID-19, and non-COVID-19 for each dataset. The proposed classifier archived an accuracy of 98.9% and 99.3% for CT and X-Ray images.

The authors published a comparison analysis depending on TL approaches in [48]. This study proposes two modified models: MobileNetV3, and ResNet18. These models were developed using a database that included five categories: “COVID-19”, “Tuberculosis”, “Normal”, “Bacterial Pneumonia”, and finally “Viral Pneumonia”. The accuracy of the proposed models was 99.3% and 99.6% for ResNet18 and MobileNetV3, respectively.

The mentioned works in this section show an improved recognition models by focusing on the analysis of the dataset used, the optimization of hyper-parameters, or the combination of the performance of several models based on various algorithms. However, feature engineering is an intriguing phase in recognition system development. Indeed, using extracted characteristics improves the performance of a recognition system. Indeed, the success of the categorization system is directly reliant on the recovered primitives. In Table IV, we summarized the performances finding of concatenation-based classifiers in comparison to our proposed classifier.

TABLE III. PERFORMANCE OF THE PROPOSED CONCATENATED CLASSIFIER ON EACH FOLD

Folds	**Loss**	**Accuracy**	**Precision**	**Sensitivity**	**Specificity**	**NPV**
F1	0.027	99.43%	99.41%	99.28%	99.81%	99.82%
F2	0.030	98.75%	98.38%	98.73%	99.60%	99.56%
F3	0.051	98.87%	99.07%	98.40%	99.59%	99.66%
F4	0.015	99.66%	99.75%	99.48%	99.87%	99.90%

TABLE IV. COMPARATIVE RESULTS FOR THE PROPOSED CLASSIFIER WITH RELATED STUDIES

Studies	Classifiers used	Accuracy	Precision	Sensitivity
[45]	COVIDetection-Net	99.44%	94.42%	94.45%
[46]	SARS-Net	97.6%	N/A	92.9%
[47]	Concatenation CNN_ResNet18_GoogleNet	99.3%	99.79%	98.8%
[48]	ResNet18	99.3%	99.23%	99.36%
	MobileNetV3	99.6%	99.5%	99.5%
Proposed classifier	**Concatenation VGG16_VGG19**	**99.66%**	**99.75%**	**99.48%**

IV. Conclusion

In conclusion, using the X-Ray images dataset, we provide a COVID-19 detection mechanism. The proposed concatenation classifier was built and tested utilizing a dataset of Chest Radiography images divided into four categories: COVID-19, Viral Pneumonia, Normal, and Tuberculosis. We integrated four separate online X-Ray picture collections to create this dataset. Concerning the novelty of this work, we use in the feature extraction phase a parallel deep feature extraction approach based on the TL models. This feature extraction approach increases the accuracy of our proposed models, thus identifying COVID-19 cases with higher accuracy. The proposed concatenation classifier achieved 99.6% accuracy and 99.48% sensitivity, respectively.

In future studies, we hope to use the proposed design to classify other illnesses, such as Parkinson's disease, heart disease, and cancer. Nonetheless, we want to use Artificial Intelligence of Things (AIoT) to enhance the resilience and accuracy of our MDSS for monitoring pandemics and tumors. This field is referred to as AIoT, and it integrates IoT infrastructure with artificial intelligence (AI) technology.

References

[1] Astuti and Ysrafil, 'Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2): An overview of viral structure and host response', Diabetes & Metabolic Syndrome: Clinical Research & Reviews, vol. 14, no. 4, pp. 407–412, Jul. 2020, doi: 10.1016/j.dsx.2020.04.020.

[2] C. Sohrabi et al., 'World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19)', International Journal of Surgery, vol. 76, pp. 71–76, Apr. 2020, doi: 10.1016/j.ijsu.2020.02.034.

[3] H. Turki and K. Khrouf, 'Data Analysis of Coronavirus CoVID-19: Study of Spread and Vaccination in European Countries', IJACSA, vol. 13, no. 1, 2022, doi: 10.14569/IJACSA.2022.0130185.

[4] S. Khan and A. Alfaifi, 'Modeling of Coronavirus Behavior to Predict it's Spread', IJACSA, vol. 11, no. 5, 2020, doi: 10.14569/IJACSA.2020.0110552.

[5] J. R. Larsen, M. R. Martin, J. D. Martin, P. Kuhn, and J. B. Hicks, 'Modeling the Onset of Symptoms of COVID-19', Front. Public Health, vol. 8, p. 473, Aug. 2020, doi: 10.3389/fpubh.2020.00473.

[6] V. Sherimon et al., 'Covid-19 Ontology Engineering-Knowledge Modeling of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2)', IJACSA, vol. 11, no. 11, 2020, doi: 10.14569/IJACSA.2020.0111115.

[7] R. Vaishya, M. Javaid, I. H. Khan, and A. Haleem, 'Artificial Intelligence (AI) applications for COVID-19 pandemic', Diabetes & Metabolic Syndrome: Clinical Research & Reviews, vol. 14, no. 4, pp. 337–339, Jul. 2020, doi: 10.1016/j.dsx.2020.04.012.

[8] Q. Kharma, K. Nairoukh, A. Hussein, M. Abualhaj, and Q. Shambour, 'Online Learning Acceptance Model during Covid-19: An Integrated Conceptual Model', IJACSA, vol. 12, no. 5, 2021, doi: 10.14569/IJACSA.2021.0120561.

[9] O. El Gannour, B. Cherradi, S. Hamida, M. Jebbari, and A. Raihani, 'Screening Medical Face Mask for Coronavirus Prevention using Deep Learning and AutoML', in 2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), Meknes, Morocco, Mar. 2022, pp. 1–7. doi: 10.1109/IRASET52964.2022.9737903.

[10] S.-W. Chen, X.-W. Gu, J.-J. Wang, and H.-S. Zhu, 'AIoT Used for COVID-19 Pandemic Prevention and Control', Contrast Media & Molecular Imaging, vol. 2021, pp. 1–23, Oct. 2021, doi: 10.1155/2021/3257035.

[11] F. Albogamy, 'IoT-based e-Health Framework for COVID-19 Patients Monitoring', IJACSA, vol. 12, no. 9, 2021, doi: 10.14569/IJACSA.2021.0120961.

[12] O. El Gannour, S. Hamida, B. Cherradi, A. Raihani, and H. Moujahid, 'Performance Evaluation of Transfer Learning Technique for Automatic Detection of Patients with COVID-19 on X-Ray Images', in 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), Kenitra, Morocco, Dec. 2020, pp. 1–6. doi: 10.1109/ICECOCS50124.2020.9314458.

[13] H. Moujahid, B. Cherradi, M. Al-Sarem, and L. Bahatti, 'Diagnosis of COVID-19 Disease Using Convolutional Neural Network Models Based Transfer Learning', in Innovative Systems for Intelligent Health Informatics, vol. 72, F. Saeed, F. Mohammed, and A. Al-Nahari, Eds. Cham: Springer International Publishing, 2021, pp. 148–159. doi: 10.1007/978-3-030-70713-2_16.

[14] S. Hamida, O. E. Gannour, B. Cherradi, H. Ouajji, and A. Raihani, 'Optimization of Machine Learning Algorithms Hyper-Parameters for Improving the Prediction of Patients Infected with COVID-19', in 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), Kenitra, Morocco, Dec. 2020, pp. 1–6. doi: 10.1109/ICECOCS50124.2020.9314373.

[15] S. Chokri, W. B. Daoud, W. Hanini, S. Mahfoudhi, and A. Makhlouf, 'AI-based System for the Detection and Prevention of COVID-19', IJACSA, vol. 13, no. 1, 2022, doi: 10.14569/IJACSA.2022.0130171.

[16] E. Fayyoumi, S. Idwan, and H. AboShindi, 'Machine Learning and Statistical Modelling for Prediction of Novel COVID-19 Patients Case Study: Jordan', IJACSA, vol. 11, no. 5, 2020, doi: 10.14569/IJACSA.2020.0110518.

[17] W. Alawad, B. Alburaidi, A. Alzahrani, and F. Alflaj, 'A Comparative Study of Stand-Alone and Hybrid CNN Models for COVID-19 Detection', IJACSA, vol. 12, no. 6, 2021, doi: 10.14569/IJACSA.2021.01206102.

[18] A. Ouhmida, A. Raihani, B. Cherradi, and Y. Lamalem, 'Parkinson's disease classification using machine learning algorithms: performance analysis and comparison', in 2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), Meknes, Morocco, Mar. 2022, pp. 1–6. doi: 10.1109/IRASET52964.2022.9738264.

[19] A. Ouhmida, A. Raihani, B. Cherradi, and O. Terrada, 'A Novel Approach for Parkinson's Disease Detection Based on Voice Classification and Features Selection Techniques', Int. J. Onl. Eng., vol. 17, no. 10, p. 111, Oct. 2021, doi: 10.3991/ijoe.v17i10.24499.

[20] A. Ouhmida, O. Terrada, A. Raihani, B. Cherradi, and S. Hamida, 'Voice-Based Deep Learning Medical Diagnosis System for Parkinson's Disease Prediction', in 2021 International Congress of Advanced Technology and Engineering (ICOTEN), Taiz, Yemen, Jul. 2021, pp. 1–5. doi: 10.1109/ICOTEN52080.2021.9493456.

[21] M. Alissa et al., 'Parkinson's disease diagnosis using convolutional neural networks and figure-copying tasks', Neural Comput & Applic, Sep. 2021, doi: 10.1007/s00521-021-06469-7.

[22] H. Moujahid, B. Cherradi, and L. Bahatti, 'Convolutional Neural Networks for Multimodal Brain MRI Images Segmentation: A Comparative Study', in Smart Applications and Data Analysis, vol. 1207, M. Hamlich, L. Bellatreche, A. Mondal, and C. Ordonez, Eds. Cham: Springer International Publishing, 2020, pp. 329–338. doi: 10.1007/978-3-030-45183-7_25.

[23] A. Jijja and Dr. Dinesh, 'Efficient MRI Segmentation and Detection of Brain Tumor using Convolutional Neural Network', IJACSA, vol. 10, no. 4, 2019, doi: 10.14569/IJACSA.2019.0100466.

[24] S. Laghmati, B. Cherradi, A. Tmiri, O. Daanouni, and S. Hamida, 'Classification of Patients with Breast Cancer using Neighbourhood Component Analysis and Supervised Machine Learning Techniques', in 2020 3rd International Conference on Advanced Communication Technologies and Networking (CommNet), Marrakech, Morocco, Sep. 2020, pp. 1–6. doi: 10.1109/CommNet49926.2020.9199633.

[25] O. Daanouni, B. Cherradi, and A. Tmiri, 'Diabetes Diseases Prediction Using Supervised Machine Learning and Neighbourhood Components Analysis', in Proceedings of the 3rd International Conference on Networking, Information Systems & Security, Marrakech Morocco, Mar. 2020, pp. 1–5. doi: 10.1145/3386723.3387887.

[26] N. Ait Ali, B. Cherradi, A. El Abbassi, O. Bouattane, and M. Youssfi, 'GPU fuzzy c-means algorithm implementations: performance analysis

on medical image segmentation', Multimed Tools Appl, vol. 77, no. 16, pp. 21221–21243, Aug. 2018, doi: 10.1007/s11042-017-5589-6.

[27] O. Terrada, B. Cherradi, S. Hamida, A. Raihani, H. Moujahid, and O. Bouattane, 'Prediction of Patients with Heart Disease using Artificial Neural Network and Adaptive Boosting techniques', in 2020 3rd International Conference on Advanced Communication Technologies and Networking (CommNet), Marrakech, Morocco, Sep. 2020, pp. 1–6. doi: 10.1109/CommNet49926.2020.9199620.

[28] O. Terrada, S. Hamida, B. Cherradi, A. Raihani, and O. Bouattane, 'Supervised Machine Learning Based Medical Diagnosis Support System for Prediction of Patients with Heart Disease', Adv. sci. technol. eng. syst. j., vol. 5, no. 5, pp. 269–277, 2020, doi: 10.25046/aj050533.

[29] B. Cherradi, O. Terrada, A. Ouhmida, S. Hamida, A. Raihani, and O. Bouattane, 'Computer-Aided Diagnosis System for Early Prediction of Atherosclerosis using Machine Learning and K-fold cross-validation', in 2021 International Congress of Advanced Technology and Engineering (ICOTEN), Taiz, Yemen, Jul. 2021, pp. 1–9. doi: 10.1109/ICOTEN52080.2021.9493524.

[30] I. Javid, A. Khalaf, and R. Ghazali, 'Enhanced Accuracy of Heart Disease Prediction using Machine Learning and Recurrent Neural Networks Ensemble Majority Voting Method', IJACSA, vol. 11, no. 3, 2020, doi: 10.14569/IJACSA.2020.0110369.

[31] O. Terrada, B. Cherradi, A. Raihani, and O. Bouattane, 'A novel medical diagnosis support system for predicting patients with atherosclerosis diseases', Informatics in Medicine Unlocked, vol. 21, p. 100483, 2020, doi: 10.1016/j.imu.2020.100483.

[32] S. Hamida, B. Cherradi, O. Terrada, A. Raihani, H. Ouajji, and S. Laghmati, 'A Novel Feature Extraction System for Cursive Word Vocabulary Recognition using Local Features Descriptors and Gabor Filter', in 2020 3rd International Conference on Advanced Communication Technologies and Networking (CommNet), Marrakech, Morocco, Sep. 2020, pp. 1–7. doi: 10.1109/CommNet49926.2020.9199642.

[33] A. Alsaeedi and M. Al-Sarem, 'Detecting Rumors on Social Media Based on a CNN Deep Learning Technique', Arab J Sci Eng, vol. 45, no. 12, pp. 10813–10844, Dec. 2020, doi: 10.1007/s13369-020-04839-2.

[34] W. Sun, P. Bocchini, and B. D. Davison, 'Applications of artificial intelligence for disaster management', Nat Hazards, vol. 103, no. 3, pp. 2631–2689, Sep. 2020, doi: 10.1007/s11069-020-04124-3.

[35] F. M. Alliheibi, A. Omar, and N. Al-Horais, 'Opinion Mining of Saudi Responses to COVID-19 Vaccines on Twitter', IJACSA, vol. 12, no. 6, 2021, doi: 10.14569/IJACSA.2021.0120610.

[36] A. R. Mahlous and A. Al-Laith, 'Fake News Detection in Arabic Tweets during the COVID-19 Pandemic', IJACSA, vol. 12, no. 6, 2021, doi: 10.14569/IJACSA.2021.0120691.

[37] P. V. Sagar, T. Pavan, G. Krishna, and M. Nageswara, 'COVID-19 Transmission Risks Assessment using Agent-Based Weighted Clustering Approach', IJACSA, vol. 11, no. 11, 2020, doi: 10.14569/IJACSA.2020.0111167.

[38] H. Ghandorh et al., 'An ICU Admission Predictive Model for COVID-19 Patients in Saudi Arabia', IJACSA, vol. 12, no. 7, 2021, doi: 10.14569/IJACSA.2021.0120764.

[39] S. Hamida, B. Cherradi, O. El Gannour, O. Terrada, A. Raihani, and H. Ouajji, 'New Database of French Computer Science Words Handwritten Vocabulary', in 2021 International Congress of Advanced Technology and Engineering (ICOTEN), Taiz, Yemen, Jul. 2021, pp. 1–5. doi: 10.1109/ICOTEN52080.2021.9493438.

[40] M. Fernandes, S. M. Vieira, F. Leite, C. Palos, S. Finkelstein, and J. M. C. Sousa, 'Clinical Decision Support Systems for Triage in the Emergency Department using Intelligent Systems: a Review', Artificial Intelligence in Medicine, vol. 102, p. 101762, Jan. 2020, doi: 10.1016/j.artmed.2019.101762.

[41] B. I. Khaleel and M. Y. Ahmed, 'Pneumonia detection using butterfly optimization and hybrid butterfly optimization algorithm', Bulletin EEI, vol. 10, no. 4, pp. 2037–2045, Aug. 2021, doi: 10.11591/eei.v10i4.2872.

[42] H. Moujahid et al., 'Combining CNN and Grad-Cam for COVID-19 Disease Prediction and Visual Explanation', Intelligent Automation & Soft Computing, vol. 32, no. 2, pp. 723–745, 2022, doi: 10.32604/iasc.2022.022179.

[43] O. El Gannour et al., 'Concatenation of Pre-Trained Convolutional Neural Networks for Enhanced COVID-19 Screening Using Transfer Learning Technique', Electronics, vol. 11, no. 1, p. 103, Dec. 2021, doi: 10.3390/electronics11010103.

[44] S. Hamida, O. El Gannour, B. Cherradi, A. Raihani, H. Moujahid, and H. Ouajji, 'A Novel COVID-19 Diagnosis Support System Using the Stacking Approach and Transfer Learning Technique on Chest X-Ray Images', Journal of Healthcare Engineering, vol. 2021, pp. 1–17, Nov. 2021, doi: 10.1155/2021/9437538.

[45] A. S. Elkorany and Z. F. Elsharkawy, 'COVIDetection-Net: A tailored COVID-19 detection from chest radiography images using deep learning', Optik, vol. 231, p. 166405, Apr. 2021, doi: 10.1016/j.ijleo.2021.166405.

[46] A. Kumar, A. R. Tripathi, S. C. Satapathy, and Y.-D. Zhang, 'SARS-Net: COVID-19 detection from chest x-rays by combining graph convolutional network and convolutional neural network', Pattern Recognition, vol. 122, p. 108255, Feb. 2022, doi: 10.1016/j.patcog.2021.108255.

[47] W. Saad, W. A. Shalaby, M. Shokair, F. A. El-Samie, M. Dessouky, and E. Abdellatef, 'COVID-19 classification using deep feature concatenation technique', J Ambient Intell Human Comput, Mar. 2021, doi: 10.1007/s12652-021-02967-7.

[48] G. Jia, H.-K. Lam, and Y. Xu, 'Classification of COVID-19 chest X-Ray and CT images using a type of dynamic CNN modification method', Computers in Biology and Medicine, vol. 134, p. 104425, Jul. 2021, doi: 10.1016/j.compbiomed.2021.104425.