Development of a clinical decision support system for the early detection of COVID-19 using deep learning based on chest radiographic images

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***Abstract*—To control the spread of the COVID-19 virus and to gain critical time in controlling the spread of the disease, rapid and accurate diagnostic methods based on artificial intelligence are urgently needed. In this article, we propose a clinical decision support system for the early detection of COVID 19 using deep learning based on chest radiographic images. For this we will develop an in-depth learning method which could extract the graphical characteristics of COVID-19 in order to provide a clinical diagnosis before the test of the pathogen. For this, we collected 100 images of cases of COVID-19 confirmed by pathogens, 100 images diagnosed with typical viral pneumonia and 100 images of normal cases. The architecture of the proposed model first goes through a preprocessing of the input images followed by an increase in data. Then the model begins a step to extract the characteristics followed by the learning step. Finally, the model begins a classification and prediction process with a fully connected network formed of several classifiers. Deep learning and classification were carried out using the VGG convolutional neural network. The proposed model achieved an accuracy of 92.5% in internal validation and 87.5% in external validation. For the AUC criterion we obtained a value of 97% in internal validation and 95% in external validation. Regarding the sensitivity criterion, we obtained a value of 92% in internal validation and 87% in external validation. The results obtained by our model in the test phase show that our model is very effective in detecting COVID-19 and can be offered to health communities as a precise, rapid and effective clinical decision support system in COVID-19 detection.**

***Index Terms*— COVID-19, deep Learning, VGG Model, clinical decision support system,**

I. INTRODUCTION

THE emergence of artificial intelligence (AI), the first concepts of which date back to the 1950s in the medical field, is the consequence of three radical upheavals: the digitalization of medical images allowing their configuration, the development of algorithms authorizing the use of data entered in natural language, and deep learning allowing from massive radiological data to develop algorithms for automatic processing of medical images. These systems now allow automatic detection of lesions and pave the way for screening for lung, breast or prostate cancer. Their reliability is higher than that of radiologists. Integrated with clinical, biological and genetic medical data, these techniques considerably modify the organization and structuring of the health world. Our team has embarked on this path for a few years by defining a priority research axis relating to artificial intelligence at the service of medical imaging [1-5]. We thus carried out a project on the fight against the handicap caused by laryngotomy by proposing an intelligent system based on Deep Learning to recognize and see the words from video images of the movement of the patient's lips.

Recently, atypical highly transmissible pneumonia between humans has been localized in China. It causes a severe respiratory gene caused by the corona virus-2 called COVID-19.

Consequently, individuals, 16 to 21% according to the WHO, fell seriously ill and 2 to 3% died following this highly contagious disease whose rate of transmissibility was around 3.77% [6]. It was therefore urgent to detect individuals who had caught the virus, put them in quarantine and start their treatment.

The diagnosis of COVID-19 is based on well-defined criteria [8-11] such as clinical symptoms, epidemiological history, positive CT and X-ray images, and positive pathogen tests based on real-time RT-PCR and virus nucleic acid sequencing [12]. To confirm these last two tests, it must be repeated several times for many cases [10-11] which constitutes a serious limit for their accuracy.

To solve this problem, we are going to use chest X-ray images as a means of detecting this virus. Indeed, atypical pneumonia due to COVID-19 will manifest itself on an image through the presence of opacities in frosted glass at the first stage of the disease which becomes pulmonary consolidation at the last stage of the disease [11-14]. Unfortunately, its characteristics of atypical pneumonia caused by COVID-19 are confused with the characteristics of other typical inflammatory pneumonias, which rounds off the task of detection of COVID-19 by the radiologist very complicated.

As a solution to this problem researchers have used artificial intelligence [7]. Researchers [14] have already established a list of characteristics extracted from images to detect the

presence of the COVID-19 virus. In literature radiologists have been able to clinically develop several characteristics of viral pathogens at the level of chest radiographic images [14]. In fact, the presence of uneven bilateral shadow distribution and opacity of the frosted glass in the form of frosted glasses [8] is a strong indication of the presence of COVID19.

By training convolutional neural networks (CNN) using these characteristics extracted from X-ray images, we could accurately predict COVID19. For this, we will propose a deep learning model based on VGG networks that we will modify to adapt it to our prediction problem. The architecture of the proposed model begins with a preprocessing of the input images followed by an increase in the data. Then, the model begins a step to extract the characteristics followed by the learning step. Finally, the model begins a classification and prediction process with a fully connected network made up of several classifiers.

The rest of the paper is organized as follows. In section II we will present our collected Dataset. In the third section we will present the architecture of our model used. Then in the fourth section we will present our simulation results. We finish our article with a general conclusion.

II. COLLECTION OF DATASETS

We set up a database composed of three classes of chest radiographic images. The first class is made up of images of patients declared positive for COVID-19 that we collected from the database published by Cohen [15]. This database contained 230 images is open to various researchers to add new images or to use the already existing images. The second class consists of 100 images of patients declared normal without any pneumonia. The third class consists of 100 images of patients who have already had typical inflammatory pneumonia. The images of the last two classes were extracted from the database published by Wang et al. [16]. We have divided the base of the collected X-ray images into two groups. A first learning group noted internal validation containing 80% of the images of the constructed base. The images of this group have been verified and annotated by radiologists to use them for the training of our CNN model. The second group noted external validation will be formed by 20% of the images of the base constructed plus ten images provided by our radiologist colleagues and will be used for the validation of our proposed CNN model.

III. DEEP LEARNING ALGORITHM

The architecture of our deep learning algorithm is presented in Figure 1. We have proposed architecture composed of 3 stages. The first step is used to pre-process and enhance the X-ray images. The second step will be used to extract the characteristics of the images and proceed to learning the neural network. The third step consists in classifying the different ones through a fully connected network formed by several classifiers of which only the high score prediction is predicted. We used the notion of learning transfer to form our model. We have chosen the VGG16 network, already pre-trained, known in the literature for its great capacity to extract the very fine characteristics present in the image. The pre-training weights have been set for the first layers of the model. While the last layer has been reserved for learning on our database of radiographic lung images.

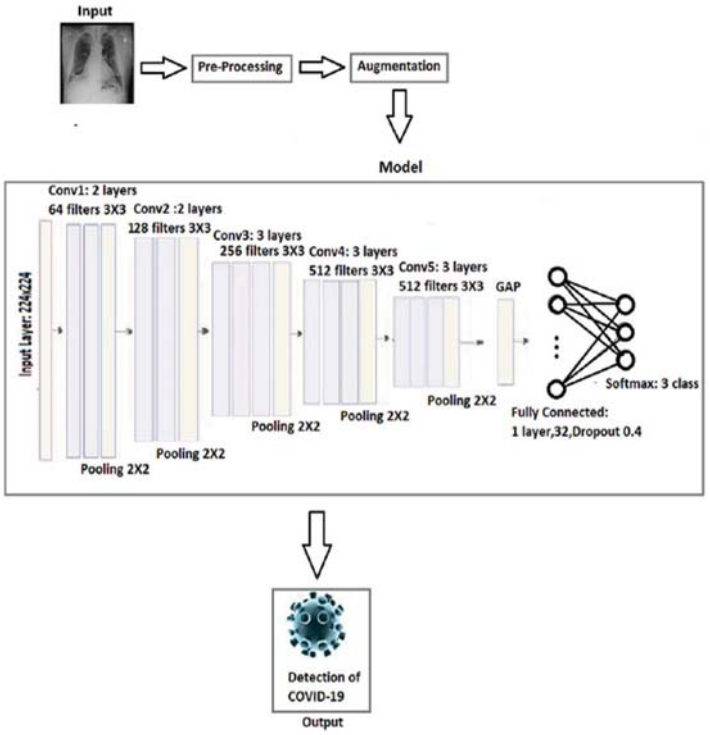


Figure 1. Proposed Deep Learning (DL) algorithm framework.

A. *Image preprocessing and feature extraction*

The model was developed using Keras, and trained using the Kaggle GPU. Adam optimization algorithm was used for hyper parameter optimization for training with learning rate 10^{-2} with a mini-batch size of 32 and train 60 epochs. Data augmentation was also used by resizing the input image to 224x224 and random flipping, scaling, and shearing. We modified the typical Vgg16 network, and fine-tuned the modified VGG model with pre-trained weights. During the training phase the layers were not trained, except the last 4 layers. The architecture characteristics of our model are presented in Table 1. The difference between VGG and our model in classification lies in the last fully-connected layers. We reduced the dimension of features before it was sent to the final classification layer.

TABLE I
THE ARCHITECTURE OF THE OUR MODEL (MODIFIED VGG)

Input	VGG Part					Modified Part (Our Model)
	Layer	Feature Map	Kernel size	Strid	Soft max	Classifier
1	2 Conv	64	3x3	1	FC1	32d linear
	Max Pool	64		2	FC2	3d Linear
3	2 Conv	128	3x3	1		
	Max Pooling	128	3 × 3	2		
5	2 × Convolution	256	3 × 3	1		
	Max Pooling	256	3 × 3	2		
7	3 × Convolution	512	3 × 3	1		
	Max Pooling	512	3 × 3	2		
10	3 × Convolution	512	3 × 3	1		
	Max Pooling	512	3 × 3	2		
	Average Pooling	512	3 × 3	1		

IV. SIMULATION RESULTS

The learning process for our algorithm was launched on a database of 300 images that we initially collected. This database is made up of three classes: a class of normal cases containing 100 images previously diagnosed before the COVID -19 epidemic, a class of typical pneumonia cases also containing 100 images and a class of cases declared positive for COVID-19 containing 100 images. An example of images of different classes is given in figure 2.

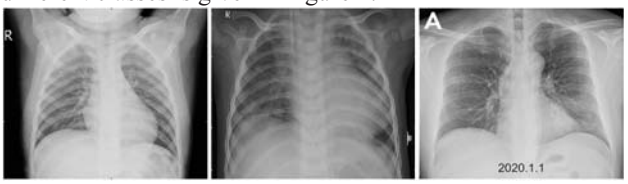
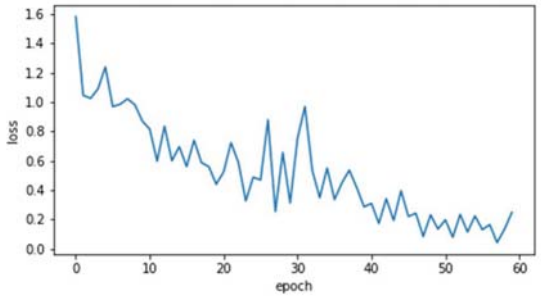
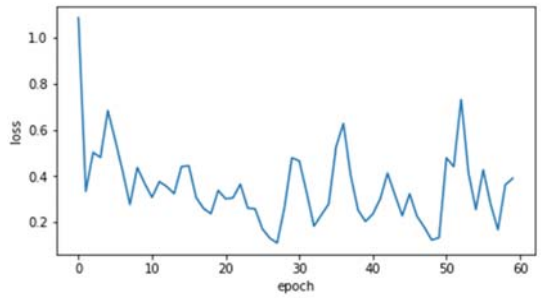


Figure 2. Chest X-rays of admitted patients. From Left to Right: Normal, Pneumonia, and COVID-19.

80% of the database images were chosen for deep learning of our model followed by internal validation. The remaining images (20%) were used for the test followed by external validation. The training loss curve is shown in figure 3 (a). To test the stability and generalization of the model, 40 images (viral pneumonia 12 images, 14 normal images and 14 positive COVID-19 images) were obtained for internal validation and 24 images (viral pneumonia 8 images, 9 normal images and COVID -19 positive 7 images) were obtained for external validation. The training loss curve is shown in figure 3 (b). Moreover we have presented in figure 4 the rate variation of true positive versus the rate of false positive obtained by our proposed model in the learning phase validation and the test phase validation.



(a)



(b)

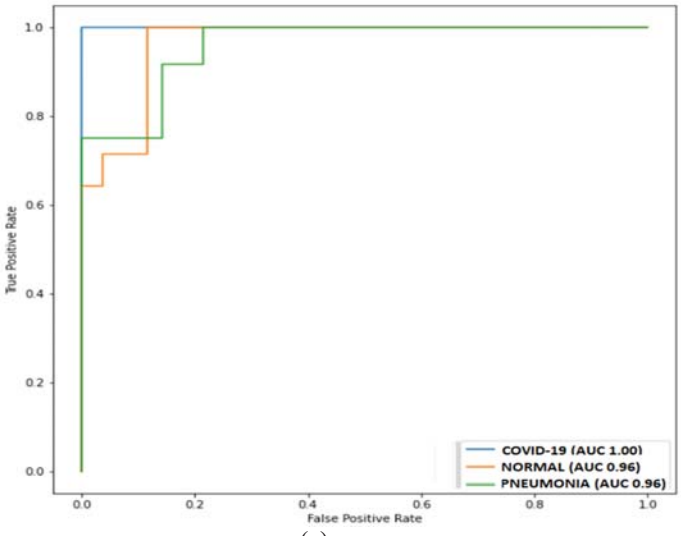
Figure 3 Model learning loss curves: (a) loss curve during the learning phase (b) loss curve during the test phase.

A. Performances of the proposed model

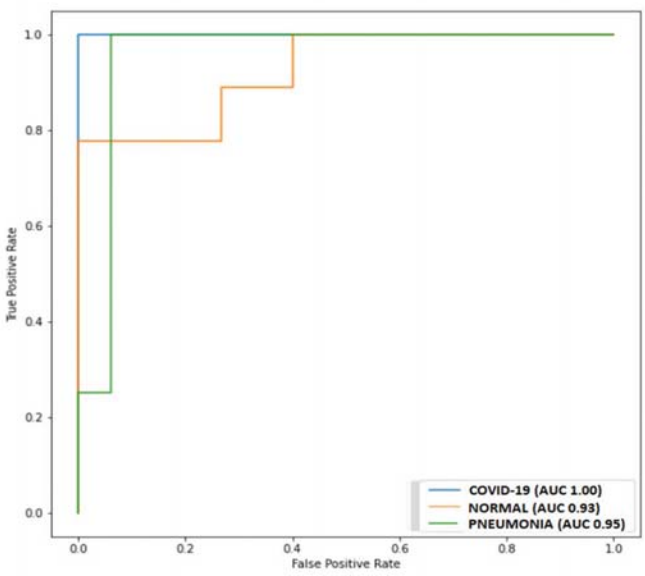
The proposed model achieved an accuracy of 92.5% in learning phase validation and 87.5% test phase validation.

For the AUC criterion we obtained a value of 97% in learning phase validation and 95% in test phase validation. Regarding the sensitivity criterion, we obtained a value of 92% in learning phase validation and 87% in test phase validation. All the results are presented in Table I.

The results obtained by our model in the test phase show that our model is very effective in detecting COVID-19 and can be offered to health communities as a precise, rapid and effective clinical decision support system in COVID-19 detection.



(a)



(b)

Figure 4 Rate variation of true positive versus the rate of false positive for our proposed model: (a) validation of the learning phase (b) validation of the test phase.

TABLE I
PROPOSED MODEL VALIDATION RESULTS FOR LEARNING PHASE AND TEST PHASE

Performance Metric	learning phase	test phase
AUC（95%CI）	*0 .97(0.96 to 0.99)*	*0.95(0.93 to 0.99)*
Accuracy, %	*92.5*	*87.5*
Sensitivity	*0.92*	*0.87*
Specificity	0.96	0.93
PPV	0.94	0.88
NPV	0.97	0.93
Kappa	0.88	0.81
F1 score (macro)	0.92	0.88

TABLE III
Comparison results of various deep learning methods developed based on chest radiographic images

Method	*number of images*	*Accuracy (%)*
Wang and Wong [22]	53 COVID19 5526 NonCOVID19 8066 Healthy	92.4
Hemdan et al. [23]	25 COVID19 25 NORMAL	90.0
Ioannis et al. [24]	224 COVID19 700 Pneumonia 504 Healthy	93.48
Tulin Ozturk et al. [25]	125 COVID19 500 Pneumonia 500 No-Finding	87.02
Proposed Method	**100 COVID19** **100 Pneumonia** **100 Normal**	**87.5**

A. Localization of the pulmonary lesions

The region of interest of dimension mxn for a class (i) is obtained by first calculating the gradient of the probability of presence P^i of each class for a given layer of the model C^k. The global average of these gradients will fix the weighting of the neurons relative to class (i).

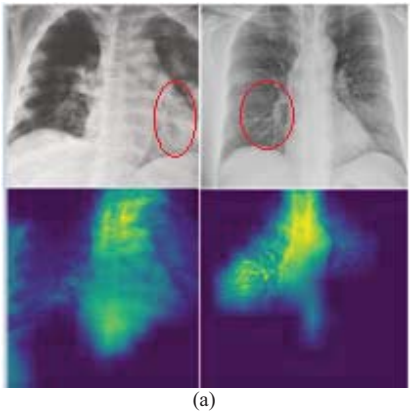
$$\beta_k^i = \frac{1}{Z}\sum_r^m \sum_s^n \frac{\partial P^i}{\partial B_{rs}^k} \quad (1)$$

In order to highlight the points of interest that have strongly contributed to the classification of our model, we first perform a linear combination of the gradient maps of all the layers of the model. Then we apply the ReLU function:

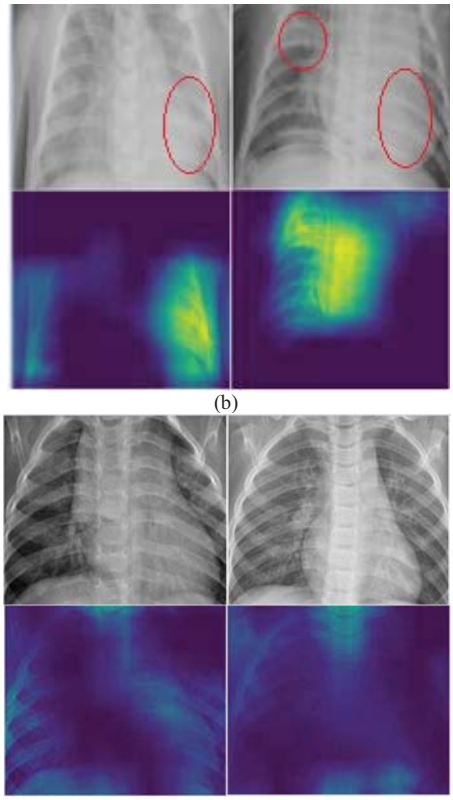
$$L^i = ReLU\left(\sum_k B_k^i B^k\right) \quad (2)$$

The regions of interest obtained by our algorithm corresponding to the three types of classes: Normal, Pneumonia and COVID-19 are shown in Figure 5. We represented with the color yellow the pixels which presented a strong gradient and which contributed enormously to the classification of our model. The blue color was assigned to the pixels which presented a weak gradient and which did not contribute to the classification of our model. Note that in the case of the images of patients declared positive for COVID-19, our algorithm focused on the region showing the opacity of the frosted glass which indicates a clinical pathological character of COVID-19 [21]. On the other hand for the images of the Pneumonia class our algorithm showed a pulmonary inflammation characterizing a typical pneumonia. For the images of the normal class no region showed a strong variation of the gradient and consequently no region was detected by our algorithm.

In addition, we gave 6 test images to our partner team from the radiology department of the Fez University Hospital, made up of renowned radiologists. The latter surrounded with a marker in red the lesions of the pathology present on the image (Figure 3 the images above). Then we compared their location with that indicated by our algorithm (Figure 5 images below). The comparison showed that there was a perfect agreement with the location of the radiologists and that of our algorithm.



(a)



(b)

(c)

Figure 5 Regions of interest extracted by our algorithm:
(a) COVID-19 class: Top to down Original image and his Grad-CAM, (b) Pneumonia classe: Top to down Original image and his Grad-CAM and (c) Normal classe: Top to down Original image and his Grad-CAM

V. CONCLUSION

In this paper we proposed a clinical decision support system for the early detection of COVID-19 using deep learning based on chest X-ray images. For this purpose, we developed an architecture composed of three phases. The first phase consists of pre-processing of input images followed by data augmentation. The second phase consists of feature extraction followed by learning. Finally, the third phase generates the classification and prediction process with a fully connected network of several classifiers. The proposed deep learning algorithm yielded an AUC of 0.97 for internal validation and 0.95 for external validation based on the number of chest X-ray images. Sensitivity was 0.92 and 0.87, specificity was 0.96 and 0.93, accuracy was 92.5% and 87.5%, negative prediction values were 0.97 and 0.93, and F1 scores were 0.92 and 0.88 for internal and external validation, respectively. The kappa values were 0.88 and 0.81 for internal and external validation.

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