Transfer Learning for Automatic Detection of COVID-19 Disease in Medical Chest X-ray Images

EL IDRISSI EL-BOUZAIDI YOUSSRA AND ABDOUN OTMAN

Abstract— **The world has experienced the spread of a dangerous virus, Coronavirus (COVID-19), that has caused the death of millions of people worldwide at an extremely rapid rate, many studies have confirmed that the virus can be detected effectively using medical images. However, it takes a long time to analyze each image by radiologists who suffer from high pressures, especially due to the high similarity of symptoms between this virus and other respiratory diseases, which can lead to the confusion of cases and, consequently, the inability to identify them quickly, which could be a problem in a pandemic situation. In this paper, a methodology is proposed for the rapid and automatic diagnosis of this virus from chest radiographic images through the use of Artificial Intelligence (AI) techniques. There are two stages of the proposed model. The first step is data augmentation and preprocessing; the second step is the detection of COVID-19 with a transfer learning technique using a pre-trained deep convolutional network (CNN) architecture to extract features, Then, the obtained feature vectors are classified into three classes: COVID-19, Normal, and pneumonia, from two open medical repositories. In the experimentation phase of our model, we evaluate a set of common metrics to measure the performance of the architecture. Experimental conclusions show an accuracy of 96.52% for all classes, then a comparison with existing models in literature demonstrates that our proposed model achieves better classification accuracy.**

Index Terms— **Artificial Intelligence, Deep Learning, Transfer Learning, COVID-19, X-ray Images.**

I. Introduction

COVID-19, a new coronavirus outbreak, has claimed many lives and killed a large number of people worldwide. According to WHO estimates as of mid-April 2021, the disease has spread to almost every country, killing more than 3,015,043 people out of nearly 141,057,106 confirmed cases since the first cases were discovered [1]. It is also noted that with the arrival of 2022, the number of infected people has increased exponentially, as well as the emergence of a very dangerous variant of this virus [2]. (see Fig. 1). As a result, many medical researchers are trying to develop drugs and antibiotics to treat sick patients, some are working on vaccines to prevent the spread of the virus. Because of the lack of detection tools and production restrictions, detection of the disease has been slow; as a result, the number of patients and injuries has increased. If COVID-19 disease is diagnosed in time, the occurrence of other diseases, as well as the prevalence and number of deaths it causes, will be reduced.

Meanwhile, computer scientists have used techniques to interpret and understand medical imaging data to quickly identify affected patients. One of the most common symptoms of COVID-19 is respiratory problems, which can be identified using chest X-ray imaging and CT scan. Chest X-rays are preferred over CT scans because they are much more time-consuming and therefore more expensive. However, only developed countries have access to suitable CT scanners. In contrast, Radiographic images remain the most common and widely available form of diagnostic imaging for more practical and therapeutic purposes. [3]. Specialists typically detect COVID-19 in the laboratory to diagnose the condition. With this technique, the specialist diagnoses COVID-19 disease in a healthy person or a person with other diseases based on the signs and fractures in the chest radiology image. This procedure has a high cost.

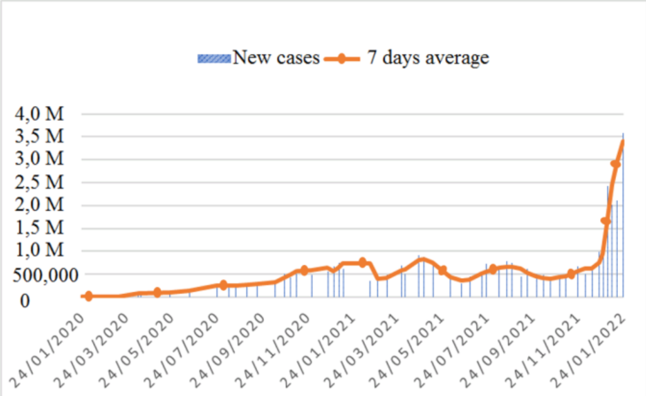

Fig. 1. New confirmed cases per day per million population worldwide.

Artificial intelligence (AI) has been successful over the past few decades in various fields, and these computational methods are among them. The contribution of AI technologies to the fight against the COVID-19 pandemic is the topic of this article. The use of computer vision and Deep Learning in the diagnosis of this disease can be helpful. Many researchers have used computer vision and Deep Learning approaches to analyze the disease since it became prevalent, with desirable impacts [4]. Diagnostic accuracy is one of the biggest challenges we face in our research due to the sensitivity of the Covid-19 diagnosis. Due to the small amount of open-source data available, our focus is on improving detection efficiency. The objective of this paper is to improve COVID-19 detection and reduce COVID-19 misreporting. To do so, we use a deep learning-based model, more precisely convolutional neural network-based on transfer learning technique, to automatically extract features from the radiographic images that describe the appearance of the disease and indicate whether it is a COVID-19 infection, which is very useful in helping health services to screen, identity, and track positive cases. The main objectives of this paper are:

- Increase the accuracy of the overall model for each of the three classes with positive prediction values> 90.
- Adopt model training strategies that require fewer epochs and less training time.
- Adopt a low parameterization, low computational complexity structure to maintain a balance between performance and computational complexity.

The following sections constitute the remainder of the paper; the literature review is discussed in Section 2. Section 3 describes the approach proposed in this paper. In section 4, the results are described and discussed. Finally, the conclusion and recommendations for future studies are presented in Section 5

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II. DIAGNOSTICS OF COVID-19: STATE OF THE ART

Computer vision and deep learning have been proven to analyze and detect COVID-19 in medical imaging (chest X-rays and CT images), allowing researchers to use advances in these technologies to establish the diagnosis of this virus. The use of artificial intelligence techniques in disease detection and measurement of infection rates has significant benefits, with encouraging results [5].

Farooq and Hafeez [6] suggested a model called COVIDResNet that uses a series of radiographic image datasets to classify patients as natural, bacterial, viral Pneumonia, and COVID-19 positive infections in stages based on the architecture of ResNet-50. A 96.23 % accuracy was obtained.

The proposed model was evaluated to Xception ResNet50V2 models as a means of classifying chest X-ray images according to the normal, COVID-19, and non-COVID pneumonia classes in another Paper [7], Transfer learning techniques were introduced with the concatenation of pre-trained models, ResNet50V2 and Xception, and the proposed approach was compared to Xception ResNet50V2 models as a means of classifying chest X-ray images according to the As part of their classification research, they used five-fold cross-validation. The accuracy of this procedure was roughly 91.4 percent.

Narin et al.[8] demonstrated multiple deep learning techniques, including ResNet-50, Inception-ResNetV2, and InceptionV3, as well as three distinct deep learning architectures. COVID-19 is distinguished from the healthy image using binary classification. According to the results, ResNet50 has the highest classification accuracy of 98.0% and recall of 96%, while InceptionV3 reaches 97% and Inception-ResNetV2 87%.

The work of Chowdhury et al [9] presented a series of methods, including a transfer technique to detect the COVID-19 virus from radiographic images of the lungs. They demonstrate using pre-trained architecture as classifiers, such as AlexNet, DenseNet-201, ResNet-18, and SqueezeNet. The SqueezeNet network obtained a classification accuracy of 98.3 % and a precision of 99%.

The Transfer Learning Based Inception V3 was used to diagnose the patient's chest infection, according to Asif and Wenhui [10] They suggest a method to automatically diagnose COVID-19. Normal radiographic imaging, pneumonia, and COVID-19 were all used to validate this model. A 96 percent classification accuracy was achieved.

Based on Xception, Khan et al [11] developed CoroNet, a solution for classifying chest radiographs to distinguish between cases of bacterial or viral pneumonia, normal, and COVID-19. As a result, they were able to achieve an average success accuracy of up to 89.6%.

For detecting COVID-19 positive cases, Sethy and Behera [12] trained a variety of different CNN models for extraction features using radiographic images of different architectures in combination with the Support Vector Machine, achieving a 95.38% overall accuracy.

Also, in [13], convolutional neural networks (CNNs) equipped with an improved and faster RCNN architecture to detect SARS-CoV2 from CT images are newly proposed. More exciting extensions of CNNs include [14] employing these networks to recognize emotions in speech while the same CNNs are used to recognize hand gestures in [15].

III. PROPOSED MODEL

We explain and detail our proposed model in this section. The different architectural components of the deep learning model are shown in Figure 2 below (see Fig. 2). The design of the structure was divided into two parts. Image preprocessing and augmentation were used in the first. In the second part, we focused on using existing convolutional neural network architectures that have been proven successful in a wide variety of classification tasks, instead of designing our architecture, For this, a deep convolutional network is defined using a transfer learning neural network based on the DenseNet121 architecture, then classification is performed using a fully connected network whose main goal is to predict classification, for our specific classification task, we adopted the final fully connected layer in 3 classes (COVID-19, Normal and Pneumonia), and defined the weight parameters. A description of the process for each modeling component is given in Figure 2.

A. *X-ray Image Pre-processing*

To establish our COVID-19 detection model, we used chest radiographic images based on COVID-19 features, such as small shadows or interstitial changes in the early stage, infiltration, and multiple frosted lenses in the progression stage, for the training and validation phases. In addition, we included images representing other types of viral and bacterial pneumonia and representative images of uninfected persons. The images in the input dataset are of different sizes, with approximate dimensions of these images ranging from 4000*3400 to 460*450 pixels.

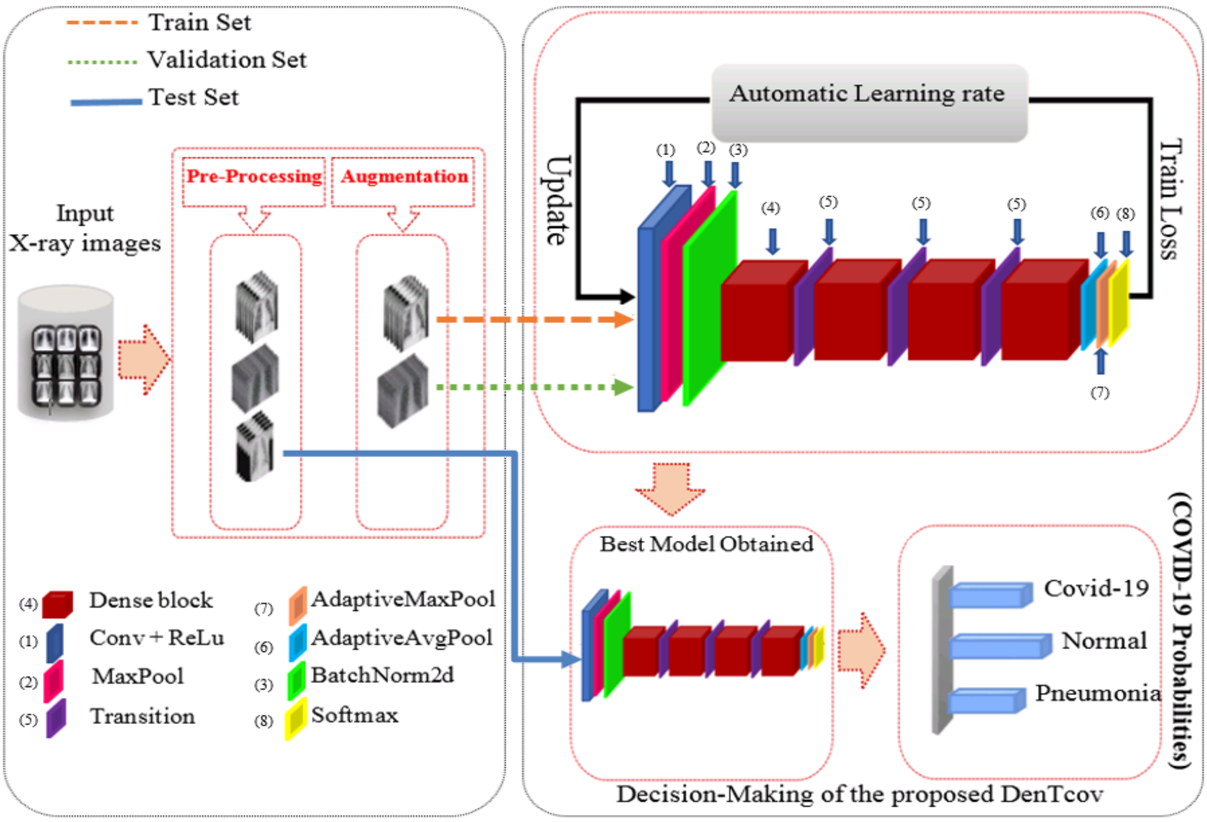


Fig. 2. Proposed deep learning methodology used to detect COVID-19.

Before sending the images to the training model, some preparatory operations must be performed. In this preliminary step, we prepare the dataset according to the corresponding deep transfer neural network, as an example: DenseNet121 needs input images of size 224 × 224 × 3 (see Tab.1), which requires resizing as part of the preprocessing process. A bilinear interpolation function was used, which is simple and commonly used. In addition, normalization of all images was performed based on the appropriate architecture. A Min-Max-Scalar function was employed to normalize an I-th image in the interval [0, 1] according to this form (1):

$$I_n = \frac{I_i - \min(I_i)}{\max(I_i) - \min(I_i)} \quad (1)$$

Where: I_i is the resized image.

B. Deep Learning Model

Deep convolutional neural networks are useful for computers vision tasks, agriculture; medical disease diagnosis [16]; and industry [17] are some of the areas where they have enabled advances. The stable and useful semantic features that these networks produce from the input data are the reason for their dominance. The main purpose of deep networks, in this case, is to detect infection in radiological images by classifying them as normal, Pneumonia, or COVID-19. VGG [18], ResNet [19], DenseNet [20], Inception [21], and Xception [22] are some of the most effective used deep convolutional networks.

1) DenseNet based classifier.

DenseNet, proposed by Huang et al [20], offers many possibilities to deal with gradient loss, optimize and facilitate feature reuse, by communicating features to all the successive layers of the dense block. The architecture of DensNet121 is described as follows: Each dense block has a different number of layers, and there are four dense blocks in total (6, 12, 24, 16 consecutive layers). Transition layers exist between each dense layer, which reduces the size of the features created by concatenation. A global average-pooling layer and a fully connected layer are used in the classification layers. See [20] for more information.

In convolutional neural networks, learned filters are applied to input images to create feature maps that summarize the occurrence of those features in the input images. These convolutional layers are proving to be very efficient and allow, by piling convolutional layers into deep models, allow for layers close to the input to learn low-level features and deeper layers to learn higher-level or more abstract features, such as shapes or certain objects.

Pooling layers of deep CNN. Pooling layers work for multi-scale analysis and input (image) size reduction to achieve feature reduction. Two common functions used in the pooling operation in CNNs are the Max Pooling and Average Pooling layers, which are employed in the proposed architecture.

C. Transfer Learning

For the automatic detection of COVID-19 using a pre-trained model based on transfer learning, we used the knowledge of an existing set of pre-trained convolutional neural network architectures, instead of proposing our architecture from scratch. For this reason, the DensNet121 architecture [20] was used as an effective means for feature extraction using its weights that are performed in the ImageNet dataset [23] using reduced parameters. Then, the classification of radiological images is performed by the pre-trained model based on the assigned class labels of the training dataset, i.e., COVID-19, Normal, and Pneumonia. For new radiological images, the model is re-trained by updating the fully connected layers of the model based on the input augmented dataset.

Our proposed model has two parts: a first component that exploits the capabilities offered by DensNet121 to transform visual elements into feature vectors; the trained model head is replaced by another head containing a series of layers for transfer learning as mentioned below, and a second component that is essentially a fully connected layer aimed at predicting a classification. In this work, we add a succession of layers to the typical DensNet121, namely adaptive Mean/Maximum pooling, batch normalization, and dropout according to [24]. We then replace the second part of DensNet121 with a fully connected network so that probabilities are computed based on our classes, normal, pneumonia, and COVID-19. This network is fine-tuned with the data and the predicted output is the class with the highest probability, the details of the architecture in TABLE 1.

TABLE 1
DETAILS ON THE PROPOSED MODEL'S ARCHITECTURE.

DenseNet121 Part	Input Layer	[224, 224, 3]	0
	Conv1_conv (Conv2D)	[112, 112, 64]	9,408
	Conv1_BatchNorm2d	[112, 112, 64]	128
	Conv1_ReLu (Activation)	[112, 112, 64]	0
	Pool1_MaxPooling2D	[56, 56, 64]	0
	Conv2_Dense_1 (6 blocks)	Input [56, 56, 64] Output [56, 56, 32]	256 36,864
	Conv2_block6_Transition	[56, 56, 256]	0
	Pool2_BatchNorm2d	[56, 56, 256]	512
	Pool2_ReLu (Activation)	[56, 56, 256]	0
	Pool2_Conv2d	[56, 56, 128]	32,768
	Pool2_AveragePooling2D	[28, 28, 128]	0
	Conv3_Dense_2 (12 blocks)	Input [28, 28, 128] Output [28, 28, 32]	512 36864
	Conv3_block12_Transition	[28, 28, 512]	0
	Pool3_BatchNorm2d	[28, 28, 512]	2048
	Pool3_ReLu (Activation)	[28, 28, 512]	0
	Pool3_Conv2d	[28, 28, 256]	131072
	Pool3_AveragePooling2D	[14, 14, 256]	0
	Conv4_Dense_3 (24 blocks)	Input [14, 14, 256] Output [14, 14, 32]	1024 36864
	Conv4_block24_Transition	[14, 14, 1024]	0
	Pool4_BatchNorm2d	[14, 14, 1024]	4096
	Pool4_ReLu (Activation)	[14, 14, 1024]	0
	Pool4_Conv2d	[14, 14, 512]	524288
	Pool4_AveragePooling2D	[7, 7, 512]	0
	Conv5_Dense_4 (16 blocks)	Input [7, 7, 512] Output [7, 7, 32]	2048 36864
	Conv5_block16_Transition	[7, 7, 1024]	0
	Pool4_BatchNorm2d	[7, 7, 1024]	2,048
Modified Part	AdaptiveAvgPool2d	[1, 1, 1024]	0
	AdaptiveMaxPool2d	[1, 1, 1024]	0
	Flatten	[2048]	0
	BatchNorm1d	[2048]	4,096
	Dropout	[2048]	0
	Linear	[512]	1,049,088
	ReLu	[512]	0
	BatchNorm1d	[512]	1,024
	Dropout	[512]	0
	Linear	[3]	1,539

Training of the network. In the training phase, the modified components of the model were fine-tuned with pre-trained weights, while the original components were not trained. We obtain the best convolutional neural network architecture for transfer learning and its hyperparameter by training the model and selecting an optimal learning rate using the cyclical learning rate technique proposed in [25] by Leslie Smith. We configure our model training process with the parameters shown in the following TABLE 2.

TABLE 2
HYPERPARAMETERS DETAILS USED IN OUR MODEL.

Parameters	Value
Batch size	64
Optimizer	Adam, SGD
Momentum	Betas = {0.9, 0.99}
Classes	3 Classes (Normal, Pneumonia, Covid-19)
Loss Function	FlattenedLoss. Useful in multi-classification problems.
Training epochs	15
Dropout	0.3
Classifier	Softmax (layer outputs the probability distribution)
Activation function	ReLu
Total params	**8,009,603**
Total trainable params	1,139,395
Total non-trainable params	6,870,208

IV. EXPERIMENTATION AND DISCUSSION

A. *Experiments*

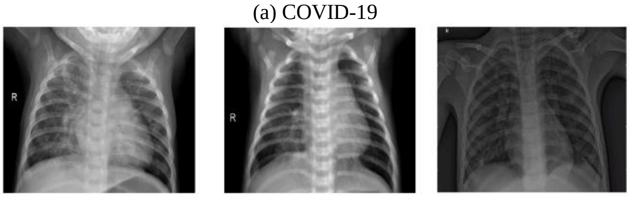
1) *Implementation environment.*

The proposed methodology is implemented in python under Google Colaboratory [26], a scientific initiative to prototype machine learning models on high-performance device technologies such as GPUs and TPUs. GPUs are used in this paper with higher computational capabilities, more appropriate for CNNs. Finally, to develop the model, the Keras library [27] was used with the TensorFlow backend [28].

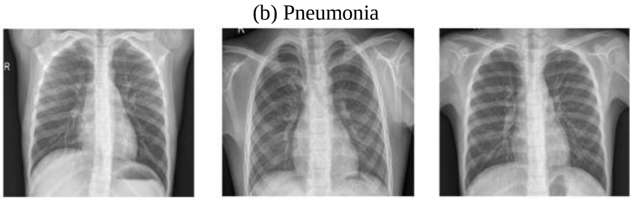
2) *Collection of Dataset.*

The dataset was obtained from GitHub, a distributed domain website created by Dr. Joseph et al. has shared [29] that includes chest X-rays of patients infected with COVID-19 as well as radiographs of other COVID19 families including ARDS, SARS, and MERS. Only COVID-19 radiographic images with a total of 180 images, 180 Normal X-ray images, and 180 Bacterial and viral pneumonia infections were included in our dataset, which came from a Kaggle search for "Chest XRay Images (Pneumonia)" [30] (see Fig. 3).

(a) COVID-19



(b) Pneumonia



(c) Normal

Fig 3. chest X-ray images.

In the pre-processing phase, the images are randomly distributed, 80% for training, and 20% of the data for validation. Upon entering the proposed model, TABLE 3 gives an overview of the data destruction, the images are reduced to 224×224×3 pixels, and the model is fine-tuned.

TABLE 3
DESCRIPTION OF INPUT DATASET USED FOR THE PROPOSED WORK.

Class	Training set	Validation set	Testing set
COVID-19	144	36	45
Pneumonia	144	36	30
Normal	144	36	33

We applied transfer learning for training. The pre-trained weights from ImageNet [23] were used to start the training, before repeating the process with the conditions of our dataset. The 1-cycle technique [25] was also used to determine the hyperparameters and train our network in each epoch to achieve the most optimal converged configuration of the trained network. Finally, the accuracy measure was used to evaluate the network's performance on the test dataset.

B. *Data Augmentation.*

The data set related to COVID-19 is limited and insufficient for training a deep neural network model. Due to this small proportion of the dataset, the augmentation of the training dataset is necessary to expand the training dataset and avoid overfitting. This augmentation involves generating new data by modifying existing data sets. In fact, with reasonable modifications by randomly applying different transformations to our training set, we obtain new augmented data (see Fig. 4).

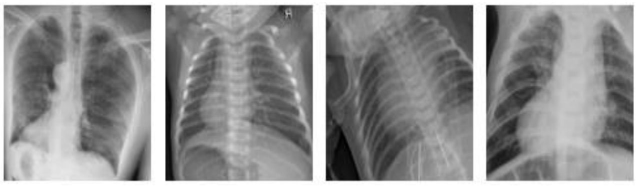


Fig. 4. An illustration of the images after applying the augmentation.

In the proposed methodology, the transformations are performed as illustrated in the following TABLE 4:

TABLE 4
PARAMETERS RELATED TO PRE-PROCESSING AND AUGMENTATION APPLIED TO DATA.

Data augmentation	Pre-processing
Random flip	Resizing to 224 ×224 ×3
Random rotation maximum angle was 10	Normalization
Random zoom 5%	-
Change in brightness and contrast	-

1) *Evaluation Metrics.*

We adopted four evaluation matrices to judge the achievement of the results obtained from the proposed model, such as accuracy (ACC), recall (Rec), precision (Prec), and F1-score (F1). True positives (Tp) refer to the number of correctly classified images, true negatives (Tn) are the number of images not belonging to a class and not classified as belonging to that class, false positives (Fp) indicate the number of misclassified images of a class, and the false negatives (Fn) corresponding to the number of images belonging to a class and found as another class, defined as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{F1-score} = 2\times\frac{Prec\times Rec}{Prec+Rec} \quad (5)$$

C. *Results and Discussion*

1) *Results*

In the presented work, a pre-trained transfer learning model DenseNet121 is trained and then validated for the classification of input X-ray images into 3 classes: COVID-19, Pneumonia, and Normal.

During the learning process, the newly added layers of the network as well as the last group of layers, i.e., the fully connected (FC) layers, were trained for 10 epochs while maintaining the ImageNet weights in the rest of the DenseNet121 network. The optimal learning rate is chosen using the cyclic learning rate implemented in [24]. This technique uses discriminative learning rates, which keep the learning rate low for initial layers because they require less adjustment and gradually increase the learning rate on later layers that require more adjustment, especially fully connected layers. Using the learning rate (max_lr) in the interval 1e-4, 1e-3, the entire network is fine-tuned the initial layers with 1e-4 and the later layers with 1e-3. Each intermediate layer was trained with learning rates between these values for 10 epochs.

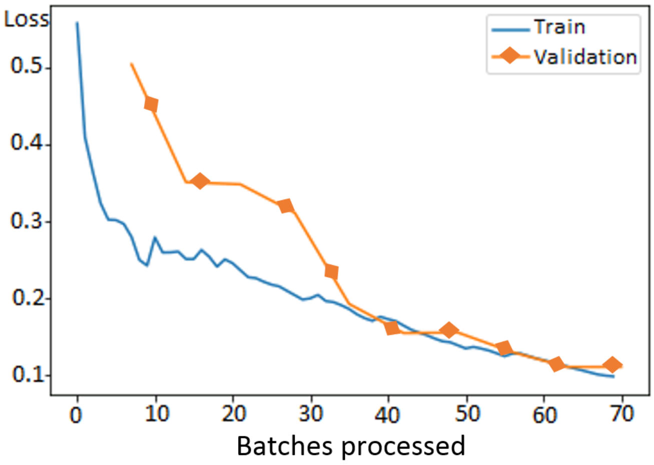


Fig 5. Convergence graph of training and validation losses for 3 classes.

To obtain rapid results to train our model, we used the 1-cycle technique to determine the hyperparameters to be able to train our model in a timely and efficiently (i.e. learning rate, momentum), This technique aims to start training the model by increasing the learning rate from a very low to a very high level, and then stopping when the loss becomes uncontrollable, as shown in TABLE 5.

TABLE 5
VALUES OBTAINED BY USING THE 1-CYCLE TECHNIQUE.

Epoch	Train loss	Validation loss	Time
0	0.196133	#	00:24
1	0.186655	#	00:24
2	0.194559	#	00:25
3	0.190275	#	00:23
4	0.191329	#	00:23
5	0.176996	#	00:23
6	0.174025	#	00:23
7	0.180905	#	00:23
8	0.188426	#	00:23

With only 20 epochs, we were able to achieve state-of-the-art accuracy of 96.52 % (from all three classes) on the dataset using this method and automatic learning rate selection. Figure 5 shows the loss convergence curves for the training and validation phases for 3-class (see Fig 5), with the loss function running through 70 epochs with the highest classification achieving an accuracy of 96.52% shown in Fig 6, and the Error Rate in Figure 7 (see Fig 7).

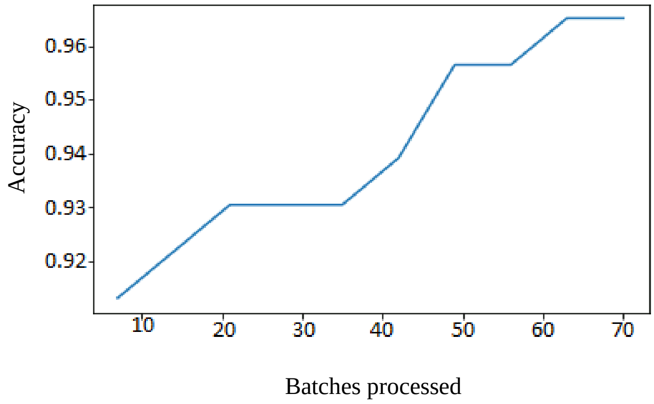


Fig 6. Accuracy convergence graph

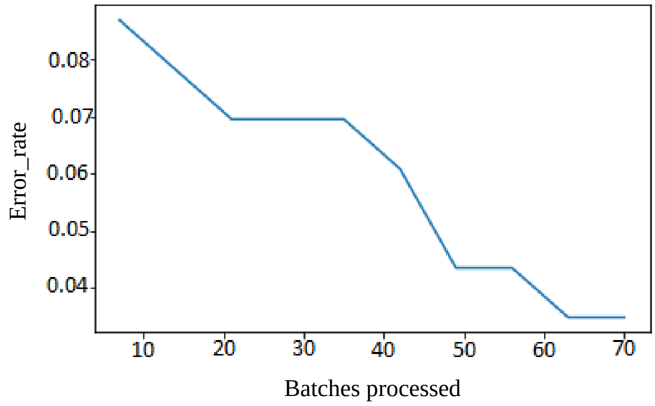


Fig 7. Error rate convergence graph

Table 6 shows the sensitivity (recall), precision, and F1 scores for each class. The proposed deep learning model yielded 100 % precision on the test dataset for the COVID-19 class, the sensitivity was 97.29% and the f1 score was 98.62%. Finally, 89.09% was obtained for precision, recall, and f1 score for pneumonia class.

TABLE 6
PRECISION, RECALL, AND F1-SCORE CORRESPONDING TO DIFFERENT CLASSES.

Metrics	COVID-19	Normal	Pneumonia
Recall	100.0 %	92.0 %	89.09 %
Precision	97.29 %	93.24 %	89.09 %
F1-Score	98.62 %	92.61 %	89.09 %

For the classification experiment performed, 10-fold cross-validation was used. To ensure that the results of the experiment are not unstable, the experiment was repeated 10 times, and the optimum classification accuracy was selected for comparison. We evaluate the efficiency in terms of correctly classified instances and incorrectly classified instances for a three-class classification, as shown in Table 7.

TABLE 7
CORRECT AND INCORRECT INSTANCES CORRESPONDING TO DIFFERENT CLASSES.

Metrics	COVID-19	Normal	Pneumonia
Correctly classified instance	36	49	69
Incorrectly classified instances	1	12	11

Our model was evaluated for a second scenario, which consists of classifying patients into two classes: COVID-19 and pneumonia. We achieved 98.6% accuracy with the higher classification, and the loss function is run over 70 epochs (see Fig. 8).

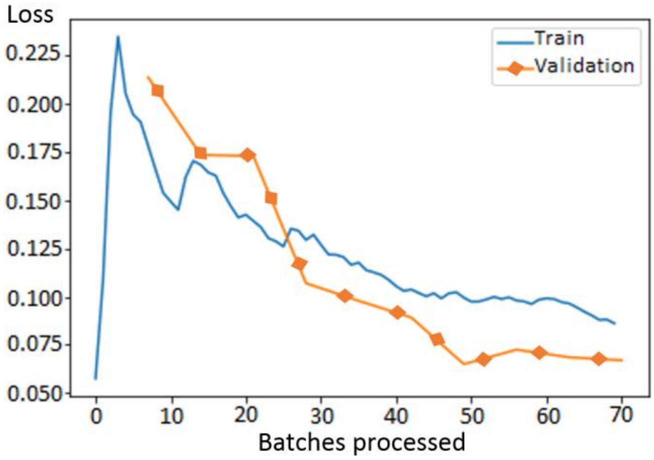


Fig 8. Convergence graph of training and validation losses for 2 classes.

The confusion matrix is needed to evaluate the performance of the classification. Figure 10 and 11 shows that our model has perfect sensitivity for the COVID-19 class, meaning that it did not ignore any of the COVID-19 instances. This is important because the goal is to identify all COVID-19 positive cases and thus limit the spread of the virus in the population. Another notable benefit of these results is that the network has a 100% positive predictive value. This demonstrates that no class was misclassified as COVID-19 from the other classes. The Pneumonia class is not well classified. The reason for this problem may be that the class includes both two sorts of pneumonia: Viral and Bacterial. Also, the progression of the disease may be different in people who develop pneumonia.

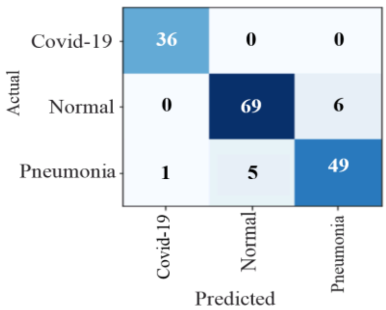


Fig 9. Confusion matrix for our model on the test dataset for 3 classes.

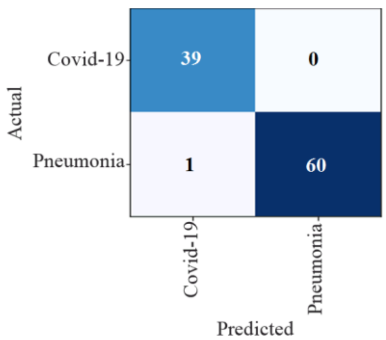


Fig 10. Confusion matrix for our model on the test dataset for 2 classes.

2) Comparative analyses

For comparison purposes, the analyses of the results in terms of accuracy, f1 score, precision, and recall of the proposed model versus concurrent deep learning models: ResNet [19], DenseNet [20], Inception [21], and Xception [22], are shown in Table 8.

TABLE 8
COMPARISON RESULTS OF THE PROPOSED AND THE COMPETITIVE MODELS

Models	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)
DensNet169	92,96	93	93	94
DensNet201	94,53	94	95	95
Xception	93,75	93	91	94
ResNet101	78,90	77	79	82
ResNet152	52,34	52	63	64
InceptionV3	87,5	89	88	88
Proposed model	96,52	96	96	95

From the results, the performance of the proposed model is significantly better than the other models in terms of accuracy, f1 score, recall, and precision, an encouraging result: the model reaches a higher sensitivity, which shows that the proposed model can be used to make decisions in the medical field.

3) Discussion

Our current work focuses on the automatic detection, from X-ray images, of the features that could be significantly related to COVID-19 disease compared to other respiratory diseases, in order, to classify it efficiently, the use of the DensNet121 architecture was effective in this task, due to the high accuracy that was achieved, 96.52% for three classes.

We compared the results in terms of accuracy achieved by the proposed methodology and existing methods. We present in this section the results obtained according to the respective studies of the authors. Apostopolus et al. [31] used a total of 224 COVID-19 image data in their study, where they achieved 93.4% accuracy with the VGG-19 CNN model for their 3 classes (COVID-19, bacterial pneumonia and normal). in another Paper [7], the proposed model was evaluated to Xception ResNet50V2 models as a means of classifying chest X-ray images according to the normal, COVID-19, and non-COVID pneumonia classes, Transfer learning techniques were introduced with the concatenation of pre-trained models, ResNet50V2 and Xception, and the proposed approach was compared to Xception ResNet50V2 models as a means of classifying chest X-ray images according to the As part of their classification research, they used five-fold cross-validation. The accuracy of this procedure was roughly 91.4%. Based on Xception, Khan et al [11] developed CoroNet, a solution for classifying chest radiographs to distinguish between cases of bacterial or viral pneumonia, normal, and COVID-19. As a result, they were able to achieve an average success accuracy of up to 89.6%. Ozturk et al. [32] developed a model using The DarkNet architecture. They obtained 98.08% and 87.02% rates respectively on two and three classes of their model. The proposed model is higher compared with other references, TABLE 9 summarizes all of the above results.

TABLE 9
A COMPARISON OF STATE-OF-THE-ART AND PROPOSED MODEL ACCORDING TO DIFFERENT CRITERIA.

State-of-the-art approaches	Accuracy 2-Class	Accuracy 3-Class	Param. (Million)
VGG-19	98.75%	93.48%	143
Xception + ResNet50V2	NA	91.40%	NA
Xception	99.00%	89.60%	33
DarkNet	98.08%	87.02%	1.1
Proposed Model	98.60%	**96.52%**	**8**

The results obtained were useful for the automatic detection of COVID-19 from radiological images, due to the high accuracy obtained, 96.52% for three classes (COVID-19, Pneumonia, and Normal), with 98.6% for two classes (Pneumonia and COVID-19). It should be noted that as the recall value increases, the number of false negatives decreases, a significant result in the medical field. Thus, the model we propose allows guiding the decision with a performance equivalent or even superior to that of the experts, thus offering a rapid diagnosis.

To better understand the logic of the decision-making process, we plan to add techniques to clarify the model's prediction of why these decisions were made. This would increase the confidence of the model as well as the possibility of discovering fascinating new observations and patterns in the radiographs.

This research is limited by certain constraints. Deep Learning (DL) is now able to capture explicit correlations in different types of data, offering great potential in terms of applications. Radiographic images contain heterogeneous objects and classification is difficult, especially areas beyond the lungs that are not significant for disease diagnosis. In addition, the amount of data collected is quite small. An increase in this set should improve the performance of the model.

V. Conclusion and future work

Finally, a promising radiological image-based technique was developed to classify COVID-19 infection among other viral pneumonia diseases using Artificial intelligence techniques. The DenseNet121 model was considered a promising model for characterizing and diagnosing COVID-19 infections in this study. A combination of transfer learning and data augmentation techniques is used to solve the overfitting issue. In the experiments, an accuracy of 96.52% for 3 classes and 98.6% for 2 classes was achieved with a high F1 score of 98.62%, confirming the effectiveness of the proposed model. This model has a low cost and can be used as an alternative to x-ray imaging in radiology departments. In the future, we expect to expand the experimental work to validate the model with larger datasets through continuous data collection. We also hope to incorporate an explanation capability component to improve the usability of the model.

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