Classification of Chest X-ray Images to Diagnose Covid-19 using Deep Learning Techniques

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Abstract: The new coronavirus pandemic has brought disruption to the world. One of the significant dilemmas to be solved by countries, especially in underdeveloped countries like Brazil, is the lack of mass testing for the population. An alternative to these tests is detecting the disease through the analysis of radiographic images. To process different types of images automatically, we employed deep learning algorithms to achieve success in recognizing different diagnostics. This work aims to train a deep learning model capable of automatically recognizing the Covid-19 diagnosis through radiographic images. Comparing images of coronavirus, healthy lung, and bacterial and viral pneumonia, we obtained a result with 94% accuracy.

1 INTRODUCTION

The new coronavirus pandemic has plagued the world since November 2019, with its appearance in the province of Wuhan (China), causing from asymptomatic infections to severe respiratory issues, leading to death. Initially, the belief was that there were just a few isolated pneumonia cases, which further aggravated the local population's situation. According to the WHO[1], the Wuhan Municipal Health Commission has already reported an outbreak of pneumonia cases on December 31, 2019. Eventually, the scientists discovered that it was a new member of the Coronavirus family.

The rapid spread of the disease has been one of the main problems for the health area. According to the "Centers for Disease Control and Prevention"[2], the contamination occurs mainly by contact with infected people, through droplets of saliva expelled by them, which land in the mouths and noses of those nearby. Besides, there may be contamination through the sharing of objects that have had contact with these droplets.

To have an idea of the pandemic dimension, at the end of June (2021), what appeared to be a simple disease claimed the lives of almost 4 million human beings across the globe[3]. Brazil occupies the 3rd place in the world ranking, with more than 500,000 deaths[4]. At this moment, the country is behind only India and the United States, which generates an emotional impasse, of people who have lost their loved ones, and political, on the part of the political authorities trying to solve the problem.

With the rapid contamination of Covid-19, there is a lack of infrastructure and medical resources worldwide. Furthermore, the diagnosis of COVID-19 is typically associated with pneumonia symptoms that can be revealed by genetic and imaging tests (Li et al., 2020; Silva et al., 2021). Countries suffer from the lack of hospital beds, respirators, exams, and, mainly, from testing the population, becoming difficult to know the real proportions of the damage to public and private health.

Due to this situation, some research areas become good agents to solve or mitigate these problems. In Computer Science, the Artificial Neural Net-

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[1]https://www.who.int/news-room/detail/27-04-2020-who-timeline—covid-19

[2]https://www.cdc.gov/coronavirus/2019-ncov/faq.html

[3]https://www.worldometers.info/coronavirus/

[4]https://www.worldometers.info/coronavirus/#countries

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works (ANNs) — characterized by the ability to learn through examples and to generalize the information learned (Spörl et al., 2011) — are an alternative to help in different areas science (Osóio and Bittencourt, 2000; Shi et al., 2020). Indeed, the computational solutions, especially those from the Computational Vision's of state-of-the-art, indicate changes in everyday life (Cui et al., 2020), such as the unmanned car, which recognizes routes and objects.

In the field of medicine, Computer Vision has made several significant contributions, mainly with the use of advanced ANN techniques (Chen, 1995). In particular, these contributions can be applied to assist in the Covid-19 diagnosis through the processing of radiographic images, in which the presence of diseases is visualized. Thus, these techniques allow the analysis and screening of cases with coronavirus, enabling an alternative to mitigate the problem of specialized mass testing in a country's population. Thus, the rapid detection of the disease can contribute to controlling its propagation (Abbas et al., 2020).

Given this problem, we decided to apply the concepts of Machine Learning (ML) and Deep Learning (DL) in a computational model, allowing the machine to automatically diagnostic the Covid-19, through the analysis of radiographic chest images, assisting in hospital screening. We trained the model to identify and catalog the images among the following classes: Covid-19; healthy lung; viral pneumonia; and bacterial pneumonia.

The main contributions of this work are listed below:

- we gather groups of images from different databases;
- we catalog and pre-process these images, making them ready for use in machine learning techniques;
- we train a model using a deep learning technique to diagnose Covid-19, bacterial pneumonia, and viral pneumonia in x-ray images;
- we make available the code and datasets regarding the model training and test processes;
- we grant access to our model, which highlights the Covid-19 class with good accuracy.

The structure of this article is organized as follows: in Section 2, we explain the general concepts related to this work; in Section 3, we mention some related works; in Section 4, we describe the steps of the proposed methodology; in Section 5, we present and discuss the model's results; lastly, in Section 6, the present our final remarks.

2 BACKGROUND

In Machine Learning, learning can take place in two ways: supervised learning and unsupervised learning (dos Santos et al., 2017). In supervised learning, a labelled data set with input patterns and their corresponding output patterns is applied to train the model. The model must learn from these examples, providing the best responses as output, according to the acquired knowledge from the original dataset. In unsupervised learning, there is no external agent to accompany this process, i.e., no type of labelled dataset is given to the learning algorithm. In this case, the model learns to identify patterns on its own and tries to classify them automatically.

Additionally, among these concepts, there is semi-supervised learning, which has been highly explored in both machine learning and data mining fields. This learning type can use available unlabelled data to improve the supervised learning tasks when the datasets are expensive or scarce/insufficient (Zhu and Goldberg, 2009).

In Information Retrieval problems, this learning can be achieved using Artificial Neural Networks (ANNs) to predict unknown examples (Chen, 1995). In this sense, ANNs are learning models that seek to simulate human brain behavior, inspired by the Central Nervous System (dos Santos et al., 2017). Thus, the ANN operation is normally performed by interconnected "neurons" that process the input data and return a series of outputs, identifying patterns in images, for example. Within this context, Convolutional Neural Networks (CNN) are a class of ANNs that was inspired by the human visual system for image processing and recognition (Da Silva and Costa, 2019).

CNN is a class of neural networks known as deep learning (DL). The main difference between CNN and simple ANNs is in the depth of the learning methods to find $f(x)$, the function that determines the model training. The DL method learns through a series of $f(x)$ functions that are composed of each other, functioning as layers (Kopiler et al., 2019): $f(x) = fn(...(f2(f1(x))...))$. The set of layers $f1, f2, ..., fn$ receive an input value, x, from the input layers, which "crosses" layer by layer during the learning process - usually called hidden layers - and returns a value as output.

Besides the CNNs, there are other ANN types, such as the Feedback ANN and the Feed Forward ANN[5]. The main characteristic of the Feed Forward ANN is recognizing and evaluating input patterns, while the Feedback ANN is commonly used due to

[5]https://www.elprocus.com/artificial-neural-networks-ann-and-their-types/

its capacity of solving optimization problems.

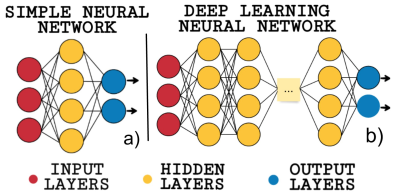

Figure 1: Simple and Deep Learning Neural Networks.

Fig. 1 shows that the approach in ANN is simpler than in DL. A CNN comprises three main layers: (i) convolutional layers, which apply the data augmentation concept, an image regularization method that avoids overfitting, in addition to increasing the data batch (this occurs by reusing the images, but changing their translation, rotation, flattening, etc., to increase the training dataset); (ii) pooling layers, which reduce the spatial dimensions of the image; and (iii) fully connected layers, which convert the 2D feature maps, the output of a filter applied to the previous layer, into a 1D feature vector, generating the final classification (Voulodimos et al., 2018). Besides the CNNs, there are other ANN types, such as the Feedback ANN and the Feed Forward ANN[6]. The main characteristic of the Feed Forward ANN is recognizing and evaluating input patterns, while the Feedback ANN is commonly used due to its capacity of solving optimization problems.

Another relevant concept is Transfer Learning, a technique that adapts a pre-trained model, which performs a general task, to perform a specific task (Da Silva and Costa, 2019). This pre-trained model, in our case, was the *resnet34*[7]. The *resnet34* is a CNN belonging to the *Residual Networks* family, which are CNNs adapted to maintain good rates of *train loss* and *validation loss* even with many layers of processing. Before working on our dataset, the *resnet34* is pre-trained with the gigantic ImageNet[8] database, which puts the Transfer Learning concept into practice.

When working with machine learning, we may encounter some problems linked to the dataset. If the dataset is built with little or "dirty" data, the trained model may present unsatisfactory results. For instance, the model may suffer overfitting due to not performing a pre-processing of the dataset before training. Besides, the model may suffer from insufficient adjustments, such as low/high number of epochs, loss function, batch size and optimization algorithm. In this case, the model fails to generalize correctly, that is, to learn the necessary classification standards.

[6]https://www.elprocus.com/artificial-neural-networks-ann-and-their-types/

[7]https://www.kaggle.com/pytorch/resnet34

[8]http://image-net.org/

2.1 Covid-19 Detection

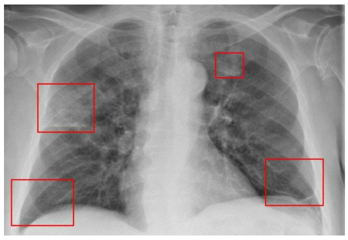

Figure 2: Patient with a clinical picture of Covid-19.

Bai *et al.* (Bai et al., 2020) observed that pneumonia caused by the Covid-19 had presented peripheral distribution with ground-glass opacities (GGO) and vascular thickening. The medical diagnostics of Covid-19 is achieved through the analyses of the lung opacities. Normally, this opacities distribution is bilateral, peripheral, and in the lower zone of the lung (Rodrigues et al., 2020; Wong et al., 2020). Despite this, due to the similarities in the images, the diagnostic of diseases by x-ray is easily confused, becoming important to diagnose the viral tests, to validate the individual situation.

Fig. 2 shows the abnormalities (opacities) located in the lung of a patient with Covid-19. Other exams carried out by the Italian Society of Medical Radiography (SIRM)[9] confirmed the Covid-19 diagnostic in the patient. The diagnostic prediction using the images happens similarly to the specialists' predictions. The machine finds opacity patterns and attributes them to specific diseases, once it has already learned these patterns previously.

3 RELATED WORKS

The Deep Learning and Machine Learning - subareas of Artificial Intelligence (AI) - have been very useful in the field of Computer Vision (CV) (Shi et al., 2020). The various AI methods allow making automated predictions of different image categories, making the visual classification process faster and simplified, without the need of a human specialist (de Oliveira et al., 2019). Deep learning has brought significant developments to image processing tasks such as object detection, image classification, and image segmentation (Ohri and Kumar, 2021).

[9]https://www.sirm.org/

CV has been applied in image recognition for several purposes, such as fish detection (Cui et al., 2020); problem solving in the electrical sector (Kopiler et al., 2019); diagnosis of pneumonia and Alzheimer in the health area (de Oliveira et al., 2019; Duarte et al., 2020); and oil recognition on beaches (Negreiros et al., 2020) in the environmental area.

With applications in the health area, especially with the pandemic caused by the coronavirus (COVID-19), AI techniques have made social contributions highlighted by several academic works with several purposes to alleviate the global crisis: prevent the spread of the COVID-19 with automatic detection of face masks (Singh et al., 2021), to monitor people wearing masks in public places, and Covid-19 diagnosis through images x-ray (Shi et al., 2020; Abbas et al., 2020; Li et al., 2020).

Shi *et al.* (Shi et al., 2020) analyzes several works on Covid-19 diagnosis, being possible to observe the preference of using the U-Net CNN specialized in biomedical images. Prioritizing the need for labeled images of lungs, mainly in studies for automatic detection of Covid-19, Zheng *et al.* [22] proposed an unsupervised learning model to generate image labels.

Abbas *et al.* (Abbas et al., 2020) used a pre-trained CNN architecture called DeTraC, which highlights its ability to focus on irregularities (overlapping images) present in the data for detecting the disease, with a class decomposition mechanism. Li *et al.* (Li et al., 2020) developed a DL model based on neural network, named COVNET, to classify images in three classes: COVID 19, CAP (Community-Acquired Pneumonia) and non-pneumonia.

Similar to the previous work, Hu *et al.* (Hu et al., 2020) proposed a semi-supervised model capable of improving the necessary time for manually labeling images based on three classes: Non-Pneumonia (NP), Community-acquired pneumonia (CAP), and Covid-19. Their work differs in a binary classification type, which compares the introduced classes in pairs, obtaining more detailed and precise results. However, the total quantity of used images (450 equally divided among the three classes) is lower than the quantity used by us in this work.

Cohen *et al.*(Cohen et al., 2020) measured the Covid-19 gravity to the patients using a linear regression model. As parameters, they used the lung extension and its opacity degree. As advantages, the work enables us to confirm the treatment efficacy and to increase the training epochs. The major disadvantage is the number of samples (153), which limited their evaluations on a large scale.

Rajaraman *et al.* (Rajaraman et al., 2020) analysed the performance of a set of CNN models, which contains one customized and eight pre-trained CNNs (VGG-16, VGG-19, Inception-V3, Xception, InceptionResNet-V2, MobileNet-V2, DenseNet-201 e NasNet-mobile). They used images from different datasets, and the results demonstrated that the precision was greater than 90% for all models. A weighted mean for the models with the “best performance” showed that the Covid-19 detection by pulmonary x-rays presented 99.01% precision.

Phankokkruad (Phankokkruad, 2020) carried out a similar analysis, considering three pre-trained CNN models to detect among Covid-19, varied types of pneumonia, and healthy lungs. The major disadvantage was the limited number of images for Covid-19, which was only 323 x-ray images. Despite that, the author used techniques to increase the data, obtaining excellent results for all CNNs: the Xception model achieved a precision of 97.19%, while the VGG-16 model achieved 95,42%, and the Inception-Resnet-V2 model achieved 93,87%.

Hu *et al.* (Hu et al., 2021) aimed to bring optimization and agility to Covid-19’s detection and training processes. The authors used deep CNN and Extreme Learning Machines (ELMs), as well as an optimization algorithm, to perform real-time detection. They obtained accuracies of 98.25% and 99.11% for the two evaluated datasets. The authors highlight the excellent training time of the network (0.9474 milliseconds). However, the image classifier was trained to recognize three types of x-ray images: covid 19, pneumonia, and healthy lung.

Sousa *et al.* (de Sousa et al., 2020) researched other works that apply deep learning techniques to identify the Covid-19 disease. They presented the main techniques used and the obtained results. Besides, they subdivided the relevant works into two types: those that used conventional radiographs and those that used computed tomographies. For the first type, Altan and Karasu (Altan and Karasu, 2020) presented the best results, achieving 99,7% of accuracy, 99,4% of sensibility, and 99,5% of F1-Score. For the second type, Ko et al. (Ko et al., 2020) presented the best results, with 99,9% of accuracy, 99,6% of sensibility, and 100% of specificity.

In this context, the prior differential of our work is using a big dataset and the model’s ability to distinguish four distinct types of categories: Covid-19, healthy lung, bacterial pneumonia, and viral pneumonia. The inclusion of pneumonia images is because they are easily confused with some cases of Covid-19. Therefore, the model acquires a specific skill in differentiating Covid-19 and pneumonia images.

4 METHODOLOGY

We used the Google Colaboratory environment (Google Colab), a free cloud tool provided by Google and built based on Jupyter Notebook to encourage research in the field of AI. In addition to providing GPU (Graphics Processing Unit) acceleration, responsible for rendering graphics in real-time, the Google Colab is free of charge, allowing better optimization of time and processing.

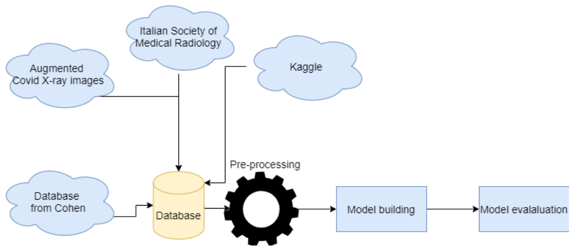

Figure 3: Applied Methodology.

Figure 3 presents the adopted methodology for this work, which is divided into the following three stages: image collection and pre-processing, model training, and model evaluation. These stages are described below.

4.1 Image Collection and Pre-processing

In the first stage of this work, we gathered 7683 x-ray images obtained from the following distinct sources: Cohen's database[10], Augmented Covid-19 X-Ray Images[11], Chest X-Ray Images[12], and Italian Society of Medical Radiography (SIRM)[13]. The Table 1 shows the total number of images collected for the classes and the dataset sources.

There are three image classes in the Cohen dataset: Covid-19, healthy lung, and pneumonia. As we intended to train the model to classify four types of lung radiographs, we separated the pneumonia class images into two others: bacterial pneumonia and viral pneumonia. In addition, we removed some repeated images, from the dataset, and the computed tomography images of the lungs, as the main objective was working with chest x-ray images.

We divided the images as follows: the testing dataset contains 10% of the total number of images, corresponding to 768 images; the validation dataset contains 20% of the 6915 remaining images, corresponding to 1383 images; and the training dataset contains the rest of the images, which corresponds to 5532 images.

Figure 4 presents some pulmonary tomography images, extracted from the collected dataset, with their respective diagnoses.

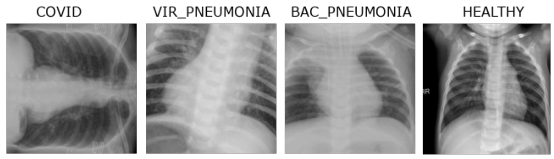

Figure 4: Examples of tomography images.

4.2 Model Training

To build the x-ray image classifier, we used the Fastai[14] library to apply supervised deep learning techniques. We imported the module vision, which contains all the functions necessary to train the model. This module used the following two sub-modules: vision.data, which contains the ImageDataBunch object, responsible for creating the training, validation, and test datasets, and vision.learner that allows us to perform the training or use a pre-trained model as a base.

To train the model, we used the following four classes of lung radiography images: healthy, with Covid-19, with bacterial pneumonia, and with viral pneumonia. To train and validate the model, respectively, we used 6915 e 1383 images from the dataset. To test the model, we used 768 images.

To train the classifier, we applied transfer learning using the *cnn_learner* method, from the *fastai.vision* module. The *cnn_learner* assists in obtaining a pre-trained model from a given architecture. We selected the architecture resnet34 once it is a neural network very applied by other researchers (Lau et al., 2020; Lei et al., 2018; Canziani et al., 2016).

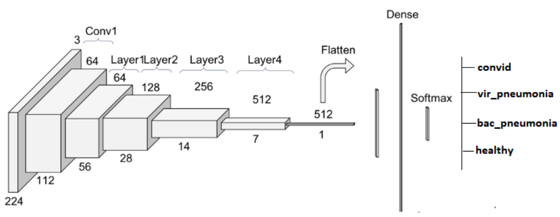

Figure 5: Neural Network Architecture.

[10]https://github.com/ieee8023/covid-chestxray-dataset

[11]https://data.mendeley.com/datasets/2fxz4px6d8/4

[12]https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

[13]https://www.sirm.org/en/category/articles/covid-19-database/

[14]https://docs.fast.ai/

Table 1: Number of images by dataset.

Datasets	Covid	Healthy	Bacterial P.	Viral P.
Cohen's database	920	-	-	-
Augmented Covid-19	866	-	-	-
Chest X-Ray Images	-	1583	2761	1493
SIRM	60	-	-	-
Total of Images	7683			

Fig. 5 represents the neural network architecture used. The image to be categorized goes through an initial 7x7 convolution layer with a 64 resource map, and is interpreted through another 34 layers of the model. The later layers are 3x3 convolutions, with a map dimension of fixed features at, respectively, 64, 128, 256, 512. During the training of this model, images of size 224 were used for standardization

4.3 Model Evaluation

Through the confusion matrix, we can make a visual analysis of our classifier's mistakes and successes. On the main diagonal, the correct predictions are located, while the other positions refer to the classifier errors. With this tool, we can also scrutinize these results in the four different terms: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These terms are used in the calculations of the main evaluation metrics by a micro-average.

To evaluate the model, we used accuracy (Acc), precision, recall, and F1-score (or f-measure). The accuracy is applied to calculate the percentage of correct answers in the general model. The precision is associated with the effective number of correct classifications. On the other hand, the recall indicates how often the classifier finds examples from the same class. Finally, the F1-score represents the harmonic mean of precision and recall.

$$Acc = \frac{VP+VN}{VP+VN+FP+FN} \tag{1}$$

$$Recall = \frac{VP}{VP+FN} \tag{2}$$

$$Precision = \frac{VP}{VP+FP} \tag{3}$$

$$F1_{score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

We also considered the construction of a model that does not present underfitting, when the model does not adapt well to the training set, and overfitting, when a model presents learning bias by memorizing the data set patterns and does not learn in a generalized way. Experimentally, we evaluated that 15 epochs in the model's training process were sufficient to present good results during training, validation, and tests.

5 RESULTS

Table 2 represents the confusion matrix of our model, which was used to evaluate the performance from the separate data used to test the X-ray image classifier. The "Covid" class corresponds to lungs affected by the Covid-19, and the "Healthy" class indicates healthy and clean lungs. The "BP" and "VP" classes indicate, respectively, bacterial and viral pneumonia.

We observed that the results of the viral pneumonia classification produced the highest error numbers, what probably happened due to this class have a smaller number of images (1493) when compared with other classes.

Table 2: Confusion Matrix.

		Predicted				
		Covid	Healthy	BP	VP	FN
Actual Class	Covid	153	1	1	3	5
	Healthy	12	248	0	16	28
	BP	1	0	184	0	1
	VP	8	46	2	93	56
	FP	21	47	3	19	90

Table 3: Metrics.

	Covid	Healthy	BP	VP
Recall	0.97	0.90	0.99	0.62
Precision	0.88	0.84	0.98	0.83
F1 score	0.92	0.87	0.99	0.71
Accuracy	0.94			

The precision of bacterial pneumonia or "BP" classification is the most striking, as shown in Table 3, as it is low even with excellent recall. To understand why this occurs, we go back to Table 2. We can notice that the FP of the bacterial pneumonia class totalizes 3, indicating that the model rarely classifies the image as "BP" when, in fact, it should be another class, as happened many times with the categories "VP" and "Healthy". To mitigate this problem, we can add more images of viral pneumonia and healthy lung, aiming at training the model more frequently with these images and, consequently, getting better values of recall, precision, and F1 score.

The model presented the best performance for the "BP" class, exceeding expectations, as we can see that it obtained 97% for all three metrics (Tab. 3). Such results indicate that the model can diagnose bacterial pneumonia with confidence, helping professionals in hospitals.

Regarding the "Covid" category, we can evidence the model's ability to generalize new images, indicating an effective adaptation of the classifier in identifying images of lungs affected by the Coronavirus. Looking at the error number of the classifier, we can notice that the "Covid" class presents three times fewer errors than the "VP" and "Healthy" classes. In this sense, we were able to build a model that identifies the COVID-19 in X-ray images, which was the main objective of our work.

Looking at Table 3, we can see that the best results belong to the "BP" class, followed by the "Covid", "Healthy" and "VP" classes. Therefore, the chances of the model correctly classifying a lung with Covid-19 as "Covid" are higher than that of classifying viral pneumonia as "VP", for example. We can also notice that the class with lower Recall, Precision, and F1 values is the VP, with 62%, 83%, and 71%, respectively. Despite the lower numbers, the general performance of the model was not affected.

In general, we can check the test results using the accuracy, which achieved 94% (Table 3). Using the same metric, but for validation, we obtained 91% accuracy. So we decided to create a test directory, noting that the validation results are very good. In this sense, we conclude that when it is required to generalize the standards for images never seen before by the classifier, it presents more imperfections, even though its results are satisfactory in the set of tests.

6 CONCLUSION

Given the current pandemic and the need to obtain an urgent and more accurate diagnosis of COVID-19 contamination, this work proposed to build a computational model capable of automatically identifying signs of the coronavirus infection in chest x-ray images. For that, we used a Convolutional Neural Network based on the resnet34 architecture, which allows excellent results in image identification tasks. In this sense, using learning transfer techniques, we built and trained a model to classify x-ray images, identifying healthy lungs, Covid-19, bacterial pneumonia, and viral pneumonia.

The model presented excellent classification results, with an accuracy of 87%. Among the four classes identified, the "Covid-19" class achieved the best results: 97% recall, 94% accuracy, and 95% F1 score. We conclude that our machine learning-based application can automatically identify the Covid-19 disease, using pulmonary radiographs, with a 95% F1-score. Thus, our solution contributes to assist in the screening of Covid-19 cases, as an alternative to the lack of mass testing for the population.

Despite the satisfactory results, medical analysis is always valuable and important. The diagnoses using the model work as a medical monitoring instrument, not eliminating the confirmation by a specialized physician. Only the radiography is not enough to define if a patient has Covid-19. Thus, to avoid overfitting and bias when implementing such an experiment in a hospital, an expanded and optimized testing is recommended (Wynants et al., 2020).

As future work, we want to improve the model training with more images, mainly of other diseases, to increase the database and optimize the accuracy, precision, and other evaluation metrics for viral and bacterial pneumonia. Furthermore, we intend to adapt the model to detect and classify more types of lung diseases, such as lung cancers and other pneumonia types.

Sourcecode. We provide the project source code publicly at the following address: https://github.com/double-blind/review/

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