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# Portable chest X-ray image generation for the improvement of the automatic COVID-19 screening

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**Abstract**

COVID-19 is a disease whose gold standard diagnosis tool, RT-PCR, is unable to provide accurate quantification of its severity in a given patient. Currently, this assessment can be performed with the help of chest X-ray imaging visualization that, however, is a manual, tedious and time-consuming task. In this context, Computer-Aided Diagnosis (CAD) systems are very useful to facilitate the work of clinical specialists in these complex diagnostic tasks, especially in view of recent advances in deep learning techniques in the field of medical image analysis. Despite their great potential, deep learning strategies require a large amount of labelled data, which is often scarce in the context of COVID-19 pandemic. To mitigate these problems, in this work we propose the use of a image translation paradigm, the Cycle-Consistent Adversarial Networks (CycleGAN) to generate a novel set of synthetic images with the aim to improve an automatic COVID-19 screening system using portable chest X-ray images.

## 1 Introduction

The COVID-19 is an infectious disease caused by the coronavirus SARS-CoV-2, characterized for its rapid spread. Currently, there are several methods to diagnose the pathology, being the RT-PCR test the one considered as the gold standard [1]. However, this diagnostic tool is insufficient when it is necessary to determine the severity of the disease in a given moment. COVID-19 can affect several parts of the body, but the respiratory tissues are the most affected by this pathology. Therefore, the visualization of the lungs is a way to determine the severity and the extension of the disease. For this, the clinicians can rely on medical imaging modalities such as chest X-ray imaging [2], as it is cheap and easy to perform. Nevertheless, despite the advantages of chest X-ray imaging, the visualization of these captures is a tedious and time-consuming task that must be manually performed by experts with several years of experience in the field. To mitigate these difficulties, the development of Computer-Aided Diagnosis (CAD) systems is extremely useful, specially given the great performance that deep learning models have demonstrated in the field of medical imaging analysis during the last years [3, 4]. The main issue in deep learning is the necessity of great amounts of labelled data to train the models, which

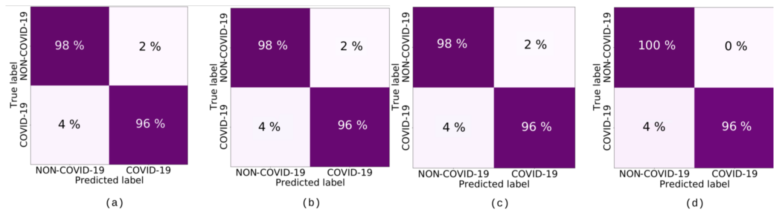


Figure 1: Confusion matrices of the 4$^{th}$ experiment using the 4 configurations of the generative model. (a) Unet-128. (b) Unet-256. (c) ResNet-6. (d) ResNet-9.

is scarce in these domains. To mitigate this problem of data scarcity, several strategies have been proposed during the last decades, being the image generation one of the most powerful. In particular, image translation models are a specific type of image generation algorithms that allow to obtain new realistic synthetic samples from the original data, converting those images from a domain A to a domain B and vice versa [5]. In this work, we present a fully-automatic approach for portable chest X-ray image generation aimed at improving the performance of an automatic COVID-19 screening. To this end, we have chosen a well-known image translation model, the Cycle-Consistent Adversarial Networks (commonly named as CycleGAN) to convert chest X-ray among different kinds of pathological scenarios. The novel set of generated images will be then used to augment the dimensionality of the original dataset, therefore improving the performance of the automatic COVID-19 screening.

## 2 Methodology

The presented methodology is divided in 2 different steps. The first step consists of portable chest X-ray synthetic image generation, training with both normal and pathological images, while the second step consists on the relevant task of the automatic COVID-19 screening. Both steps were performed following the same training details as stated in [6], for a fair comparison between both strategies. The dataset to evaluate the methodology was provided by the Complexo Hospitalario Universitario de A Coruña (CHUAC), specifically tailored for this scenario and composed of 720 images with 3 possible labels, having 240 images of Normal cases (*i.e.*, patients without pulmonary affectation that could have other kind of diseases), 240 images of Pathological cases (*i.e.*, patients without COVID-19 but that have other pulmonary pathologies) and 240 genuine COVID-19 cases.

**Portable chest X-ray synthetic image generation:** for this part of the methodology, we performed the portable chest X-ray synthetic image generation using the CycleGAN [7] with 4 different configurations for the generative model, having 2 Unet architectures (Unet with 7 downsampling blocks denoted as Unet-128 and Unet with 8 downsampling blocks denoted as Unet-256) and 2 ResNet architectures (ResNet with 6 residual blocks denoted as ResNet-6 and ResNet with 9 residual blocks denoted as ResNet-9). Given the 3 different classes, 3 different pathways are followed for the image translation: Normal to Pathological and vice versa, Normal to COVID-19 and vice versa and Pathological to COVID-19 and vice versa.

**Automatic COVID-19 screening:** for this part of the methodology, we adapted a Densely Connected Convolutional Neural Network (DenseNet), in particular, a DenseNet-161 pre-trained on ImageNet dataset.

# 3 Results and conclusion

To evaluate the performance of the proposed strategy, we conducted 4 experiments. The first 3 experiments evaluate the separability among the generated samples while the fourth experiment was conducted to measure the performance improvement that the proposed data augmentation strategy implies. In the latter case, to make a fair comparison between the baseline (*i.e.*, training without data augmentation) and the data augmentation approach, the training process is performed with the augmented dataset, while test is only performed using original images. The results of the first 3 experiments show a proper separability among generated images in all the scenarios (*i.e.*, distinguishing between Normal and Pathological, between Pathological and COVID-19 and between Normal and COVID-19). In particular, for the 3 scenarios, the F1-Score with the best configuration reaches a 1.00 for both classes involved on each training process. On the other hand, the fourth experiment results show that the proposed data augmentation approach obtains satisfactory results. Figure 1 shows the confusion matrix of the fourth experiment, where correct classification ratios are always over 0.96 for both COVID-19 and NON-COVID-19 classes. Additionally, we also compared our data augmentation strategy with the previous work of *De Moura et al.* [8], showing an improvement in terms of F1-Score that comes from 0.93 to 0.99 for the NON-COVID-19 class and that comes from 0.84 to 0.99 in the case of the COVID-19 class.

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# References

[1] W. F. Sule and D. O. Oluwayelu, "Real-time rt-pcr for covid-19 diagnosis: challenges and prospects," *The Pan African Medical Journal*, vol. 35, no. Suppl 2, 2020.

[2] J. A. Santos and J. P. A. Cañal, "Chest x-ray findings and temporal changes among adult patients with covid-19 admitted in a tertiary referral center," *European Journal of Radiology Open*, vol. 8, p. 100385, 2021.

[3] P. L. Vidal, J. de Moura, J. Novo, and M. Ortega, "Multi-stage transfer learning for lung segmentation using portable x-ray devices for patients with covid-19," *Expert Systems with Applications*, vol. 173, p. 114677, 2021.

[4] J. de Moura, J. Novo, and M. Ortega, "Fully automatic deep convolutional approaches for the analysis of covid-19 using chest x-ray images," *Applied Soft Computing*, vol. 115, p. 108190, 2022.

[5] X. Chen and C. Jia, "An overview of image-to-image translation using generative adversarial networks," in *International Conference on Pattern Recognition*, pp. 366–380, Springer, 2021.

[6] D. I. Morís, J. J. de Moura Ramos, J. N. Buján, and M. O. Hortas, "Data augmentation approaches using cycle-consistent adversarial networks for improving covid-19 screening in portable chest x-ray images," *Expert Systems with Applications*, vol. 185, p. 115681, 2021.

[7] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," in *Computer Vision (ICCV), 2017 IEEE International Conference on*, 2017.

[8] J. De Moura, L. R. García, P. F. L. Vidal, M. Cruz, L. A. López, E. C. Lopez, J. Novo, and M. Ortega, "Deep convolutional approaches for the analysis of covid-19 using chest x-ray images from portable devices," *IEEE Access*, vol. 8, pp. 195594–195607, 2020.