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BRIEF COMMUNICATION

COVID-19 Detection from Chest X-Ray Images Using CNNs Models: Further Evidence from Deep Transfer Learning

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Abstract

Introduction: The early automatic diagnosis of the novel coronavirus (COVID-19) disease could be very helpful to reduce its spread around the world. In this study, we revisit the identification of COVID-19 from chest X-ray images using Deep Learning.

Methods: We collect a relatively large COVID-19 dataset comparing with previous studies that contain 309 real COVID-19 chest x-ray images. We also prepare 2,000 chest x-ray images of pneumonia cases and 1,000 images of healthy chest cases. Deep Transfer Learning is used to detect abnormalities in our image dataset. We fine-tune three, pre-trained convolutional neural networks (CNNs) models on a training dataset: DenseNet 121, NASNetLarge, and NASNetMobile.

Results: The evaluation of our models on a test dataset show that these models achieve an average sensitivity rate of approximately 99.45 % and an average specificity rate of approximately 99.5 %.

Conclusion: A larger dataset of COVID-19 X-ray images could lead to more accurate and reliable identification of COVID-19 infections using Deep Transfer Learning. However, the clinical diagnosis of COVID-19 disease is always necessary.

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Introduction

On December 2019, the novel coronavirus (COVID-19) has started to spread in China, then in other multiple countries around the world. [1-3] The early automatic diagnosis of this disease may be very beneficial for reducing its spread. [4] Deep Learning is one artificial intelligence method that can be helpful in detecting COVID-19 infections from medical images such as X-ray images, specifically when we have a small image dataset. [2,4,5]

Earlier studies have used Deep Learning for the detection of COVID-19 from chest X-ray images. Minaee et al. prepared a dataset of 5071 chest X-ray images including 71 COVID-19 images and 5000 non COVID-19 images. [2] They selected 40 COVID-19 images and 3000 non COVID-19 to include in the test set, as well as 31 COVID-19 (496 after augmentation) and 2000 non COVID-19 images for the training set. They trained four popular Deep Learning models, including ResNet18, ResNet50, DenseNet-121, and SqueezeNet, to detect COVID-19 infections. The best performing model achieved a sensitivity rate of 97.5%, and 95% of specificity. [2] Apostolopoulos and Mpesiana evaluated the performance of different state-of-the-art CNNs architectures on two datasets. [4] The first one contains 1427 chest X-ray images including 224 images with COVID-19 infection, 700 images with confirmed common bacterial pneumonia, and 504 images of healthy cases. The second dataset includes 224 images with COVID-19 infection, 714 images with confirmed bacterial and viral pneumonia, as well as 504 images of healthy cases. [4] According to their results, the best achieved accuracy, sensitivity, and specificity is 96.78%, 98.66%, and 96.46% respectively. [4] Ozturk et al. proposed the DarkCovidNet Model for the identification of COVID-19 from chest X-ray images. [6] They evaluate their model on a datasets including 127 chest X-ray images of COVID-19 infection as well

Table 1. Number of X-ray images in each class split.

Split	COVID-19	Healthy	Pneumonia
Training set	247	799	1598
Testing set	62	201	402

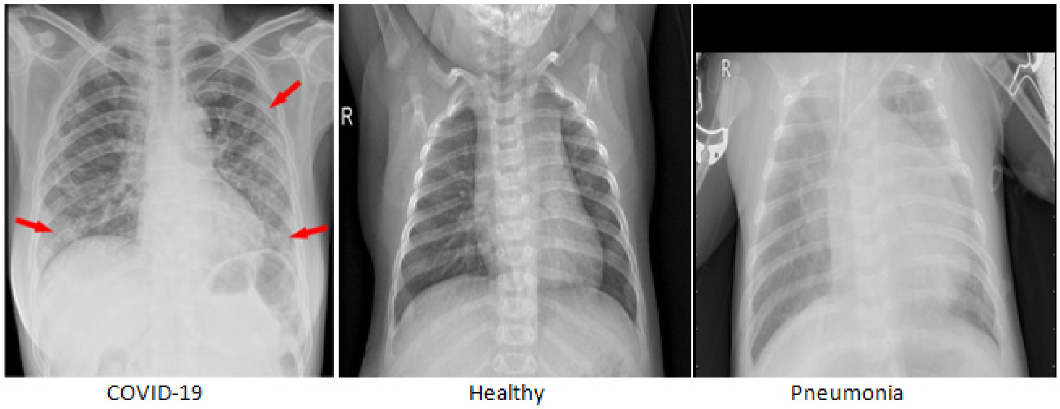

Figure 1. An example image from each class in the dataset.

as 500 healthy and 500 pneumonia chest X-ray images. [6] Their model produced a classification accuracy of 98.08% for binary classes (COVID-19 vs. Healthy) and 87.02% for multi-class cases (COVID-19 vs. Healthy vs. Pneumonia). [6]

In this study we use Deep Transfer Leaning to identify COVID-19 infection on a relatively large COVID-19 dataset (without augmentation) comparing with previous studies, in order to get more reliable diagnostic performance, based on two evaluation metrics; sensitivity and specificity.

Methods

Datasets

A total of 309 COVID-19 chest X-ray images (excluding lateral images) are collected; 236 COVID-19 images are obtained from the datasets of Cohen et al [7,8] and 73 other COVID-19 images are obtained from Kaggle dataset. [9] We also prepare 2,000 pneumonia and 1,000 healthy chest X-ray images, collected from the dataset of Kermany et al. [10] All images are resized to 224 x 224 pixels. We split our datasets into training set (80%) and testing set (20%), as it is descript in **Table 1** above. Data augmentation techniques are not used in this study.

Models

The Deep Transfer Learning method is used in this study, because the samples in our datasets are small and not sufficient to train a CNN model from onset. [2,4,5] Transfer learning consists of extracting features learned on one problem, and using them on a new, similar problem. [11] In our case, we extract features learned on the ImageNet dataset, a large dataset including of 1.4M images and 1000 classes [5], and leveraging them in the detection of COVID-19 infection.

We fine-tune three pre-trained deep CNNs models on the train dataset: DenseNet 121 [12], NASNetLarge, and NASNetMobile. [1] Firstly, we instantiate the proposed models pre-loaded with weights trained on ImageNet datasets. [5] We do not include the classification layers at the top, to make the models ideal for feature extraction. [5] Then, we construct a new classifier and add it on top of the base models. The new classifier consists of a pooling layer and a dense fully connected layer. Finally, we freeze the convolutional base before training our models.

The training is done for 10 epochs, with a batch size of 16. We use ADAM optimization with a learning rate of 0.001. We train our models with categorical cross entropy. The implementation is conducted in Python 3 using Keras [11] and Tensorflow [5].

We use sensitivity and specificity metrics to evaluate our models' performance, since the whole dataset is imbalanced. [2] These evaluation metrics are defined as follows [2]:

$$\text{Sensitivity}= \frac{\text{True positive (TP)}}{\text{Total positive COVID-19 Images}} \qquad \text{Specificity}= \frac{\text{True negative (TN)}}{\text{Total negative COVID-19 Images}}$$

Table 2. Sensitivity and Specificity rates of DenseNet 121, NASNetLarge and NASNetMobile models.

Models	Sensitivity	Specificity
DenseNet 121	98.4%	99.8%
NASNetLarge	100%	99.5%
NASNetMobile	100%	99.3%
Average	99.45%	99.5%

Table 3. Confusion matrices of the proposed models.

Models	Predicted labels / Actual labels	Healthy	COVID-19	Pneumonia
DenseNet 121	**Healthy**	176	0	25
	COVID-19	0	61	1
	Pneumonia	11	1	390
NASNetLarge	**Healthy**	163	0	38
	COVID-19	0	62	0
	Pneumonia	11	3	388
NASNetMobile	**Healthy**	189	0	12
	COVID-19	0	61	0
	Pneumonia	11	4	381

Where: TP represents images correctly predicted as COVID-19, TN represents images correctly predicted as Non-COVID-19.

Results

Table 2 shows the achieved sensitivity and specificity rates by the proposed models. NASNetLarge and NASNetMobile reach a sensitivity rate of 100%, while DenseNet 121 outperforms the two other models in term of specificity rate.

Table 3 shows the confusion matrices of DenseNet 121, NASNetLarge and NASNetMobile models, respectively. We can see from this table that our models confuse in the identification between COVID-19 and pneumonia in some cases.

Discussion

In this study, we revisited the detection of COVID-19 form chest X-ray images using Deep Learning. In order to get a more reliable diagnostic performance, we used a relatively large COVID-19 dataset of real chest X –ray images (without augmentation). Our datasets contains 309 chest X-ray images, 2000 pneumonia and 1000 healthy chest X-ray images. The datasets were split into a training set (80%) and a test set (20%). We fine-tuned three pre-trained deep CNNs models: DenseNet 121, NASNetLarge, and NASNetMobile.

We evaluated the performance of our models on the test dataset based on two evaluation metrics: sensitivity, specificity. The proposed models show a good COVID-19 diagnostic performance, where they achieve an average sensitivity rate of approximately 99.45 % and an average specificity rate of approximately 99.5 %. From the confusion matrices, we see that these models confuse in the detection between COVID-19 and pneumonia in some cases.

Since the whole dataset is imbalanced, more metrics are needed to evaluate the performance of our models, such as, the ROC curves and Precision-Recall curves. The used set of COVID-19 X-ray images in this study is limited. Thereby, a larger COVID-19 image dataset could lead to a more reliable diagnosis. [2] The automatic diagnosis of COVID-19 using artificial intelligence could be helpful, but should not replace clinical diagnosis.

References

1. World Health Organization. Pneumonia of unknown cause – China [press release] (2020 Jan 5) [cited 2020 Jun 1]. Available from: https://www.who.int/csr/don/05-january-2020-pneumonia-of-unkown-cause-china/en/
2. Minaee S, Kafieh R, Sonka M, Yazdani S, Soufi GJ. Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning. arXiv preprint arXiv:2004.09363. 2020 Apr 20.
3. Boudrioua MS, Boudrioua A. Predicting the COVID-19 epidemic in Algeria using the SIR model. medRxiv. 2020 Jan 1. https://doi.org/10.1101/2020.04.25.20079467
4. Apostolopoulos ID, Mpesiana TA. Covid-19: automatic detection from X-ray images utilizing transfer learning with

convolutional neural networks. Phys Eng Sci Med. 2020 Jun;43(2):635–40. https://doi.org/10.1007/s13246-020-00865-4 PMID:32524445

5. TensorFlow Core. Transfer learning with a pretrained ConvNet [tutorial on the Internet]. [place unknown]: TensorFlow; 2020 [updated 2020 Jun 12; cited 2020 Jun 3]. Available from: https://www.tensorflow.org/tutorials/images/transfer_learning
6. Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Rajendra Acharya U. Automated detection of COVID-19 cases using deep neural networks with X-ray images. Comput Biol Med. 2020 Apr 28:103792. https://doi.org/10.1016/j.compbiomed.2020.103792 PMID:32568675
7. Cohen JP, Morrison P, Dao L. COVID-19 Image Data Collection. arXiv 2020. arXiv preprint arXiv:2003.11597. 2020 Mar 25.
8. Cohen JP, Morrison P, Dao L, Roth K, Duong TQ, Ghassemi M. COVID-19 image data collection: Prospective Predictions Are the Future. arXiv preprint arXiv:2006.11988. 2020 Jun 22.
9. Dadario AMV. COVID-19 X rays [dataset on the Internet]. [place unknown]: Kaggle; 2020 [updated 2020 Mar 18; cited 2020 Jun 5]. Available from: https://www.kaggle.com/dsv/1019469
10. Kermany D, Zhang K, Goldbaum M. Labeled optical coherence tomography (OCT) and chest X-Ray images for classification. Mendeley data. 2018 Jan 6;2. http://dx.doi.org/10.17632/rscbjbr9sj.2
11. Chollet F. Transfer learning & fine-tuning [guide on the Internet]. [place unknown]: Keras; 2020 [revised 2020 May 12; cited 2020 Jun 2]. Available from: https://keras.io/guides/transfer_learning/
12. Huang G, Liu Z, Van Der Maaten L, Weinberger KQ. Densely connected convolutional networks. InProceedings of the IEEE conference on computer vision and pattern recognition 2017 (pp. 4700-4708).
13. Zoph B, Vasudevan V, Shlens J, Le QV. Learning transferable architectures for scalable image recognition. InProceedings of the IEEE conference on computer vision and pattern recognition 2018 (pp. 8697-8710).