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

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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 collected a relatively large COVID-19 dataset—compared with previous studies—containing 309 real COVID-19 chest X-ray images. We also prepared 2,000 chest X-ray images of pneumonia cases and 1,000 images of healthy controls. Deep transfer learning was used to detect abnormalities in our image dataset. We fine-tuned three, pre-trained convolutional neural network (CNN) models on a training dataset: DenseNet 121, NASNetLarge, and NASNet-Mobile.

Results: The evaluation of our models on a test dataset showed that these models achieved 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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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

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 × 224 pixels. We split our datasets into training set (80%) and testing set (20%), as it is described 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 NAS-NetMobile.[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]:

Sensitivity = \[\frac{\text{True positive (TP)}}{\text{Total positive COVID-19 images}}\]

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    | 98.40%      | 99.80%      |
| NASNetLarge     | 100%        | 99.50%      |
| NASNetMobile    | 100%        | 99.30%      |
| Average         | 99.45%      | 99.50%      |

Table 3. Confusion matrices of the proposed models.

| Models          | Actual          | Predicted     | 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      |           |

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.
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