CORONA-19 NET: Transfer Learning Approach for Automatic Classification of Coronavirus Infections in Chest Radiographs

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Abstract. Coronavirus disease has been rampaging the world since its onset in the Wuhan region of China with cases skyrocketing every day. A crucial step for mitigating the havoc in this situation is the early screening of the infected patients and isolating them. Given the overwhelming number of people falling prey to this pandemic, it becomes very difficult for hospitals to provide these services within the required time. The power of Artificial Intelligence can be leveraged to solve the issue of delay in the diagnosis of coronavirus by automating the process. In this study, we propose our method, a transfer learning approach on deep convolutional neural networks to classify chest radiographs of patients as healthy or infected with Coronavirus based on the fact that Coronavirus attacks the epithelial cells of lungs resulting in pneumonia. The data used for this study has been curated from various public resources online. Our proposed model was able to achieve a validation score of 100% on the curated dataset along with high specificity and sensitivity of 1.00. This work aims to serve as a first cut solution to the automated diagnosis and doesn’t claim to be the exact solution without further validation by medical professionals.

Keywords: COVID19 · Coronavirus · Deep convolutional neural networks · Transfer learning · Chest radiography

1 Introduction

Coronavirus, since it’s onset, has caused a pandemic throughout the world. The ones who succumb to this are stricken with acute respiratory disorders which have seen to turn fatal in many cases. One of the measures to curb the damage caused by this is the early diagnosis of the infected individuals so that they can be given proper medical care as well as isolated from the rest for preventing further spread of the virus. The primary process for the diagnosis involves polymerase chain reaction testing. However, owing to the complexity of the procedure and lack of adequate experts it is not preferable to meet the immediate diagnostic requirements of the patients.
Adding on, the limited supply of the test kits for it makes the situation even worse. A possible substitute to this is making use of chest radiography like CT Scans [2, 7] and X-Rays. However, the problem persists since there is a shortage of radiologists for the current situation. Hereby the concept of deep convolutional neural networks comes handy to build an image classifier that could extract meaningful features from the chest radiographs and differentiate between corona infected [12] and healthy ones [8]. Posteroanterior radiographs of chests are used due to their greater availability for model training and previous results obtained that support its use for the detection of pneumonia.

In our experiment, we propose Corona-19 Net, which is a model built on top of MOBILE-NET V2 [13] architecture owing to its modularity and composite design, we were able to achieve promising results in terms of validation accuracy, sensitivity, and specificity scores. The model is tuned to detect infections due to Coronavirus and thus the manifestations of the virus with dexterity. The modular design and light weight-edness of the architecture further facilitates the easy deployment of it to client-side web applications to develop automatic diagnosis systems which can easily be used in hospitals (Fig. 1).

Fig. 1. Posteroanterior radiographs of Chest showing (i) Healthy patients and (ii) COVID-19 infected patients.

2 Methods

2.1 Dataset Description

The dataset used for this study comprises:

- 68 chest radiograph images of healthy patients curated from the RSNA Pneumonia Detection Challenge on Kaggle [1].
- 69 Covid-19 chest radiograph images of COVID-19 infected images curated from COVID-19 Database, SIMA, and Radiopedia [4].
Due to the small size of the dataset available various preprocessing and augmentation methods were performed to obtain a large dataset to enable the model to perform proper feature extraction and learn better from its features.

2.2 Model Architecture

To obtain an accurate image-classification model for the chest radiographs, we used a transfer-learning approach rather than training a deep convolutional neural network [14] from scratch. This is because for our study we had to compensate for the low quality and a limited number of images curated from public datasets. Transfer learning aids to leverage the previous knowledge of feature extraction that was obtained by training on large benchmark datasets like ImageNet [5] or COCO.

For our experiment, we primarily make use of MobileNetV2 architecture which comprises two categories of blocks. There is a residual block of stride 1. While for downsizing another block of stride 2 is used. Each type of block has 3 layers. $1 \times 1$ convolution with ReLU6 is the first layer this time. The second layer is the depthwise convolution. Again $1 \times 1$ convolution is used in the third layer without non-linearity. Using ReLU again in the deep network has the power of a linear classifier on the non-zero volume part of the output domain. The depthwise separate convolution layers result in a significant decrease in model complexity. While smaller model size aids in faster training and better accuracy [10, 11] (Fig. 2).

| Input     | Operator     | t | c | n | s |
|-----------|--------------|---|---|---|---|
| $224^2 \times 3$ | conv2d      | - | 32 | 1 | 2 |
| $112^2 \times 32$ | bottleneck  | 1 | 16 | 1 | 1 |
| $112^2 \times 16$ | bottleneck  | 6 | 24 | 2 | 2 |
| $56^2 \times 24$ | bottleneck  | 6 | 32 | 3 | 2 |
| $28^2 \times 32$ | bottleneck  | 6 | 64 | 4 | 2 |
| $14^2 \times 64$ | bottleneck  | 6 | 96 | 3 | 1 |
| $14^2 \times 96$ | bottleneck  | 6 | 160 | 3 | 2 |
| $7^2 \times 160$ | bottleneck  | 6 | 320 | 1 | 1 |
| $7^2 \times 320$ | conv2d 1x1 | - | 1280 | 1 | 1 |
| $7^2 \times 1280$ | avgpool 7x7 | - | - | 1 | - |
| $1 \times 1 \times 1280$ | conv2d 1x1 | - | k | - | - |

Fig. 2. Synopsis of our underlying MobileNetV2 architecture.

The table depicts the arrangement of the bottlenecks where column t shows the expansion rate of the channels, column c represents the number of input channels, column n represents the frequency of repetition of the block while s indicates if the first repetition of a block using a stride of 2 for the downsampling process. For further customization of the architecture, the output obtained is fed to an average pooling layer comprising the kernel filter of size $4 \times 4$ to downsample the input and then passed to the flatten layer for converting a matrix of features into vectors. The vectors are then fed to a dense layer where relu activation function is used again to introduce non-linearity. For the avoidance of overfitting, the output is fed to the dropout layer. In the end, a
dense layer is added to classify the output with a softmax activation function. The learning rate of our model is set to $5 \times 10^{-5}$ with a batch size of 16 and trained for a cycle of 100 epochs.

3 Results

3.1 Model Evaluation

To evaluate the robustness of our proposed architecture, we take into consideration a thorough and versatile analysis based upon various metrics. In the confusion, the matrix comprises classes COVID and Normal where (Fig. 3):

![Confusion Matrix](image)

**Fig. 3.** Confusion Matrix of the model for (1) COVID, (2) Normal.

- **True positives (TP):** It gives a measure of how many times the model correctly classifies COVID positive patients as COVID positive.
- **False Positives (FP):** It gives a measure of how many times the model incorrectly classifies COVID positive patients as COVID negative.
- **True Negatives (TN):** It gives a measure of how many times the model correctly classifies COVID negative patients as COVID negative.
- **False Negatives (FN):** It gives a measure of how many times the model incorrectly classifies COVID negative patients as COVID positive.
- **Precision:** It gives a measure of how many predictions of patients being COVID positive are true. For our proposed model we got a precision of: 1.
Precision = TP/TP + FP.

Recall: It gives a measure of the number of classifications of the COVID-positive patients the model can predict correctly. For our proposed model we got a recall of: 1.

Recall = TP/TP + FN.

F1 score: The F1 score being a function of precision and recall determines the number of instances our model accurately classifies without missing a significant number of instances. For our proposed model we got a score of 1.

\[
\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

Accuracy: It is a measure of the number of correct predictions. For our proposed model the validation accuracy was found to be 100%.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]

Specificity: It is a percentage of COVID Negative patients that were classified as COVID Negative. For our proposed model the score was 100% (Fig. 4).

\[
\text{Specificity} = \frac{TN}{TN + FP}
\]

**Fig. 4.** Training Loss and Accuracy on COVID-19 Dataset.

Sensitivity: It is the percentage of COVID Positive patients that were classified as COVID Positive. For our proposed model the score was 100%.
Sensitivity = TP / (TP + FN)

It was also observed that our architecture strikes a great balance between both test and validation accuracy by achieving 100% in both parameters.

3.2 Performance Validation of Our Architecture

For a benchmark check of our architecture, we used other transfer learning approaches to develop our model [6]. The final performance metrics of each approach were examined to validate our proposed way.

3.2.1 VGG-16

VGG16 [9] is a 16 layer model trained on imagenet [5]. The model takes a 224 * 224 image size input image where filters with 3 * 3 receptive filters were used. Three fully connected layers follow a full stack of convolutional layers which consists of a ‘softmax’ function in the last layer (Fig. 5).

3.2.2 VGG-19

VGG19 is a 19 layer model also trained on imagenet. Similar to VGG16 it has fully connected layers, the first and second layers have 4096 channels each, while the third layer consists of an ILSVRC classification and consists of 1000 channels. Analogous to VGG16, it also has a soft-max layer added at the end (Fig. 6 and Table 1).
Pneumonia is a respiratory disorder caused by multiple classes of microorganisms such as [15] and bacteria. Hence in an attempt to achieve a chest radiograph classification exclusively for CoronaVirus cases, we used a similar transfer learning approach for multiclass classification in which we had 3 classes, i.e. healthy, Viral (that comprises Corona) and Bacterial. The additional data for the training was curated from the RSNA Pneumonia Detection Challenge on Kaggle and pre-processed similarly. Considering the Virus and COVID class together would lead to strong overlapping of features and reduce the feature extraction capabilities of the model. Post-training, the validation accuracy was observed to be around 92% for the multi-class case (Fig. 7).

### 4 Discussion

Pneumonia is a respiratory disorder caused by multiple classes of microorganisms such as [15] and bacteria. Hence in an attempt to achieve a chest radiograph classification exclusively for CoronaVirus cases, we used a similar transfer learning approach for multiclass classification in which we had 3 classes, i.e. healthy, Viral (that comprises Corona) and Bacterial. The additional data for the training was curated from the RSNA Pneumonia Detection Challenge on Kaggle and pre-processed similarly. Considering the Virus and COVID class together would lead to strong overlapping of features and reduce the feature extraction capabilities of the model. Post-training, the validation accuracy was observed to be around 92% for the multi-class case (Fig. 7).
Conclusion

Our work proposes an automatic diagnostic system for the prediction of Corona Virus using chest radiographs of patients. The underlying model is a deep convolutional neural network designed using a transfer learning approach for achieving highly accurate predictions using an openly available dataset. To validate our work, various performance metrics were used to confirm their outcomes. Furthermore, we have discussed an additional study for a multi-class classification for the same taking into account patients suffering from pneumonia but not caused by COVID-19 as an edge case for the model. This work is meant to be a first cut solution for assisting medical professionals and requires further feedback and a larger dataset to improve and serve as a de facto solution to the early diagnosis of the pandemic.

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