Detection of COVID-19 from Chest X-rays Using Resnet-50

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Abstract: COVID-19 is a pandemic caused by SARS-COV2 which started from December, 2019 and is being spreading since then. There are more than 12 million cases in India and more than 130 million cases worldwide according to the current statistics. One of the basic challenges we face today is the early detection of this disease and putting the patients in special care as soon as possible. It’s fast spreading nature makes the situation more complex and putting together all the solutions we have today it seems like the wave is not under control. Current diagnosing methods and cures have its own drawbacks and it is clear that we need an alternate solution. The aim of the study is to evaluate performance of state-of-the-art pre-trained model ResNet-50 on COVID-Chest X-ray dataset consisting of 1000 samples. Resnet-50 achieved 96% accuracy with 0.98 sensitivity and 0.95 specificity.

1. INTRODUCTION:

COVID-19 is caused by SARS-COV-2 which is acute respiratory syndrome coronavirus. It started from December 2019 in China and has become a pandemic since then. According to the report, there are more than 130 million cases worldwide [1]. Most commonly used method for screening is RT-PCR by using throat swab [2]. With increasing positive cases day by day there is shortage of RT-PCR kits and the whole process takes about more than 3 hours to complete [3]. It is being reported that this method may give you false results [4]. There are lot of research done on COVID-19 detection using multimodal images including CT, X-rays [5][6]. Some research even claims that detecting COVID-19 from multimodal images using artificial intelligence have more sensitivity as compared to RT-PCR test [7].

Machine learning and deep learning methods have become revolutionary from past few years in the field of computer vision and medical image processing for both classification and prediction problems [8]. The scarcity of samples available for positive cases makes this area of research more challenging. Concepts of transfer learning and pre-trained models have been used in previous researches which showed promising results, although these methods have not been yet used as alternative methods as they were experimentally effective but practically ineffective. [9][10].

2. RELATED WORKS
There are plenty of literature available that is based on computer vision and artificial intelligence in COVID-19 detection including machine learning and deep learning. Among all, CNN showed promising results and is most recommended method by various researchers. Although dataset used by most of the researchers varies.

Emtiaz Hussain et al. used a novel CNN architecture called CoroDet where they used raw CT and X-ray images and carried out 2 class, 3 class and 4 class classification. They obtained classification accuracy of 99.1% for 2 class classification, 94.2% for 3 class classification, and 91.2% for 4 class classification [11]. Ali Narin et al. used various pre-trained models like Resnet-50, Resnet-101 and Resnet152 with 5-fold cross validation on four classes. They obtained best results for Resnet-50 with an average accuracy of 98.4% [12].

Ezz El-Din Hemdan et al. used COVIDX-Net which includes seven different transfer learning algorithms including VGG-19, DenseNet-121, Inception v3 etc on 50 chest X-ray images with 25 positive cases and achieved f1 scores 0.86, 0.91 for normal and COVID cases respectively [13]. Arman Haghanifar et al used various sources for collecting chest X-ray images where they implemented popularly known transfer learning algorithm Chex-Net and derived an architecture called COVID-CXNet for classification [14].

MICHAEL J. HORRY et al. used multimodal images including CT, X-ray and Ultrasound, implemented an optimized VGG-19 pre-trained model for classification. They achieved precision of up to 86% for X-Ray, 100% for Ultrasound and 84% for CT scans [15]. Vishal Sharma et al used residual attention network and highlighted important area in feature maps for classification where they achieved testing accuracy of 98% and a validation accuracy of 100% [16]. Shervin Minaee et al. created a novel dataset called Chest X-ray 5k from various publically available sources and this dataset includes 5k chest X-ray images. They used transfer learning algorithms like Resnet-50, DensetNet-121, Resnet-18 and SqueezeNet for classification and obtained 0.98 sensitivity, 0.90 specificity [9].

Ioannis D. Apostolopoulos et al. used multiple datasets that includes healthy, COVID positive cases, bacterial and viral pneumonia cases where various transfer learning algorithms including VGG-19, Inception, Xception, MobileNet v2 were implemented for multi-class classification [17]. They achieved accuracy, sensitivity, and specificity as 96.78%, 98.66%, and 96.46%.

Linda Wang et al. used 13,945 chest X-ray images and carried out classification by using firstly introduced open access publically available COVID-19 detection architecture called COVID-Net [18]. Bejoy Abraham et al. used two publically available datasets and collected features by using multi-CNN. They further used Bayesnet for classifying the features and obtained 0.911 AUC with 97% accuracy [19]. Debabrata Dansana et al. used transfer learning models like VGG-19, Inception_v2 and decision tree model on multimodal images including CT and X-ray [20]. They achieved 91% validation accuracy for VGG-19 and Inception_v2.
3. MATERIALS AND METHODS

A. DATASET USED: 1000 Chest X-ray images were collected from publically available COVID Chest X-ray dataset.

![Sample Chest X-ray from dataset](image)

B. EXPERIMENTAL SETUP: INTEL CORE i7 8th Gen Processor with 8GB RAM and 4GB NVIDIA GPU. PyTorch was used for training and testing the model with all the necessary packages mainly FastAI v2.

C. PROPOSED METHODOLOGY

![PROPOSED METHODOLOGY](image)

1. Pre-Processing includes resizing image to 100*100 with splitting 80% of samples from dataset for training and rest for testing. Data augmentation methods like rotation, zoom, cropping were used in order to create more complexity in image block. This will help the model to learn more features from the data.
RESNET 50 – RESNET uses residual blocks that mainly includes skip connections which is a shortcut path for gradient flow. This reduces issues like vanishing gradient even if the network is too deep. Element-wise addition of gradient is carried out in residual blocks [21].

RESNET-50 is a convolution neural network that is 50 layers deep and here we are using the model whose layers are pre-trained on ImageNet. This architecture is capable of doing classification of images in 1000 object categories [22].
3. Fine Tuning: The first few layers are pre-trained on ImageNet so we had kept those weights and extracted features while the rest of the layers were used for extracting dataset-specific features. Fine-tune learning avoids the model to be trained from scratch rather we just have to train the last few layers which is fast and more accurate [23].

4. Mixed Precision Training: Using lower precision formats than 32-bit has its own benefits including low memory requirements and enabling less training time of highly deep layered neural networks [24]. Mixed precision is the use of both 16-bit and 32-bit only according to the requirements as for some computations there is no need of 32-bit processing. This method was developed by NVIDIA and was provided in PyTorch extension. In PyTorch we can use automatic mixed precision which automatically switches the GPU computations between 16-bit and 32-bit [25].

4. RESULTS AND DISCUSSIONS:

| Parameter Name | Type/Value |
|----------------|------------|
| Epochs         | 5          |
| Batch Size     | 32         |
| Num_workers    | 0          |
| Input Size     | 100*100*3  |

Table 1. Hyper-parameters Details

Since the model was pre-trained on ImageNet, we only need the first few layers for geometrical information and last layers of the model is removed. The new layers are added for learning only dataset specific features. Therefore, the first few layers are frozen so that the weights are not updated during training since we need those pre-trained features. In this way
we only need to train the newly added layers on the dataset during the training. So the newly added layer’s weight will be updated and rest all other weights of the model will remain same. This is the reason that this model was able to achieve top class results with just 5 epochs in total of 5min execution time.

![Confusion Matrix of Resnet-50](image)

**Fig 7. Confusion Matrix of Resnet-50**

The confusion matrix clearly shows only 5 actual Non COVID were falsely predicted as COVID and 2 actual COVID were falsely predicted as Non COVID. This proves that the model is not only better in terms of accuracy but also sensitivity and specificity.

![Classification Report and Testing Data Prediction Block](image)

**Fig 8. Classification Report and Testing Data Prediction Block**

The classification report shows the model showed 0.95(precision), 0.98(recall) and 0.96(f1-score) for COVID positive samples and 0.98(precision), 0.95(recall) and 0.96(f1-score) for non COVID samples. The model achieved 96 percent accuracy on the testing data.
5. CONCLUSION

This work focused on the working principle of transfer learning and explored the use of Pre-trained model Resnet-50 on chest X-rays. This study shows how use of these concepts in medical image processing and AI will help in fast and reliable detection of COVID-19 with extreme accuracy. So, it is believed that this will contribute in overcoming the current diagnosing and screening problems for COVID-19 detection as it seems like the pandemic is not stopping soon. The proposed model obtained best results with 96 % accuracy and it proved to be very sensitive and specific to the dataset.

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