Comparison of Classification Models Based on Deep learning on COVID-19 Chest X-Rays

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Abstract. COVID-19, is a deadly, dangerous and contagious disease caused by the novel corona virus. It is very important to detect COVID-19 infection accurately as quickly as possible to avoid the spreading. Deep learning methods can significantly improve the efficiency and accuracy of reading Chest X-Rays (CXRs). The existing Deep learning models with further fine tune provide cost effective, rapid, and better classification results. This paper tries to deploy well studied AI tools with modification on X-ray images to classify COVID 19. This research performs five experiments to classify COVID-19 CXRs from Normal and Viral Pneumonia CXRs using Convolutional Neural Networks (CNN). Four experiments were performed on state-of-the-art pre-trained models using transfer learning and one experiment was performed using a CNN designed from scratch. Dataset used for the experiments consists of chest X-Ray images from the Kaggle dataset and other publicly accessible sources. The data was split into three parts while 90% retained for training the models, 5% each was used in validation and testing of the constructed models. The four transfer learning models used were Inception, Xception, ResNet, and VGG19, that resulted in the test accuracies of 93.07%, 94.8%, 67.5%, and 91.1% respectively and our CNN model resulted in 94.6%.

1. Introduction

The COVID-19 pandemic started in December 2019 and the world is working on finding efficient detection and treatment methods. The pandemic has proven to be a deadly disease caused by the severe acute respiratory syndrome corona virus 2 (SARS-CoV-2) virus strain. The disease is contagious and is transferred by water droplets from an infected person. Symptoms include acute cough, fever, drop in oxygen levels leading to shortness of breath, body pain, loss of taste, etc. Also there exist asymptomatic cases clinically known as carriers. In addition to finding efficient detection and treatment in symptomatic people, it is challenging and is harder to track and identify carriers and to stop spread the disease further. The WHO Coronavirus (COVID-19) dashboard statistics indicate there have been 223,022,538 confirmed cases of COVID-19 including 4,602,882 deaths as of 4.47 PM CEST, September 10, 2021 [1]. The Govt of India statistics on COVID-19, there have been a total of 3,32,80,330 confirmed cases including 4,42,317 deaths as of 08.00 PM IST (GMT+5.30), September 11, 2021 [2].
India has the second highest number of COVID-19 cases after United States in the world. Around 15% vaccination and has vaccinated 73,05,89,688 including fully and partially vaccinated count. so far and having around 3,91,516 being active cases [2].

The high spread of the virus has caused it to mutate into newer and deadlier variants in multiple countries. The current vaccines provide some protection against these new variants as they elicit a broader immune response that involve a range of antibodies and cells. The world is still learning about the virus and its capabilities. The spread of the virus should be stopped as much as possible to prevent mutations of the virus that might reduce the efficacy of the existing vaccines. This creates a need for accurate detection of the disease and isolation of the affected which will be very important to patients and doctors.

Real-time reverse transcription polymerase chain reaction (RTPCR) test is used to detect COVID-19, but the results of RTPCR takes at least a day or two. The chest X-ray(CXR) is the most common imaging modality used to diagnose various lungs related problems and that it provides results rapidly. CXR is less costly and is in the reach of common man in comparison to other modalities. Chest X-ray have shown 69% sensitivity and recommends it to be used at the initial screening for COVID-19 [3]. The use of CXR to diagnose infection due to COVID-19 for the first time is illustrated by hospitals in Spain [4, 5] Researchers illustrated the use of Machine learning and Deep learning with limited number of on CXR and CT imaging modalities to classify detect the COVID-19 infection from other infections like Pneumonia, tuberculosis [6, 7, 8]. Classification of COVID-19 infection on CXR or CT imaging modalities is presented using the pretrained CNN models [9] and few other works proposed new models or dynamic CNN [10]. Application of AI to detect COVID-19 is investigated from 1400 plus CXR images with and without augmentation [11]. Image Enhancement methods with lung segmentation applied on CXR images to detect COVID-19 with 94-95% accuracy [12].

The research work on classification so far have the limitation owing to data imbalance and limited data. This paper presents a comparative study of deep learning tools used to classify COVID-19 patients faster and help in reducing the spread of this deadly disease. This research explores fine tuning of existing methods of classification with larger datasets using deep learning techniques. It illustrates classification of COVID-19 CXR from Normal and Viral Pneumonia cases and presents the comparison of techniques in terms of accuracy and loss. Five experiments are performed, one is using CNN and remaining four are performed using state-of-the-art pre-trained models using transfer learning. The accuracy falls in the range of 94.6% to 94.8% with CNN and Xception model that is higher compared to other methods.

2. Methodology

2.1. Dataset

The training was performed on a publicly available dataset [1, 2] of 3616 COVID-19 CXRs, 10192 Normal CXRs and 1345 Viral Pneumonia CXRs. This data was split into 90% for training, 5% for validation and 5% for testing randomly. This split is finalized due to the amount of data points that is available. More focus is given to training of the network hence 90% is chosen for training. The remaining 10% of randomly selected data that consisted of a total of 1514 images is chosen for validation and testing.

Chest X-ray images used are collected from the publicly available datasets. Samples of Chest X-Ray images of COVID-19, Normal and Viral Pneumonia are shown in Figure 1, Figure 2 and Figure 3 respectively.

The details of the data collected from various publicly accessible datasets are listed in the Table 1.
Figure 1. COVID-19 CXR. Figure 2. Normal CXR. Figure 3. Viral Pneumonia CXR.

Table 1. Details of chest X-Ray data collected for the experiments.

| Database                          | Total of images | Source(s)                                      |
|-----------------------------------|-----------------|------------------------------------------------|
| COVID-19 Chest X-Ray              | 3615            | 2473 pad chest dataset, 183 Germany Medical School, 559 SIRM, GitHub, Kaggle & Twitter, 400 GitHub |
| Normal Chest X-Ray                | 10192           | 8851 RSNA, 1341 Kaggle                        |
| Viral Pneumonia CXR               | 1345            | 1345 Kaggle                                   |

2.2. CNN Model

This model is built using TensorFlow. It has 13 layers of which 5 are Convolutional 2D layers, 5 Max Pooling 2D layers, 2 Dense layers and 1 flatten layer. The first 10 layers are Convolutional
layers where each convolutional layer is followed by a Max Pooling 2D layer. The first convolution layer uses 16 filters of window size 5x5. The second convolutional layer uses 32 filters of window size 3x3. The other 3 convolutional layers use 64 filters of window size 3x3. All convolution layers use Rectified Linear Unit (ReLU) as the activation function. All the Max Pooling 2D layers are of window size 2x2. The eleventh layer is a Flatten layer that flattens the pooled feature map to a single row to be passed to the fully connected layer. The twelfth layer is a Dense layer having 512 units and uses ReLU as the activation function. The final layer is a Dense layer having 3 units and uses Softmax as the activation function to perform 3-class classification. The model uses Adam as the optimizer with a learning rate of 0.001 and categorical cross entropy as the loss function. The model has an input shape of 299x299x3. Figure 4 graphically shows the CNN model.

ImageDataGenerator from TensorFlow is used to automatically import the image and its classes and feed it to the model. The input image pixel values are re-scaled to 1/255. The images are also augmented having rotation range of 40 degrees, width shift, height shift and shear range of 20% with horizontal flip. A batch size of 100 was used for training and 20 for validation. The model was trained for 50 epochs and used the EarlyStopping callback by TensorFlow to stops training if no improvement is seen in the loss value for over 3 epochs.

2.3. Transfer learning models
TensorFlow Keras Applications module is used to import the architectures with pre-trained weights. The last fully connected layers in all the models are left out. The layers in imported models are set to be non-trainable. The models are imported with ImageNet weights.

2.3.1. Inception v3: Inception v3 is one of the widely used image recognition model. On the ImageNet, it has attained an accuracy greater than 78.1%. The model is a convolutional neural network that is 48 layers deep.

Our model adds four more layers are added to the imported Inception v3 architecture. The first one is a flatten layer that converts the data to a single row to be passed to the fully connected layer. The second layer is a Dense layer having 1024 units and using ReLU as the activation function. The third layer is a Dropout layer that randomly deactivates 20% of the
previous layer units to get a regularized effect. The final layer used is a Dense layer having 3 units and uses Softmax as the activation function to perform 3-class classification.

ImageDataGenerator from TensorFlow is used to automatically import the image and its classes and feed it to the model. The input image pixel values are re-scaled and augmented as performed in the CNN model experiment. The batch size used for training and validation and the callbacks used is the same as that of the CNN model. This model uses the same optimization and loss functions as used in the CNN model experiment. The model was trained for 50 epochs.

2.3.2. Xception: An Xception model is considered to be an extension of the Inception architecture. In Xception model the standard Inception modules are replaced with separable convolutions. It is a convolutional neural network with 71 layers deep. In our experiment we add again four more layers to the imported Xception architecture. These added layers are similar to those added in the Inception v3 experiment. ImageDataGenerator was used to automatically import the images and its classes and feed it to the model. The images are re-scaled and augmented as performed in the CNN model experiment. The batch size used for training and validation and the callbacks used is the same as that of the CNN model. This model uses the same optimization and loss functions as used in the CNN model experiment. The model too was trained for 50 epochs.

2.3.3. ResNet50: VGG19 is a variant of the VGG model consisting of 19 layers. Again four layers are added to the imported VGG19 architecture and they are similar to those added in the Inception v3 experiment. ImageDataGenerator was used to automatically import the images and its classes and feed it to the model. The images are re-scaled and augmented as performed in the CNN model experiment. The batch size used for training and validation and the callbacks used is the same as that of the CNN model. This model also uses the same optimization and loss functions as used in the CNN model experiment. The model was also trained for 50 epochs.

2.3.4. VGG19: ResNet stands for Residual Network which is a classic neural network used for many computer vision tasks. It is a convolutional neural network that is 50 layers deep. 3 layers are added to the imported ResNet 50 architecture. They are similar to the ones added in the Inception v3 experiment without the Dropout layer. ImageDataGenerator was used to automatically import the images and its classes and feed it to the model. The images are re-scaled and augmented as performed in the CNN model experiment. The batch size used for training and validation is the same as that of the CNN model. The EarlyStopping callback stops training if there is no improvement in the loss parameter for over 5 epochs. This model uses the same optimization and loss functions as used in the CNN model experiment. The model was trained for 50 epochs.

To solve any Image classification problems, researchers most commonly follow two important approaches listed below:

- Training a Convolutional Neural Network (CNN) from the scratch.
- Transfer Learning – Use a pre-trained network.

Although, the first method offers a high level of customization, extracting higher output for accuracy is not possible with limited data. In case, if the dataset is vast (~1 million images) and the images include perfect image labels and annotated data then it is highly recommended to train a CNN architecture from scratch.

Since the image dataset obtained for training has less than 10,000 images, a transfer learning-based method is more suitable.
3. Results and discussion

The training, validation and testing accuracies and losses are measured for each experiment and is tabulated in Table 2 and Table 3 respectively.

| Models      | Training Accuracy | Validation Accuracy | Testing Accuracy |
|-------------|-------------------|---------------------|------------------|
| CNN         | 96.12%            | 93.63%              | 94.6%            |
| Inception v3| 93.27%            | 92.38%              | 93.07%           |
| Xception    | 93.36%            | 92.97%              | 94.8%            |
| VGG19       | 86.48%            | 91.43%              | 91.1%            |
| ResNet50    | 69.62%            | 67.99%              | 67.5%            |

Table 3. Table of Losses.

| Models      | Training Accuracy | Validation Accuracy | Testing Accuracy |
|-------------|-------------------|---------------------|------------------|
| CNN         | 0.1051            | 0.1815              | 0.1597           |
| Inception v3| 0.1772            | 0.2149              | 0.1992           |
| Xception    | 0.1740            | 0.2134              | 0.1497           |
| VGG19       | 0.3254            | 0.2345              | 0.2384           |
| ResNet50    | 0.8863            | 0.7055              | 0.7339           |

It is observed that the CNN model and the Xception model do well in classifying COVID-19 Chest X-Ray images from Normal and Viral Pneumonia CXRs. The ResNet50 model however, struggles to achieve an accuracy that is closer to the other models.

The results suggest that the proposed CNN model architecture or Xception architecture can be extended to applications that can be distributed across medical facilities that can predict the presence of COVID-19 real-time with great accuracy.

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