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Automatic Classification of the Severity of COVID-19 Patients Based on CT Scans and X-rays Using Deep Learning

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Abstract**: The 2019 novel coronavirus (COVID-19), which originated from China, has been declared a pandemic by the World Health Organization (WHO) as it has surpassed over eighty three million cases worldwide, with nearly two million deaths. The unexpected exponential increase in positive cases and the limited number of ventilators, personal safety equipment and COVID-19 test kits, especially in Low to Middle Income Countries (LMIC), had put undue pressure on medical staff, first responders as well as the overall health care systems. The Real-Time Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR) test is the decisive test for the diagnosis of COVID-19, but a significant percentage of positive tests return a false negative result. For patients in LMICs, the availability and affordability of routine Computerized Tomography (CT) scanning and chest X-rays is better compared to an RT-PCR test, especially in rural areas. Chest X-rays and CT scans can aid in the prognosis and management of COVID-19 positive patients, but are not recommended for diagnostic purposes. Using Deep Convolutional Neural Networks (CNN), three network based pre-trained models (AlexNet, GoogleNet and Resnet50) were used for the automatic classification of positive COVID-19 chest X-Rays and CT scans based on their severity into three classes- normal, mild/moderate, severe. This classification can aid health care workers in performing expeditious analysis of large numbers of thoracic CT scans and chest X-rays of COVID-19 positive patients, and aid in their prognosis and management. The images were obtained from public repositories, and were verified and classified by trained and highly experienced radiologist from Agha Khan University Hospital prior to simulations. The images were augmented and trained, and ResNet50 was concluded to achieve the highest accuracy. This research can be used for other lung infections, and can aid the authorities in the preparations of future pandemics.

Keywords: AlexNet, Coronavirus, COVID-19, Deep Learning, GoogleNet, ResNet50, RT-PCR

1. INTRODUCTION:

A global pandemic of Coronavirus Disease 2019 (COVID-19) was first reported in Wuhan, China in December 2019, and has since spread worldwide at an exponential scale. Till date, there are no proven or effective therapies or vaccines for this virus, and the expanding research and knowledge provides significant potential drug targets. However, these would require extensive testing and trials before being deployed globally [1].

COVID-19 is an acute resolved disease, but can be fatal as it leads to significant alveolar damage and regressive respiratory failure [2]. Most patients show moderate symptoms, and some exhibit fever, cough and dyspnea. In critically ill cases, the infection causes pneumonia, severe acute respiratory syndrome, septic shock which can lead to multi-organ failure, and death [3].

The definitive diagnosis of COVID-19 is by Reverse Transcription Polymerase Chain Reaction (RT-PCR) [4]. As the time between the symptom onset and RT-PCR test taken increases, the chance of a false negative result increases [5]. However, countries worldwide are employing the real time RT-PCR as the primary detection technique for diagnosing COVID-19. Many health care systems, especially of Low to Middle Income Countries (LMIC) are lacking the support needed in setting up and using RT-PCR [6]. This results in asymptomatic patients not being diagnosed, isolated and treated quickly enough. Given the highly infectious nature of the virus, they run the risk of further contaminating a larger population [7].

Initially, a number of studies using deep learning were conducted as a means of diagnosing COVID-19 patients using Computerized Tomography (CT) scans and X-rays and results are given in [8-12]. In [13], a tailored deep Convolutional Neural Network (CNN) was designed for the detection of COVID-19 patients using their X-rays. In [14], the diagnostic value and consistency of chest CT was compared with RT-PCR, and it was concluded that chest CT may be considered as a primary tool for the detection and diagnosis of COVID-19 in epidemic areas. The study in [15] investigated the changes in CT scans of COVID-19 positive patients from confirmation till recovery. It concluded that lung abnormalities on the CT scans displayed the highest severity approximately 10 days after initial onset of symptoms.

National Health Service (NHS) workers have been using CT scans or chest X-rays as a means of diagnosing COVID-19 due to its ease of use and affordability [16]. However, this is not recommended by the American College of Radiology, as a CT scan or chest X-ray does not give an accurate distinction between COVID-19 and other respiratory infections such as influenza, Severe Acute Respiratory Symptom (SARS) and Middle East Respiratory Symptom (MERS). A high percentage of COVID-19 positive patients display a normal CT scan or chest X-ray regardless of being infected, which can lead to an inexperienced health worker to conclude that they are healthy while being highly contagious [17]. The excessive use of imaging equipment on COVID-19 positive patients can also prove to be hazardous for healthcare providers and other patients as the risk of contamination increases [18].

According to [19], CT scans and chest X-rays of confirmed COVID-19 positive patients can be classified into three categories- mild/moderate, severe and normal, as shown in Figure 1. The classification of COVID-19 positive patients into the normal category does not indicate that they are healthy, but are infected with the virus whilst not displaying any abnormalities in their lung CT scan or X-rays. Using deep learning to classify a CT scan or chest X-ray based on its severity into these three classes can be beneficial in the prognosis and management of COVID-19 positive patients. In financially stressed countries, for example Pakistan, a lot of hospitals, especially in the rural regions, do not have a radiologist available for 24 hours and performing a chest X-ray or CT scan is easier than an RT-PCR test. A doctor can use Deep Learning to classify chest X-rays or CT scans of COVID-19 positive patients based on their severity, and conclude if the patient is exhibiting normal, mild/moderate or severe COVID-19 lung infection. It can also help in the monitoring of the escalation and de-escalation of recovery, especially in ICUs which are filled to their maximum capacity [20].

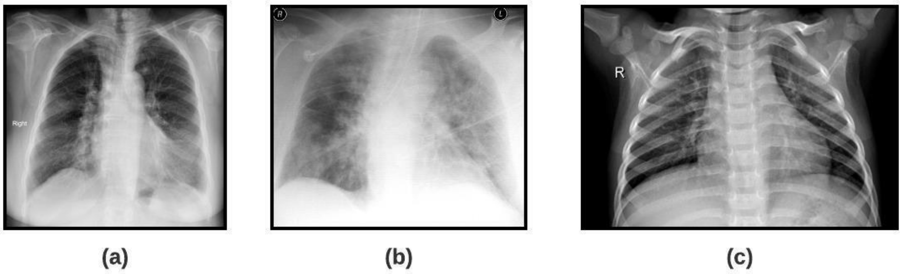

Figure 1 Infected Chest X-rays and CT scans of COVID-19 patients (a) Mild/Moderate (b) Severe (c) Normal

The images of COVID-19 patients were obtained from public repositories and were analyzed and classified by highly experienced radiologists from Agha Khan University and Hospital and, based on their severity, grouped into normal, mild/moderate and severe prior to training and simulations. In this study, three pre-trained networks (AlexNet, ResNet50 and GoogleNet) were used to train the images for the automatic classification of chest X-rays and CT scans into the three classes (Normal, Severe and mild/ Moderate) and the results are discussed in detail in Section 0. The ResNEt50 model was able to classify the images with the highest accuracy.

2. MATERIALS AND METHODS

This study automatically classifies CT scans and chest X-rays of positive COVID-19 patients into normal, mild/moderate or severe categories for the management and prognosis of patients. This is implemented using deep learning networks trained to extract low to high level features from CT scans and X-ray images acquired from COVID-19 databases using designed and trained filters. These features are then used to distinguish the class of the image i.e. normal, mild/ moderate or severe. Three pre-trained CNN models (AlexNet, GoogleNet and Resnet50) were trained and fine-tuned for classification purposes using transfer learning. All the simulations were carried out in MATLAB.

A. Deep Learning

Deep learning is a branch of machine learning emphasizing on feature extraction and image classification, especially for medical image classification [21]. Artificial intelligence is applied using machine and deep learning for the extraction, analysis and recognition of patterns from image data. Deep learning employs deep CNN for mass feature extraction using convolution. The layers process nonlinear information while transforming data into more abstract levels. Deeper networks result in more complex information being extracted as higher layers within the network smother irrelevant attributes or features, while enhancing significant information [8].

1) Image Classification:

One of the most fundamental tasks in image processing is image classification, i.e. to assign one or more labels (e.g. severe, normal etc.) to an image. The image is represented by the low or mid-level features which are extracted and labelled using a classifier [21]. The ability to extract and analyze image features is the key process of image classification.

The model network is initially trained for a specific task (e.g chest X-rays, brain MRI etc.) using labelled training inputs. The trained network can now be used to estimate an unlabelled testing input to achieve an output label.

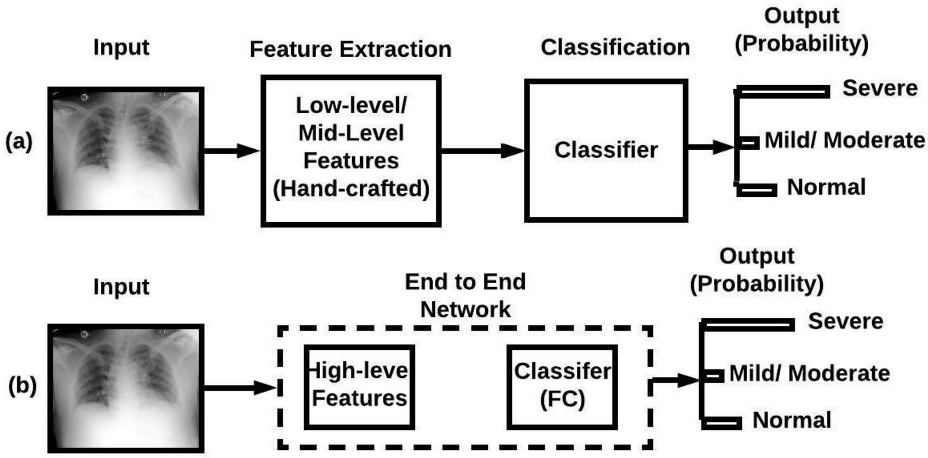

Figure 2 Image Classification (a) Traditional (b) Deep Learning [21] (FC) = Fully Connected Layer

As illustrated in Figure 2 (a) in traditional image classification, low-level (hand-crafting) or mid-level features (grey scale density, colour, texture, shape and position) were initially extracted and then used as input to the classifier for classification tasks. This was done by using a neural network with several (hidden) layers between its input and output. Deep learning is focused on automatically combining low, mid and high level feature extraction and classification on one network which is trained in an end-to-end manner, as shown in Figure 2(b). This allows for great success in image classification, detection and segmentation, especially in medical image processing [21].

2) Network Architecture:

The basic architecture of all the CNN networks can be seen in Figure 3. It can be briefly divided into stages, described as data augmentation or pre-processing, feature extraction (convolution layer and pooling layer) and classification (fully connected layer). CNNs require a large dataset to increase the accuracy, and therefore the images are first augmented using various techniques, details of which are given in Image Classification.

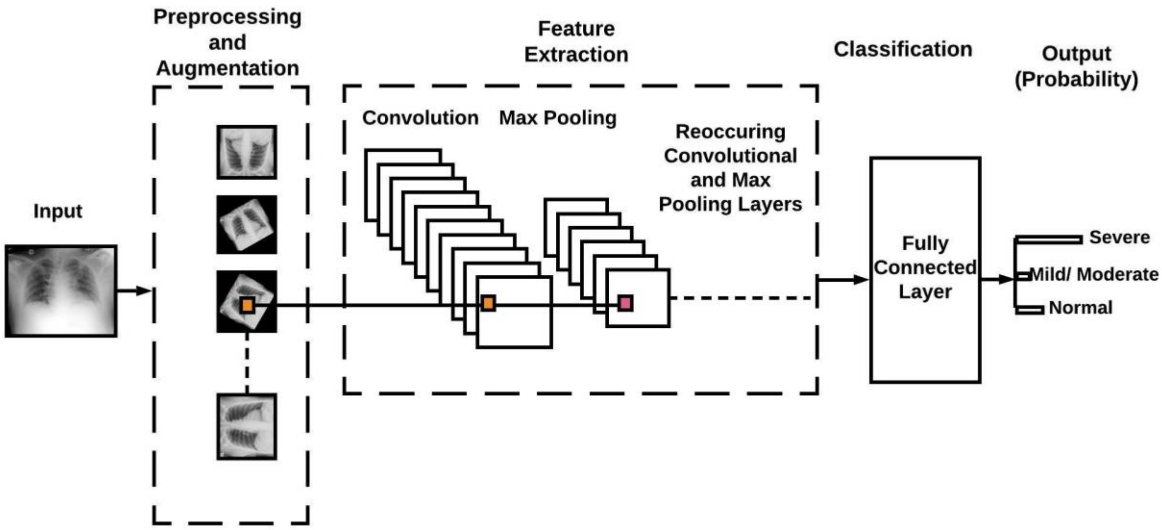

Figure 3 Basic CNN Architecture for Severity Classification of COVID-19 Chest Images

During training of the network, augmented images are passed through the convolutional and pooling layers repetitively and then to the fully connected layers for image classification. For feature extraction, image data passes through a series of convolutional filters, with reoccurring pooling and fully connected layers in between. The convolutional filters filter small patches of the input images. Similar to vision processing of the human brain, the filters detect the more relevant and obvious features in the images such as lines and shapes, leading to filtration and detection of higher order features such as textures. The output is usually more than one class labels or probabilities [22].

3) Transfer Learning:

Transfer learning is using the knowledge gained by a pre-trained model to learn another set of data [23]. It involves training of CNNs using a large dataset to extract significant characteristics, and transferring this knowledge to re-train another CNN from scratch with a smaller population of training images i.e. COVID-19 X-rays images [8]. This is done to ensure success as the training of a CNN for classification tasks requires the utilization of large datasets and the dataset of COVID-19 patients is limited. The final layers are changed during training to output three categories, mild/moderate, Normal and Severe.

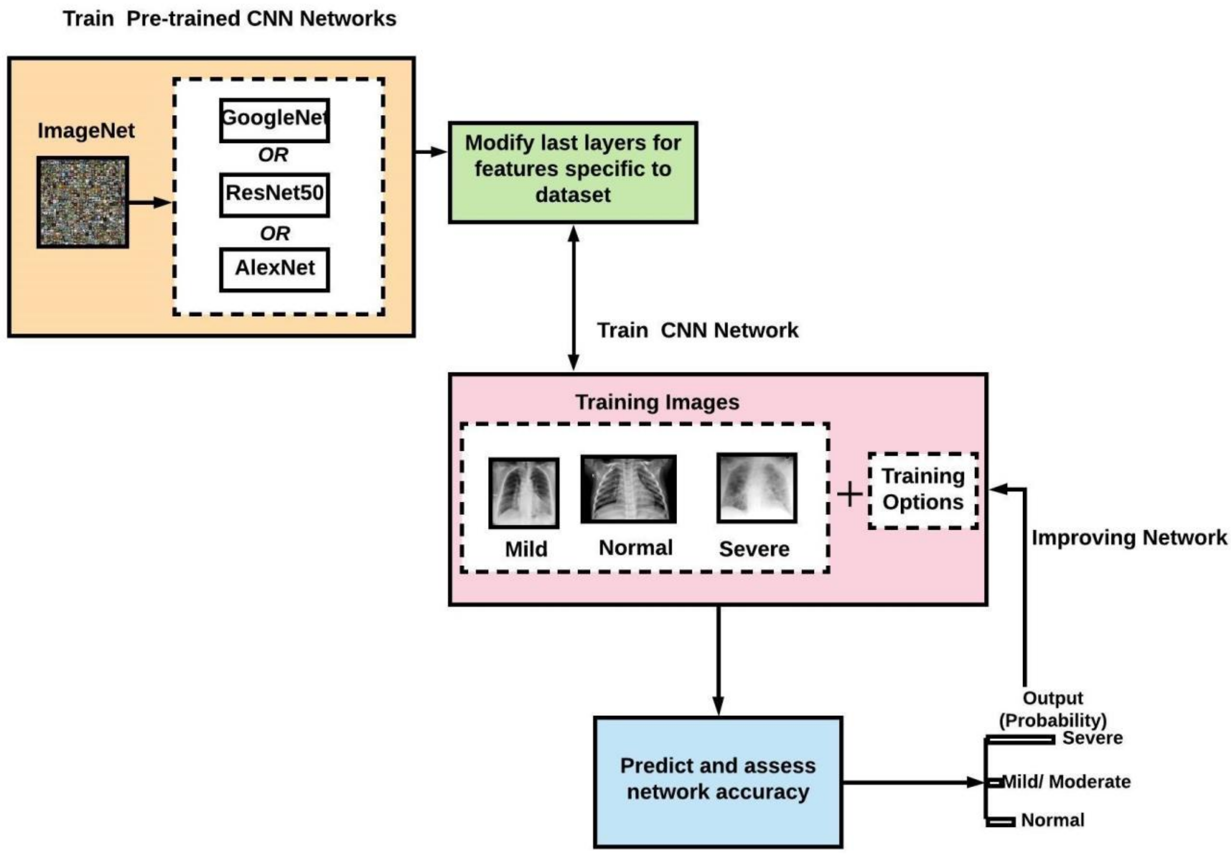

Figure 4 Training Methodology

As illustrated in Figure 4, the three pre-trained CNN models used were AlexNet, ResNet50 and GoogleNet. These networks have already been trained using a large dataset (e.g. ImageNet) and are re-trained for the COVID-19 dataset [24]. The parameters of the last fully connected layer of the pre-trained models were updated during retraining as per the requirements of the COVID-19 dataset, while the other parameters of the network were consistent with the parameters of the pre-trained model [21].

Using the knowledge in feature extraction obtained in the initial training, the CNN now processes the chest X -ray images to extract their features. The pre-trained model retains its learned weights and initial architecture, and acts only as a feature extractor, which are inserted into a new network for classification tasks [8]. The results are analysed and the accuracy is measured, and modifications are made to the network training options to increase the network efficiency. This is repeated until the network is optimized.

4) AlexNet:

The generalized architecture of AlexNet is shown in Figure 5, and shows that it is an 8-layer deep CNN. The last fully connected layer of AlexNet (fc8) was changed and the weight learn rate factor and Bias Learn Rate Factor were set to 10.

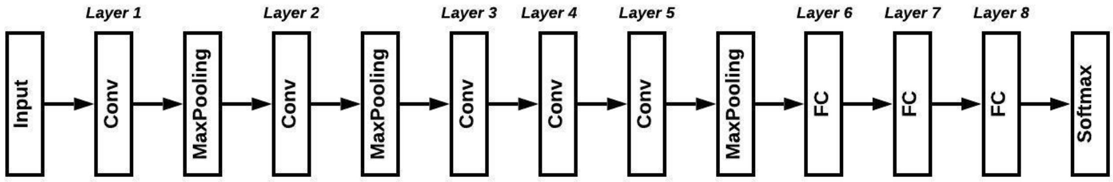

Figure 5 Simplified AlexNet Architecture (Conv) = Convolution Layer, (FC) = Fully Connected Layer

5) ResNet50:

Traditionally, the CNN network was believed to perform better based on its depth i.e. deeper CNNs would result in higher efficiencies as they extract low, middle and high level features. The output of the upper convolutional layer is the input of the next convolutional layer. With limited training data, the classification and recognition worsens. As networks become deeper, the accuracy gets saturated and degrades rapidly, leading to a high training error. This cannot necessarily be avoided using a shallower network. ResNet networks aim to minimize the degradation in deep CNNs [25].

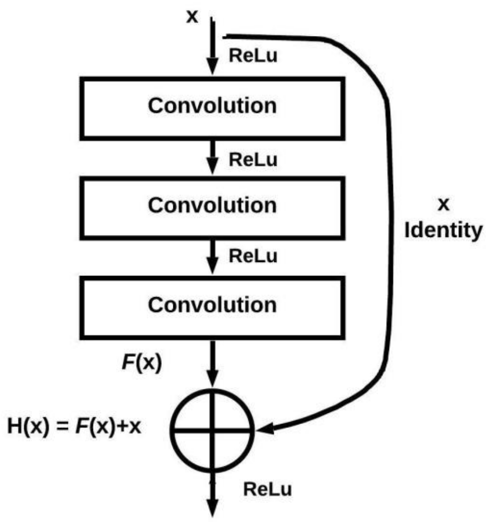

Figure 6 ResNet50 Residual Block [25]

ResNet50 uses the shortcut connection, skipping one or more layers and performing identity mapping. As illustrated in Figure 6, x is the input feature, and F(x), output from the stacked layers, and is the residual knowledge. The output H(x) is the addition of F(x) and the output of shortcut connections performing identity mapping. With this method, even if the contribution of any one layer is near zero, the work of the previous layers is not ignored as the input (x) is added to the output [26].

A simplified illustration of ResNet50 is shown in Figure 7. It has a total of 50 layers, with 26 million parameters. The last fully connected layer of ResNet (fc1000) was changed and the weight learn rate factor and Bias Learn Rate Factor were set to 10.

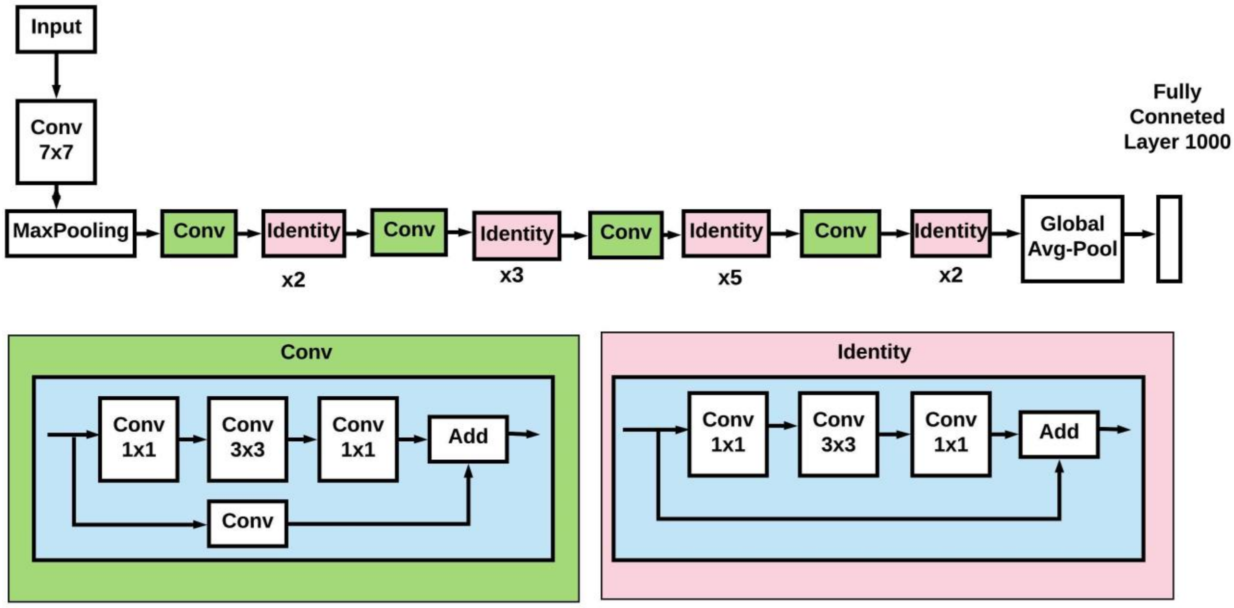

Figure 7 ResNet-50 architecture [27] (Conv) = Convolutional Layer (Avg) = Average

6) GoogleNet:

GoogleNet is a CNN with 22 layers (with weights). It works with an efficient inception module, which acts as a local network topology and a network within a network, as illustrated in Figure 8. These are stacked on top of each other within the GoogleNet architecture [26].

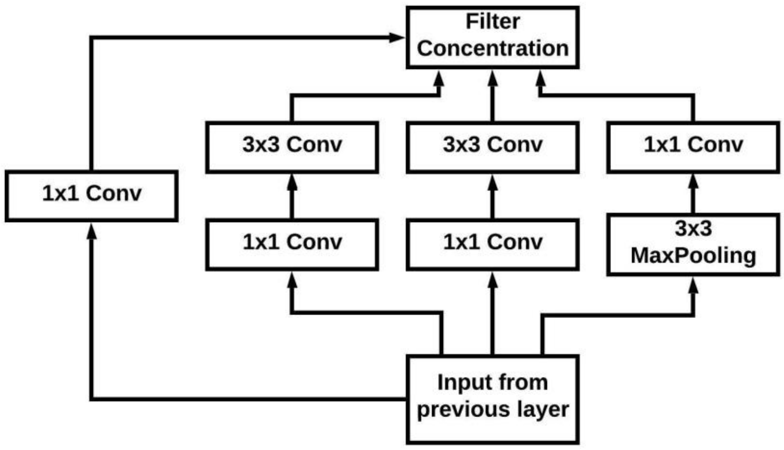

Figure 8 GoogleNet Inception Module [28] (Conv) = Convolutional Layer

As illustrated in Figure 9, the network is 22 layers deep when counting layers with parameters. The final architecture contains multiple inception modules stacked one over the other [28]. Note: Auxiliary layers are not shown in Figure 9 as it is based on the GoogleNet architecture shown in MATLAB. The last fully connected layer of GoogleNet (loss-3 classifier) was changed and the Weight Learn Rate Factor and Bias Learn Rate Factor were set to 10.

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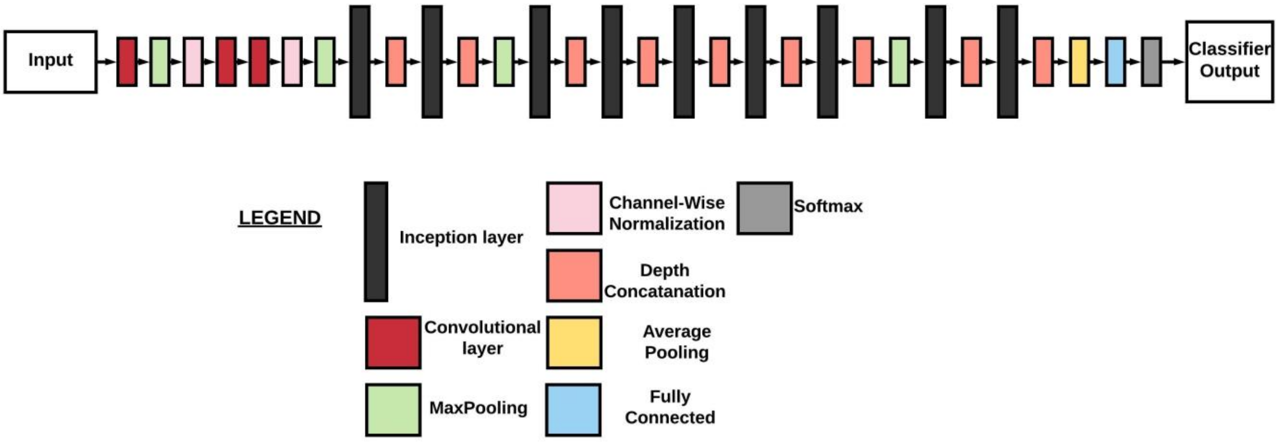

Figure 9 GoogleNet Architecture [28]

B. Datasets

The chest X-ray images of COVID-19 patients were obtained from the open source GitHub repository shared by Dr. Joseph Cohen [29]. This dataset consists of chest X-rays and CT images of patients with Acute Respiratory Distress Syndrome (ARDS), COVID-19, Middle East respiratory syndrome (MERS), pneumonia and Severe Acute Respiratory Syndrome (SARS). All the images used in the study were verified by trained radiologists from Agha Khan University Hospital to ensure that images used in the simulations were off COVID-19 positive patients to reduce probabilities of error. The data was divided into three groups- mild/ moderate, severe and normal. There were 106 mild/mod, 50 severe and 1335 normal images which were used.

1) Data Augmentation:

Large number of images, preferably in the hundreds of thousands, are needed to prevent overfitting. Due to the lack of a large image database availability (i.e. CT scans and chest X-rays of COVID-19 positive patients), data augmentation techniques were applied on the images prior to training. Augmentation was carried out in MATLAB using Image Batch Processor Application. The imaging techniques used are mentioned in **Table 1** and were chosen randomly out of the thousands of possibilities available.

Table 1 Types of Augmentation

Types of Augmentation	**Description**
Gaussian Blurring	Apply randomized Gaussian Blur/ Noise to image
Invert 300	Invert image by 30 0 clockwise
Noise	Randomized salt and pepper noise to image
Resize	Resize image to 0.75 off the original image
RGB to HSV	Converts the Red, Green, and Blue values (RGB) of an image to Hue, Saturation, and Value (HSV) values of an image
Affine	2D-Affine geometric transformation combining vertical and horizontal stretch to the image
Translate	Translates image A by a random translation vector
Rotation	Image Rotated 300, 600, 900 and 1800 anticlockwise
Flip	Flips an image upside down and from left to right (mirror image)
B & W	Converts RGB to grayscale
Gray	RGB image converted to grayscale

As shown in Figure 10, each image undergoes augmentation individually. An image was loaded in MATLABs Image Processor Application, and underwent augmentation techniques mentioned in **Table 1**.

The first left hand image is one of the COVID-19 chest X-ray. The results of the image undergoing each augmentation is then shown. In this example, one image was now augmented to produce 15 more images, therefore increasing the total data 15 times. The results of the augmentation on the total dataset are given in **Table 2**.

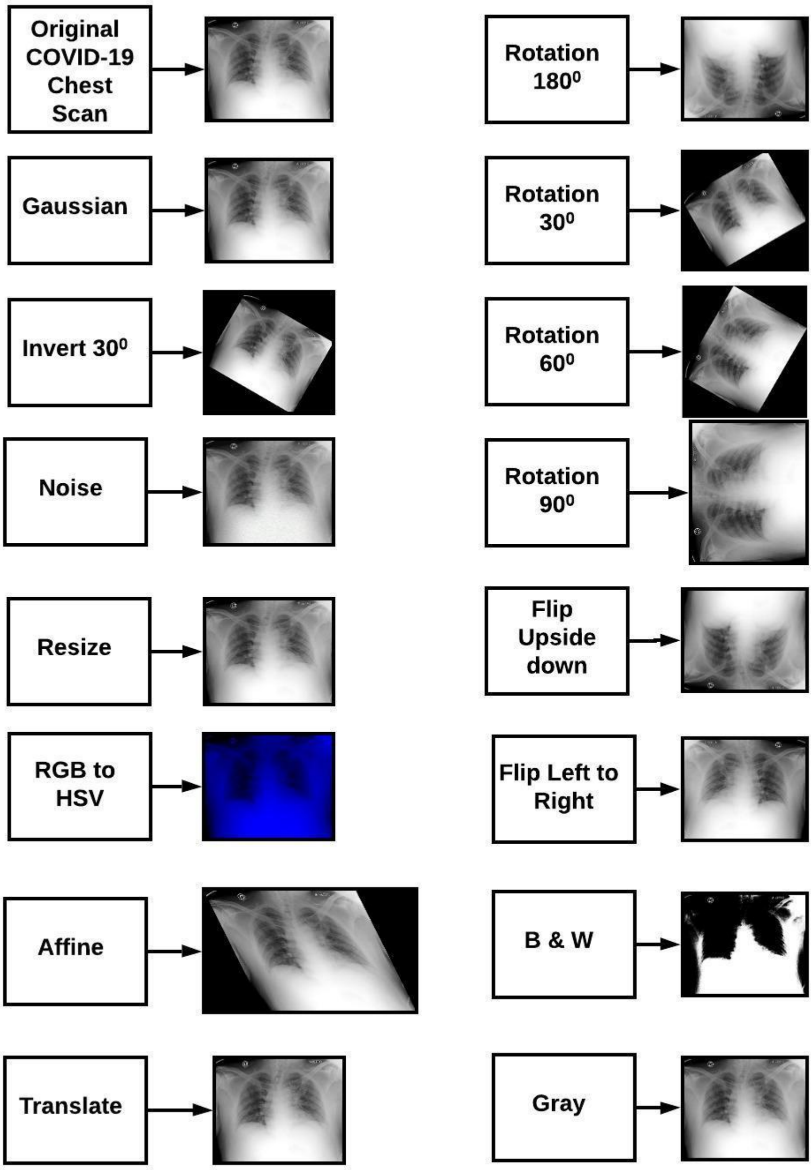

Figure 10 Augmentation of Images

Table 2 Augmentation Results

Data Type	No. Of Images	No. Of Images (Augmented)
Mild/Moderate	106	1696
Normal	260	4160
Severe	50	800

C. Implementation

All simulations were carried out in MATLAB using the Deep Network Designer Application. Augmented images were divided into a training set (70%), validation set (15%) and testing set (15%). All the images were resized according to the requirements of the pre-trained networks. For example, AlexNet accepts images that are 227x227x3 pixels.

A pre-trained network (AlexNet, GoogleNet, ResNet50) was chosen and fine-tuned for this specific task. The learning rates were also reset for faster learning. The final classification layer was changed according to the requirements of the classifications.

The network was trained using Stochastic Gradient Descent with Momentum. The hyperparameters used were: maximum number of epochs = 6, mini-batch = 64, learning factor = 0.7, patience = 5, validation frequency = 6, gradient threshold = 35. The weights and bias of the last layer were set at 10.

3. RESULTS AND DISCUSSION

The CNN pre-trained models AlexNet, ResNet50 and GoogleNet were trained and tested on chest X-ray and CT scan images. The results are shown in Table 3. It is observed that the highest accuracy was achieved by Resnet50, and AlexNet was very close. If the time for simulations was taken into account, the time for AlexNet was significantly less as compared to ResNet50. Accuracies were calculated for both augmented and non-augmented images for comparison.

Table 3 Simulation Results

Network	Average Accuracy (non-augmented)	Average Accuracy (Augmented)
AlexNet	81.48%	83.70%
GoogleNet	78.71%	81.60%
Resnet50	82.10%	87.80%

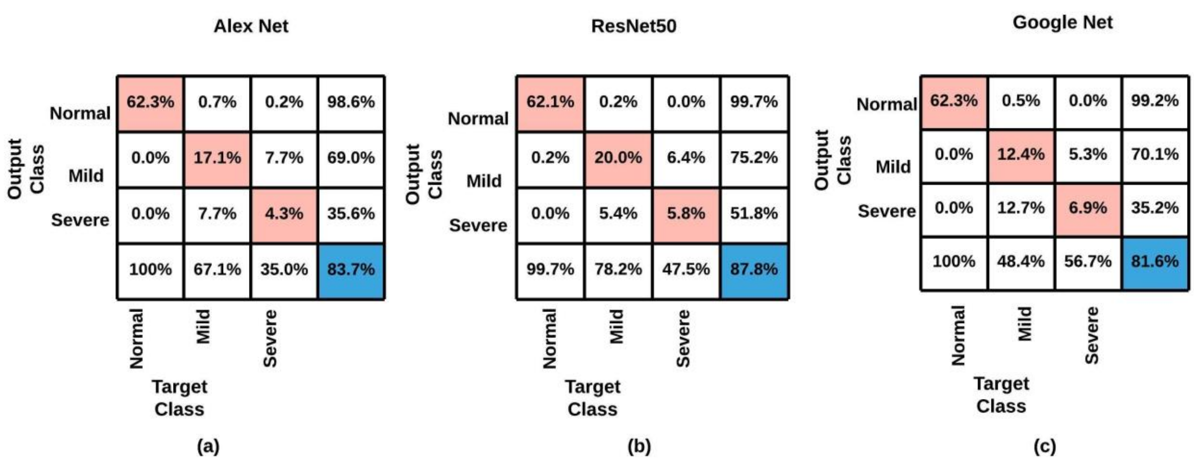

Figure 11 Convolution Matrix (a) AlexNet (b) ResNet50 (c) GoogleNet

The Convolution Matrices for the three models are shown in Figure 11. The Output class (predicted class) is shown in the rows and the Target Class (true class) is shown in the columns. The correctly classified results are shown in the shaded diagonal cells, and the rest correspond to the incorrectly classified images. The far right column shows the percentages of predictions correctly classified. The bottom row shows the percentages of images belonging to each class which are correctly classified. The overall accuracy is shown in the bottom right cell.

In the Resnet50 matrix shown in Figure 11 (b), out of the total data, it can be seen that 62.1% of the Normal COVID-19 images were correctly classified as Normal, 20.0% of the Mild/Moderate images were correctly classified as Mild/ Moderate and 5.8% of the Severe images were correctly classified as Severe. 0.2% of the Mild images were incorrectly classified as Normal, 5.4% of the Mild images were incorrectly classified as Severe and 6.4% of the Severe images were incorrectly classified as Mild.

Out of the total number of Normal predictions made, 99.7% were correct, 75.2% of the total Mild predictions were correct and 51.8% of the total Severe predictions were correct. Out of the total Normal images in the data, 99.7% were correctly predicted as Normal, out of the total Mild/Moderate images in the data, 78.2% of cases are correctly predicted as Mild/ Moderate and out of the total Severe images in the data, 47.5% are correctly predicted as Severe. Overall, 87.8% of the predictions were correct.

The results between augmented and non-augmented results don't differ by a large margin. However, when trained on non-augmented images, GoogleNet was unable to detect a test Severe image correctly. However, when tested with augmented images, it was able to detect the Severe image correctly. Therefore augmentation had increased the ability of the GoogleNet to detect a Severe image. Resnet50 model shows a better result as compared to the other networks.

It was noted that in the COVID-19 positive data downloaded, most of the chest X–rays and CT scans of COVID-19 positive patients were of children. In this study, the ages of the patients were not taken into account, and this could be investigated in the future. These results can be improved with a larger number of images prior to augmentation. The training time of the three trainings were not taken into account, and this could be another area of investigation. More pre-trained models, such as Inception-ResNetV2 can also be trained for more comparative analysis.

4. CONCLUSION

This study focused on the automatic classification of CT scans and chest X-rays of COVID-19 positive patients into Normal, Severe and Mild/ Moderate. Deep learning was used to train three pre-trained models ie AlexNet, GoogleNet and ResNet50 with transfer learning. ResNet50 obtained the highest accuracy and AlexNet was only slightly less. GoogleNet was unable to predict a Severe image when training was done with non-augmented images, but made correct prediction with augmented images. The accuracies will increase with higher number of images, and due to the limited number of medical images available, the accuracies were less than expected. This study would save precious time, and also to be safer for health workers having limited contact and exposure to highly contagious patients, especially in LMICs where resources are limited. In areas especially where trained radiologists are not available at all times, the automatic classification of the severity of the X-rays will be able to

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provide quick prognosis and management of COVID-19 positive patients. The authorities would be able to isolate and treat patients faster, somewhat containing the spread with improved efficiency [30]. This study could prove beneficial for future pandemics, especially concerning lung infections as it could be used for the classification of other lung diseases such as acute pneumonia and SARS.

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