Classification of COVID-19 from chest X-ray images using a deep convolutional neural network

Sanskruti Patel[a]
[a]Associate Professor, Faculty of Computer Science and Applications, Charotar University of Science and Technology, Changa, India.
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Abstract: The COVID-19 pandemic, also known as the coronavirus pandemic, is one of a major outbreak spreading across many countries around the world. It impacts severely on the health and life of many people all around the world. Medical imaging is a widely accepted technique for the early detection and diagnosis of disease that includes different techniques such as X-ray, computed tomography (CT) scan etc. For diagnosis COVID-19, chest X-ray is the imaging technique that plays an important role. In the recent years, deep neural networks have been successfully applied in many computer vision tasks including medical imaging. In this paper, we have experimented and evaluated DenseNet model for the classification of COVID-19 chest X-ray images. For that, a publicly available dataset contains 6432 chest X-ray images categorizes into 3 classes were used. Transfer learning and fine-tuning is applied for training the three variant of DenseNet model namely DenseNet121, DenseNet169 and DenseNet201. After evaluating the performance, it has been found that DenseNet201 achieved highest validation accuracy i.e. 0.9367 and lowest validation loss i.e. 0.1653 for classification of COVID-19 in chest X-ray images.

Keywords*:* Deep learning, Transfer learning, COVID-19, Medical Imaging, Chest X-ray

1. Introduction

The 2019 novel coronavirus (2019-nCoV), or named SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2), officially named as COVID-19 is originated from Wuhan, China and spreading across 218 Countries and Territories across the world. There are nearly 63,087,142 confirmed cases are reported word wide (Worldometer., 2020) with nearly 1,465,368 deaths reported till date. There is no a precise medicine or vaccines available till the date and still the treatments are under investigation (Home., 2020). COVID-19 is an infectious disease and mainly transmitted through droplets generated when an infected person coughs, sneezes, or exhales. The disease was totally unknown earlier the outbreak started and it is considered as a greatest challenge as it causes a socio-economic crisis. Most common symptoms of COVID-19 are dry cough, fever and tiredness. It may lead to severe symptoms like difficulty in breathing, chest pain etc. (Who.int. online., 2020), though some infected person does not develop any symptoms (Who.int. online., 2020),. The virus can be easily spread from person to person that affects the upper respiratory system, which makes this disease dangerous. Therefore, early detection can help to treat, isolate or hospitalize people who are infected. There are many testing techniques are available for testing of this virus like RT-PCR, RT-LAMP, electrochemical and optical biosensors for RNA detection (Shabhani., 2020).

Apart from laboratory detection methods, there are many other methods available for detecting COVID-19. It includes X-ray or computed tomography (CT) scan. It has been found that, chest CT has a high sensitivity for diagnosis (Ali., 2020) and X-ray images indicates visual indexes associated with COVID-19 (Kanne, 2020). Expert radiologists can only interpret the abnormalities from such images. Therefore, integrating automatic methods for identification help the diagnosis procedure and provide early diagnosis with high accuracy (Minaee et al., 2020). Recent advancements in the field of artificial intelligence, machine learning and deep learning shows very promising results for automatic identification, classification and detection from visual images. Especially, deep neural networks have been successfully applied in many computer vision tasks including medical imaging in the recent years.

Recent development in the field of machine learning captures the attention from prevalent culture, academia and industry. These advancements in the machine learning are driven by prominent progresses in artificial neural networks, often termed as deep learning, a set of algorithms and techniques that empower computer to learn and discover complex hidden patterns in large data sets. With the increased access to data, easy to access software frameworks and availability of high computing hardware infrastructure made neural network deeper than ever before. Deep leaning models propose state-of-the-art approaches in variety of application in computer vision, robotics and natural language processing (Ganatra et al., 2020).

Nowadays, healthcare providers capture and produce massive amount of data, which provides extremely important information and signal that can be processed and help in surpassing traditional analysis process. This rapid growth in medical images demands extensive efforts by medical expert that is highly subjective, susceptible to human error. Alternate solution is using recent machine learning techniques to automate the complex process of medical diagnosis using medical data. Deep Learning algorithms are highly expedient to integrate, analyse and make predication based on huge, varied datasets (Patel et al., 2018). Deep Learning algorithms help in various medical applications like one-dimension biosignal analysis (Ganapthy et al., 2018), various medical events prediction, e.g. cardiac arrests (Park, 2018) and seizures (Kuhlmann et al., 2018), survival monitoring (Katzman et al.), computer assisted detection, drug inspector and discovery (De Fabritiis KDEEP., 2018), electronic health record analysis, increased operational efficiency (Tsui., 2018), electronic health record investigation (Rajkomar., 2018) and diabetic retinopathy detection (Patel., 2020).

Medical image analysis is an active field of research for machine learning, partly because the data is relatively structured and labelled Medical image analysis is an active field of research for machine learning, partly because the data is relatively structured and labelled. Medical imaging is an active research field for machine learning, because of huge data availability, data is reasonably structured and labelled, which makes it processing convenient and easy. Medical images produced by various sources are either 2-dimensional or 3-dimensional. X-rays are 2-mensional whereas CT or MRI scan images are 3-dimnesional. Studies of both types of images are crucial in order to identify normal and abnormal organ out of it. Deep Learning CNNs (Convolutional Neural Network) are the well-suitable for the task of image recognition and classification. CNNs help in many ways like image localization, classification, segmentation and annotation. CNNs are the most popular machine learning algorithm in computer vision task due to its specialty in preserving local image relations, while carrying out dimensionality reduction. It helps in capturing important features from an image and reduces the number of parameters required to compute by the algorithm and hence increase the efficiency of computing. CNNs are capable to take both 2-dimensional and 3-dimensional images as input and process it. This makes it useful in designing various systems for hospital use, using some modalities like 2-dimensional X-ray images. The structure of the paper is as follows. Section 2 provides the summary of the work done. Section 3 briefly describes about the Densely Connected Convolutional Networks (DenseNet). Section 4 explains the materials and methods including dataset description, hardware and software and experimental set up. Section 5 discusses about the results analysis

2. Survey of Literature

Different CNN-based deep neural network is able to achieve noteworthy result in ImageNet contest. It is the most important image classification and segmentation challenge in the computer vision field. Nowadays, variety of CNN-based deep neural networks is widely used for medical image classification task. Utilizing CNN as feature extractor in medical image classification can avoid complex and costly process of feature extraction.

Qing et al. (Li proposed a CNN using shallow ConvLayer for classifying lung disease from image patches. The dataset used for the experimentation consist total 16220 patches from 92 HRCT images and authors able to achieve 94% precision using proposed model.

Wang et al., (2017) presented CNN based system for big chest X-ray films dataset. Authors have used the Stanford Normal Radiology Diagnostic Dataset. It consists around 4,00,000 CXR with 108,948 frontal-view CXR for the experimentation and accomplished 0.90 and 0.91 precision and recall respectively. Authors in the paper (Kermany., 2018) used InceptionV3 based transfer learning approach on medical image dataset having 1,08,312 optical coherence tomography (OCT) image samples. They were gained 96.6% average accuracy, with 97.8% sensitivity and 97.4% specificity.

Moreover, Vianna (2018) build transfer learning based system for X-ray image classification which consider as the significant development for the computer-aided-diagnosis system. To avoid the problem of overfitting data augmentation was effectively utilized and by training ResNet18 from scratches able to achieve 86.38% validation accuracy. Thomas and Robertas (2018) proposed CapsNet based network. Based on breast cancer histology images, it classifies 4 categories of breast tissue. They were able to achieve 87% accuracy and same high sensitivity.

Rajkomar et al. (2017) used pre-trained modified GoogLeNet CNN to train 150,000 training samples obtained by augmenting 1850 chest x-ray images. They classification was done into frontal or lateral view with near 100% accuracy. The work presented also demonstrates importance of pre-training and data augmentation in automated diagnostic model.

Authors in the paper (Che Azemin et al, 2020) applied pre-trained ResNet-101 on NIH Chest X-ray dataset consist of 100,000 images to detect abnormality in chest X-ray images and to predict COVID-19 of the patient. Authors achieved sensitivity 77.3%, specificity 71.8%, and accuracy 71.9%. Shervin Minaee et al. (2020) presented Deep-COVID model for predicting COVID-19 from chest X-Ray images using transfer learning. They have used publicly available dataset of 5000 images, out of that 2000 images were used for training ResNet18, ResNet50, DenseNet-121 and SqueezeNet and 3000 radiograms were used for evaluation task. Most to evaluated models were able to achieve sensitivity of 98% (± 3%). Densely Connected Convolutional Networks (DenseNet) CNN models provide very promising results for visual object recognition. DenseNet, known as Densely Connected Convolutional Networks, is a new addition in deep CNN models that provides progressive results on benchmark datasets (Huang et al., 2017, Douillard, 2020). DenseNet was developed to solve the vanishing gradient problem arises in conventional CNN based architectures. It concatenates the output of the earlier layer with the forthcoming layer. In a conventional CNN model, an input image is passed through the neural network which gives predicted outputs. For that, each convolutional layer receives the output of the previous convolutional layer for feature map generation. This feature map is subsequently passes to the next convolutional layer. Hence, there is a direct connection between each layer and its subsequent layer. i.e. For L layers, there are L direct connections (DenseNet., 2020).

The DenseNet architecture modifies the standard CNN architecture by connecting each layer to every other layer. DenseNet is composed of dense blocks. A typical architecture of DenseNet is represented in figure 1 where the layers are densely connected together. Hence, the output feature maps of all previous layers are received by each input layer.

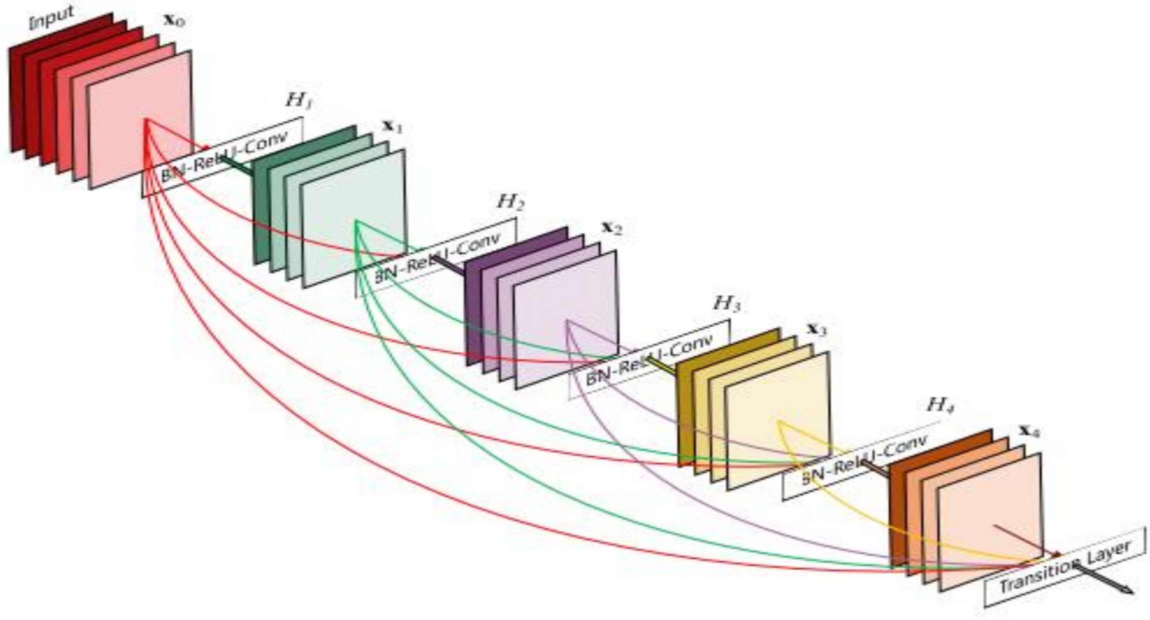


Figure 1. DenseNet Architecture(Huang., 2017)

There are L(L+1)/2 direct connections for L layers. It means that, each layer uses the feature maps of all prior layers as inputs, while the feature map generated by that layer is used as an input for each consequent layer that encourages feature reuse within a network (Jordon., 2020). As compare to an equivalent traditional CNN, DenseNets require fewer parameters, as it removes learning redundant feature maps. There are many versions of DenseNet; DenseNet-121, DenseNet-160, DenseNet-201, etc. Here the number indicates the number of layers existing in the architecture of neural network. The DenseNet normally distributed into Dense Blocks where a number of filters are different, but dimensions within the block are the same. To apply batch normalization, Transition Layer is used using downsampling. The Figure 2 represents the architecture of DenseNet with four dense blocks (Huang., 2013 and Singhal, 2020).

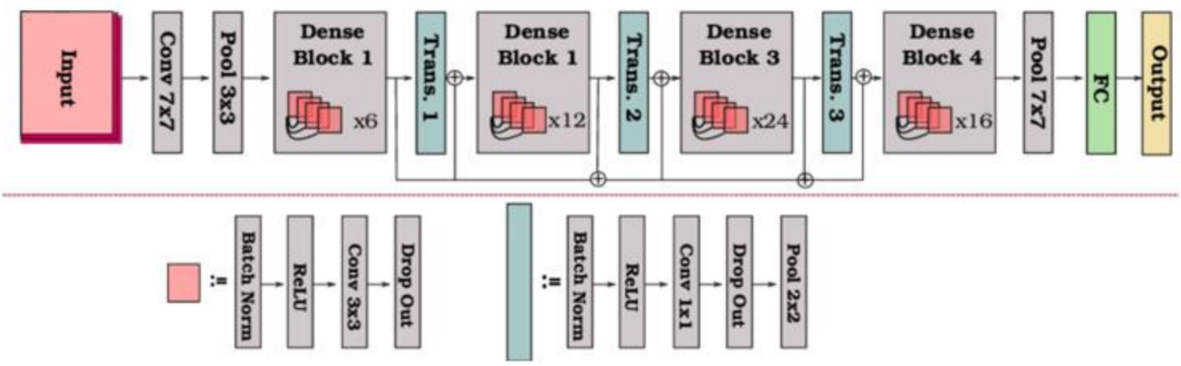


Figure 2. DenseNet Architecture with Dense Block and Transition layers (Huang., 2017)

3. Materials and Methods

This section describes the details regarding experiments carried out for classification of COVID-19 in Chest X-ray Images. The section 4 summarizes the details of hardware and software used, dataset of chest X-ray images, model hyper parameters, data augmentation and evaluation metrics.

3.1 Hardware and Software

For this research, the experiment is carried out using Google Colab (Bisong, 2019). To execute deep learning experiments, it is very much essential to have certain libraries, APIs and Environment set up. Google offered a cloud development environment called Colaboratory, known as Google Colab, which is free for public use. It is a browser-based cloud platform which makes possible to make complex models on large datasets using Jupyter Notebooks. Jupyter Notebook offers a Python shell for execution of Python code. Moreover, we have used standard software API Keras and Tensorflow along with Python, Sklearn, Matplotlib and NumPy. Python is a widely used scripting language for data science, machine learning and deep learning tasks. It is a high-level, open source language enabled with good community support. Variety of libraries and frameworks are available in Python for implementing deep learning algorithms include NumPy, Matplotlib, Sklearn and frameworks. Keras is a high level API that uses Tensorflow or Theano as a backend. It is very simple and provides convenient methods to build CNN models. TensorFlow is an open-source library that offers both high-level and low-level APIs. It contains set of functions that support all types of numeric calculations required to solve machine learning and deep learning tasks. It works on a concept of multidimensional arrays called tensors. It offers multiple level of abstraction while developing and training the model.

3.2 Dataset Description

The dataset used in this experiment has a total of 6432 image files and it is taken from kaggle (Patel, dataset repository. The dataset is structured into 2 folders namely train and test and both train and test contain three subfolders that denotes the classes presented in the dataset. There are three classes available in the dataset namely Covid19, Pneumonia and Normal. Among of 6432 x-ray images, the test data has 20% of entire images that is used to evaluate the performance of the deep learning model. The images contains in the dataset are collected from various publicly available resources (Cohen.and Mooney). In the training set, there are 460 files available for COVID-19, 1266 files available for Normal and 3418 files are available for Pneumonia class respectively. In the test set, there are 116 files available for COVID-19, 317 files available for Normal and 855 files are available for Pneumonia class respectively. The figure 3 represents the sample chest X-ray image of Covid 19, Normal and Pneumonia class respectively.

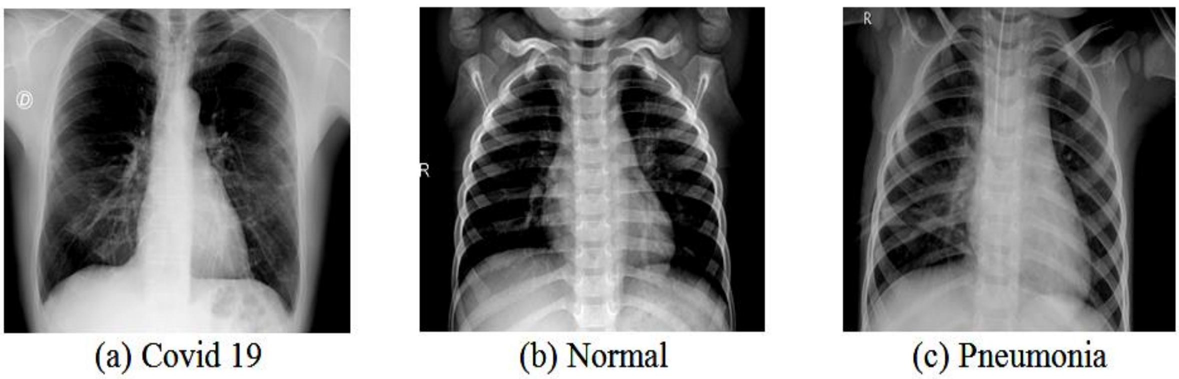


Figure 3. Sample images from chest X-ray dataset represents Covid 19, Normal and Pneumonia class

3.3 Transfer learning and fine-tuning of Model

CNN models are successfully applied on various computer vision tasks. When a CNN model is applied to a real-time application dataset, it is required to train this CNN first. Train a CNN model from scratch is very time consuming and computationally expensive process (Ganatra., 2020). Therefore, a common approach is to apply a pre-trained CNN model that has already been trained on a huge dataset like ImageNet that contains millions of labeled images (imagenet., 2020). Here, the weights are reused in one or more layers from a pre-trained model by either keeping all weights fixed or fine-tune. Transfer learning is a process of applying the knowledge obtained during solving one type of a problem to an altered but correlated problem (Pan et al., 2010). It is beneficial for such tasks where there is a scarcity of training samples. In medical image classification for uncommon or emerging diseases, there are less training samples are available.

In transfer learning, there are two methods to apply a pre-trained model for an altered task. In the first method, the pre-trained CNN is used as a feature extractor and for classification; the last fully connected layer(s) is replaced respective to the number of classes presented in the dataset. It means that a classifier is trained on top of a pre-trained model to perform classification. In alternative method, the pre-trained CNN model is fine-tuned by training a whole network or part of it.

In this experiment, we have implemented transfer learning for training the three versions of DenseNet namely DenseNet121, DenseNet169 and DenseNet201.

3.4 Model Hyper-parameters

A training pipeline for a CNN model contains many different activities. A dataset is accumulated first that splits into training and validation dataset. The training dataset contains 5144 belonging to 3 classes. A validation dataset contains 1288 images. We have used the same validation dataset as a test dataset. The optimum training process always reduces the errors and increases the accuracy. When consistent accuracy and loss obtained, training could be stopped. Hyper parameter selection is one of the crucial parts of the training pipeline. They include the value of variables that determine how the network is trained. They are used to control the training process and have a significant effect on model performance. The hyper parameters are Number of Epochs, batch size, learning rate, optimizer function, etc.

We fine-tuned each variant of DenseNet model for 20 epochs. The learning rate is set to 0.001 and the batch size used is 32. The SGD is used as an optimizer function and softmax is used as an activation function. All images are resized into 224 X 224 for passing in the network.

3.5 Data Augmentation

Data augmentation expands the dataset artificially by modifying the available samples in the dataset. It helps to add variations in the dataset and make model enable to learn robust features that helps to reduce the overfitting problem. As mentioned in earlier section, CNN model requires adequate training data to train a model. Limited accessibility of medical imaging data is one of the major challenges for the success of deep learning in medical imaging (Dutta., 2020). Data augmentation improves the prediction performance of a model and also increases the ability to generalize the model. There are many augmentation techniques available like flipping, rotation, zooming, rescaling etc. We have applied horizontal flipping and rotation as an augmentation technique for this experiment. Rotation techniques rotate the image by a specified degree, whereas Flipping technique flips the image either vertically or horizontally. It reverses the rows or columns of pixels.

3.6 Evaluation Metrics

The model is evaluated after training is completed to check it correctness. There are several evaluation metrics are available to evaluate classification models like F1 score, sensitivity, specificity, accuracy, loss etc. in this experiment, to evaluate the performance of a model, we have considered accuracy and loss metrics. Accuracy is the ratio of number of correct predictions to the total number of input samples. The following is the formula to calculate the accuracy.

$$Accuracy = \frac{\text{True Postive} + \text{False Negative}}{\text{Total number of samples}}$$

During the training, the objective is to reduce the loss by optimizing the network weights. A loss is typically an error occurred while prediction. A loss function is used to find the value of a total loss and it matches the target value and the value predicted by the model for calculating the total loss. We have used categorical cross entropy function to measure a loss while training and validation as it is well suited for classification task. It is possible to estimate the model's loss for updating the weights in the next evaluation and thus reduce the loss. Typically, mean square error and cross-entropy are used to measure the loss function. We have used cross-entropy to measure loss. The following is the formula of the loss function.

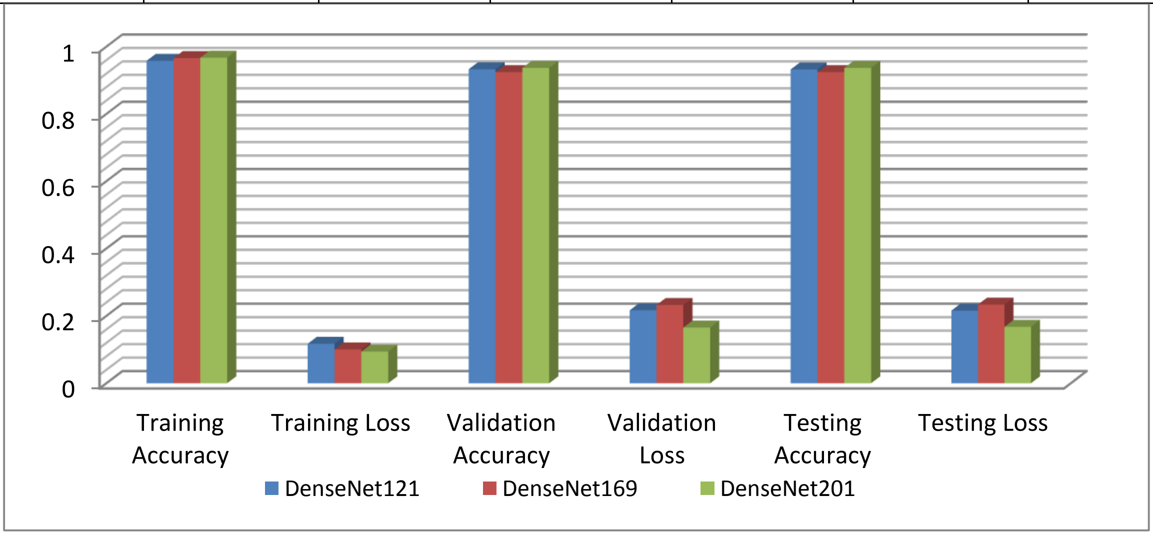
$$\text{Loss} = -\sum_{i=1}^{\substack{\text{output}\\\text{size}}} y_i \cdot \log \hat{y}_i$$

4. Results and Discussion

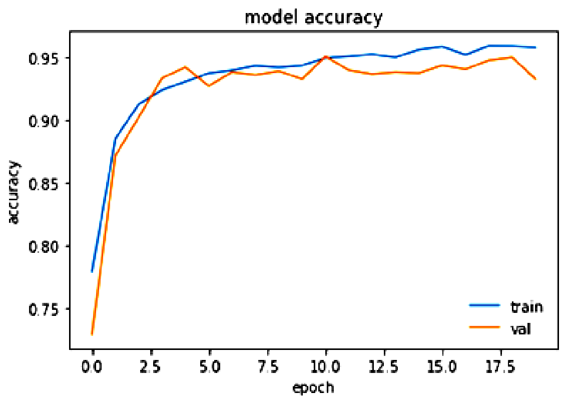
A pre-trained DenseNet model is implemented and evaluated against the chest X-ray image dataset. The model is experimented on the dataset that contains total of 6432 images that are categorized into 3 classes. The method of transfer learning is used to train the model. We have considered three variants of DenseNet model available for experiment in keras (2020) namely DenseNet121, DenseNet169 and DenseNet201. The DenseNet in kears is already trained on ImageNet dataset. The results of the performance of these variants of DenseNet are represented in the table 1.

Table 1. Accuracy and Loss for DenseNet121, DenseNet169 and DenseNet201

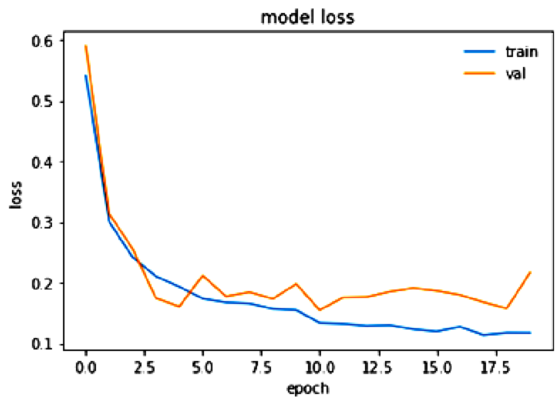
DenseNet Model	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Testing Accuracy	Testing Loss
DenseNet121	0.9579	0.1170	0.9328	0.2164	0.9320	0.2155
DenseNet169	0.9658	0.1005	0.9242	0.2323	0.9242	0.2332
DenseNet201	0.9671	0.0938	0.9367	0.1653	0.9367	0.1674



From the results obtained, it is found that DenseNet201 model outperforms against two other models. It provides 0.9671, 0.9367 and 0.9367 accuracy during training, validation and testing. Moreover, it provides 0.0938, 0.1653 and 0.1674 losses during training, validation and testing. DenseNet201 offers the lowest loss during all three phases i.e., training, validation, and test. The values obtained for accuracy and loss can be graphically described to determine the performance of the CNN model. The figure 4, figure 5 and figure 6 represented the training and validation accuracy and loss of all three variants of DenseNet model. A line plot is used to show the loss and accuracy over the epochs for both the training and validation.

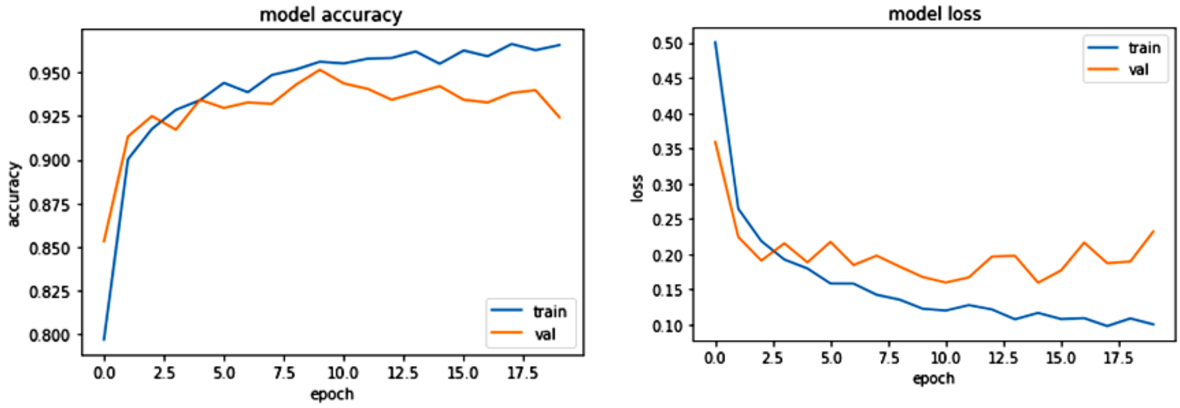


(a) DenseNet121 Accuracy



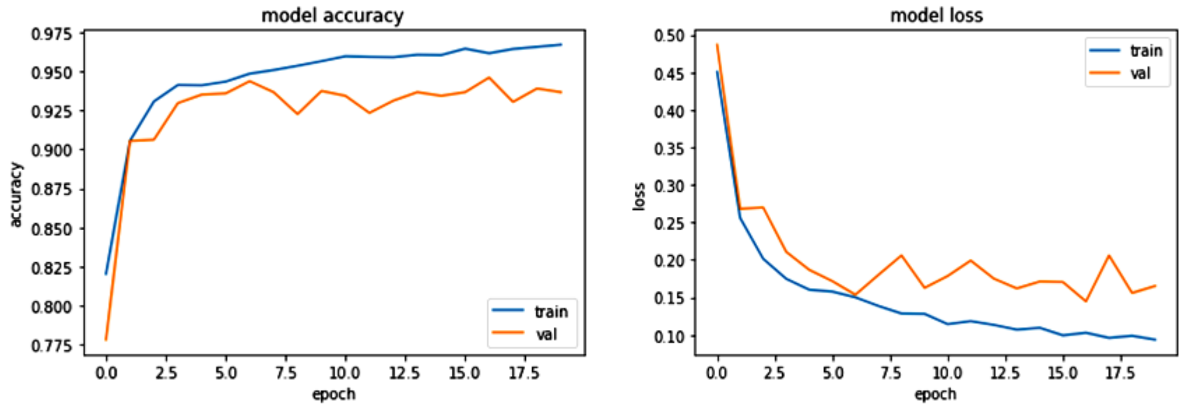
(b) DenseNet121 Loss

Figure 4. Accuracy and Loss for the DenseNet121



(a) DenseNet169 Accuracy (b) DenseNet169 Loss

Figure 5. Accuracy and Loss for the DenseNet169



(a) DenseNet201 Accuracy (b) DenseNet201 Loss

Figure 6. Accuracy and Loss for the DenseNet201

5. Conclusion

Medical imaging is a widely accepted technique for the early detection and diagnosis of disease that includes different techniques such as X-ray, MRI and CT scan etc. Imaging-based test can provide a fast detection of the COVID-19 and consequently contribute to control the spread of the disease. Deep learning techniques are successfully employed for classification of medical imaging. In this paper, a deep convolutional neural network, DenseNet is applied for classification of COVID-19 in chest X-ray images. We have used transfer learning and fine-tuning to train the model. The three variants namely DenseNet121, DenseNet169 and DenseNet201 are implemented and evaluated against the dataset. The DenseNet201 gives the highest validation accuracy i.e. 0.9367 and lowest validation loss i.e. 0.1653. At present, there is a limited dataset publically available for experiment that helps to detect the COVID-19 from chest X-ray images. However, we aim to extend the experimental work with larger datasets in the future.

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