Study and Implementation of deep-learning based models for COVID-19 detection using Chest X-Ray images

A report submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology

in

Electronics and Communication Engineering

by

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2022-2023

Declaration by the Students

We hereby declare that the project work presented in this report entitled "***Study and Implementation of deep-learning based models for COVID-19 detection using Chest X-Ray images"***, submitted in partial fulfillment for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering during the academic year 2022-2023, has been carried out by us and that it has not been submitted in part or whole to any institution for the award of any other degree or diploma.

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Certificate by the Examiner

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in partial fulfillment of the requirements for the degree of Bachelor of Technology in Electronics and Communication Engineering has been examined by me and is found satisfactory for the award of the degree.

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ABSTRACT

This report is based on an article named – “Automated COVID-19 detection in chest X-ray images using fine-tuned deep learning architectures” – by Aggarwal et.al. [1] Coronavirus (COVID-19) is an infectious illness brought on by the SARS-CoV-2 virus. COVID-19 was deemed a pandemic in 2020 due to its rapid growth and high mortality rate. People with COVID-19 infection have experienced recognisable radiographic characteristics along with symptoms like fever, shortness of breath, and a dry cough. Their COVID-19 is being detected via a RT-PCR (Reverse transcription-polymerase chain reaction) assay, but its accuracy is quite poor. As a result, chest CT imaging and X-ray imaging are popular and favoured.

Numerous medical imaging technologies, such as computed tomography (CT) and X-ray, have greatly helped to control the COVID-19 epidemic by aiding in early identification. To speed up the identification and categorization of COVID-19 patients from other pneumonia groups, they undertook a comparative investigation of highly calibrated deep learning architectures. The models used for this analysis are ResNet50v2, MobileNetV2, NASNetMobile, Xception, InceptionV3, VGG19, InceptionResNetV2, and DenseNet201, and are adjusted utilising a fresh layer set replacing the network's head.

In the study done by Aggarwal et.al., two datasets were analyzed. dataset-1 contains the Covid, Normal, Bacterial and Viral Pneumonia. In contrast, dataset-2 contains images of three classes: Covid, pneumonia, and normal.

Their Dataset consisted of 209 images of Covid-19, and 250 images each of Normal, Viral, and Bacterial Pneumonia, and they obtained accuracies of 97% using DenseNet121 on the second dataset, and 81% using MobileNetv2 on the first dataset.

Our version of the study was performed on 1200 radiographs (300 from bacterial pneumonia, 300 from Viral Pneumonia, 300 from COVID, and 300 from normal cases). As for the diagnosis network: For the second Dataset, DenseNet121 had obtained a 98% accuracy, and for the first Dataset, the most accurate model was Inceptionv3, which had an 85% accuracy.

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1. *Introduction*

The infectious condition known as coronavirus illness is caused by the SARS-CoV-2 virus (COVID-19). Most virus-infected individuals will experience a mild to severe respiratory disease, but will recover without the need for special care. However, some people will get serious illnesses and need medical care.

Worldwide, there were 6,641,249 fatalities and 648,250,254 cases as of December 1, 2022. The virus primarily spreads between persons who are in close touch with one another, according to the WHO (global health agency). When a person speaks, sings, sneezes, or coughs, the virus may be transferred through their lips or nose in minute liquid particles. When airborne infectious particles are breathed at close range or come into direct contact with the eyes, nose, or mouth, another person may then get the virus. The chance of developing the illness increases if a person touches their eyes, nose, or mouth after handling objects or surfaces that have been exposed to the virus. Regardless of whether they have symptoms, sick people can still spread the virus to others.

The early stages of the sickness and the two days previous to the beginning of symptoms appear to be the most contagious for infected people, according to laboratory findings. Contagiousness may last longer in people who are sick with serious conditions. Although it is possible for someone who never exhibits symptoms to spread the virus to others, additional research is required to determine how frequently this happens.

Due to rising mortality and rapid spread of infection [2], monitoring and treatment as well asthma patient's accurate and timely identification of her COVID-19 also has a significant impact. Using (RT-PCR) method as a standard reference for detection of COVID-19 [3, 4] was not proved to be reliable, it also has its own drawbacks. It takes time and money. Studies have shown that chest X-rays are similar to computed tomography (CT) scans in humans. Infection with COVID-19 also exhibits certain pneumonia-like indicators, such as frosted glass and interlobular septal thickening, pleural thickening, bronchography, and opacity [5]. These imaging traits can be utilized to identify and distinguish patients with COVID-19 infection from those who are not affected [6]. According to researchers, a chest x-ray is almost as good as a CT scan. X-rays may show to be a useful diagnostic and surveillance technique for COVID-19 instances. a method based off thoracic radiology also found to have several advantages over conventional methods. They can examine numerous instances at once and offers quick results. Since it can be used at all hospitals, it is especially helpful in places where kits are scarce or unavailable. This justification makes it possible to deploy deep learning-based models for automation.

In this study they have proposed the identification this COVID-19 using chest X-ray.

The main contributions of their research are [1]:

(1) The suggested transfer learning model now includes a new set of layers. Chest X-ray images of healthy individuals, patients diagnosed with COVID-19, and those diagnosed with pneumonia are classified by combining precisely calibrated parameters.

(2) Contrast enhancement on pictures is performed using the preprocessing method known as Clipped Adaptive Histogram Equalization (CLAHE).

(3) In order to prevent model overfitting concerns due to the small dataset size, data augmentation was also carried out.

(4) Comparison between ResNet50v2, MobileNetV2, NASNetMobile, Xception, InceptionV3, VGG19, InceptionResNetV2, and DenseNet121 were executed.

(5) The different models are compared based on their the accuracy, precision, F1 score, sensitivity, and specificity metrics.

2. Related work

Deep learning has recently demonstrated effectiveness in automatically detecting and diagnosing illnesses by locating the underlying patterns in medical imagery [7]. For a variety of issues, including the classification of skin cancer [8], detection of breast cancer[9], identification of pneumonia[10], detection of arrhythmias[11], and many other applications and methods have been developed. Deep learning techniques have been proposed by a number of studies to identify the precise markers in chest X-rays for the identification of COVID-19. On a small number of datasets, these techniques have yielded encouraging results, but they still require a great deal of development and testing before being put to use.

Additionally, Sety. et. Al. [12] integrated a variety of SVM based ConvNets, and the ResNet50 model with SVM produced the best outcomes [12]. DarkNet is a deep-network model described by Ozturk et al [13], that uses 17 convolutional layers alongwith Leaky-ReLU as the activation. The multi-class classification accuracy of this model is 87.02%. Using chest X-ray images, Narin et al.[14] trained the ResNet50 model with 98% accuracy for binary classification.

DeTrac is a unique architecture developed by Abbas et al.[15] that is based on the same transfer learning concept as well as the decomposition of classes. There were 3 stages to it: For feature extraction in Phase-1, a pretrained ConvNet(CNN) was utilised, training in Phase-2 was done by the optimizer for stochastic gradients, and about the classification in the 3rdPhase, a layer for the decomposition of classes was included. On X-ray pictures, this model has a 95.12% accuracy rate. Using CT scans for 3 classes, namely COVID-19, Normal, and Pneumonia, examined two ConvNets were examined [16]. The second design employed the attention mechanism with completely linked layer whereas the first one was ResNet23 based.

The majority of investigations have concentrated on binary classification utilising samples of COVID-infected and healthy people's X-rays. Only a small number of studies, nevertheless, have separated the various classifications into distinct categories. In order to assess each suggested transfer learning model's proficiency in precisely detecting the COVID-19 from X-ray pictures, the major goal of this endeavour is to give a comparative assessment of the proposed models. Eight transfer-learning designs have been shown and contrasted in this paper. According to experimental findings, eight transfer-learning architectures performed well on specially created datasets, and it has been suggested that these models may be improved by swapping out their old layers with a new set of completely linked ones. Multiple sources have been used to create two distinct datasets. The models are evaluated on Dataset 1, which has four classes, as well as Dataset 2, which has three classes (Normal, COVID, Viral Pneumonia, and Bacterial Pneumonia) (Normal, COVID, and Pneumonia). The new fully linked head includes a model regularization layer called Dropout to prevent overfitting.

3. *Methodology and datasets*

In this research, they have taken a dataset from multiple sources. Building a CNN model for the precise and timely identification of COVID illness with chest radiographs is the main objective of this work. The flow chart for the suggested approach is given in Figure_1.

3.1 *Dataset description*

Dataset - 1

Class	Train	Test
Normal	250	50
Covid-19	250	50
Viral Pneumonia	250	50
Bacterial Pneumonia	250	50

Dataset - 2

Class	Train	Test
Normal	250	50
Covid-19	250	50
Pneumonia	250	50

Table 1 : Dataset description

For building the datasets, the data has been sourced from two different repositories which are publicly accessible: the Covid 19 images are sourced from J. P. Cohen's open-source repository [17]. And the combined images of Pneumonia and Normal Chest X-Rays (CXR) are sourced from the one created by Kermany[18].

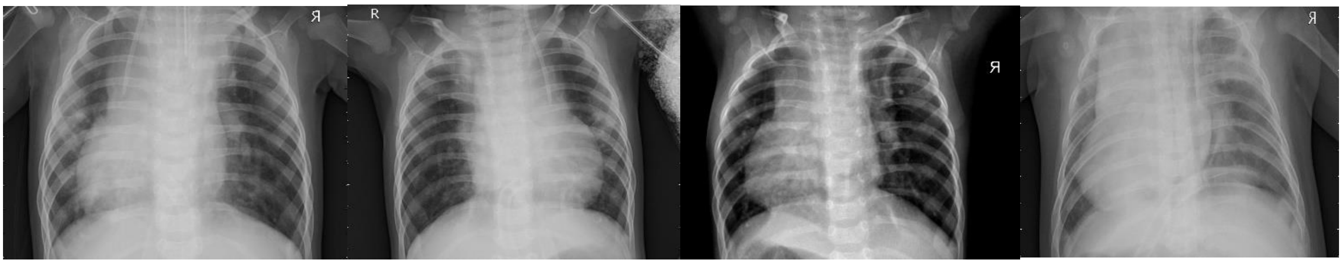

Figure 1 : Sample Chest X-Ray images from the dataset belonging to COVID-19 class

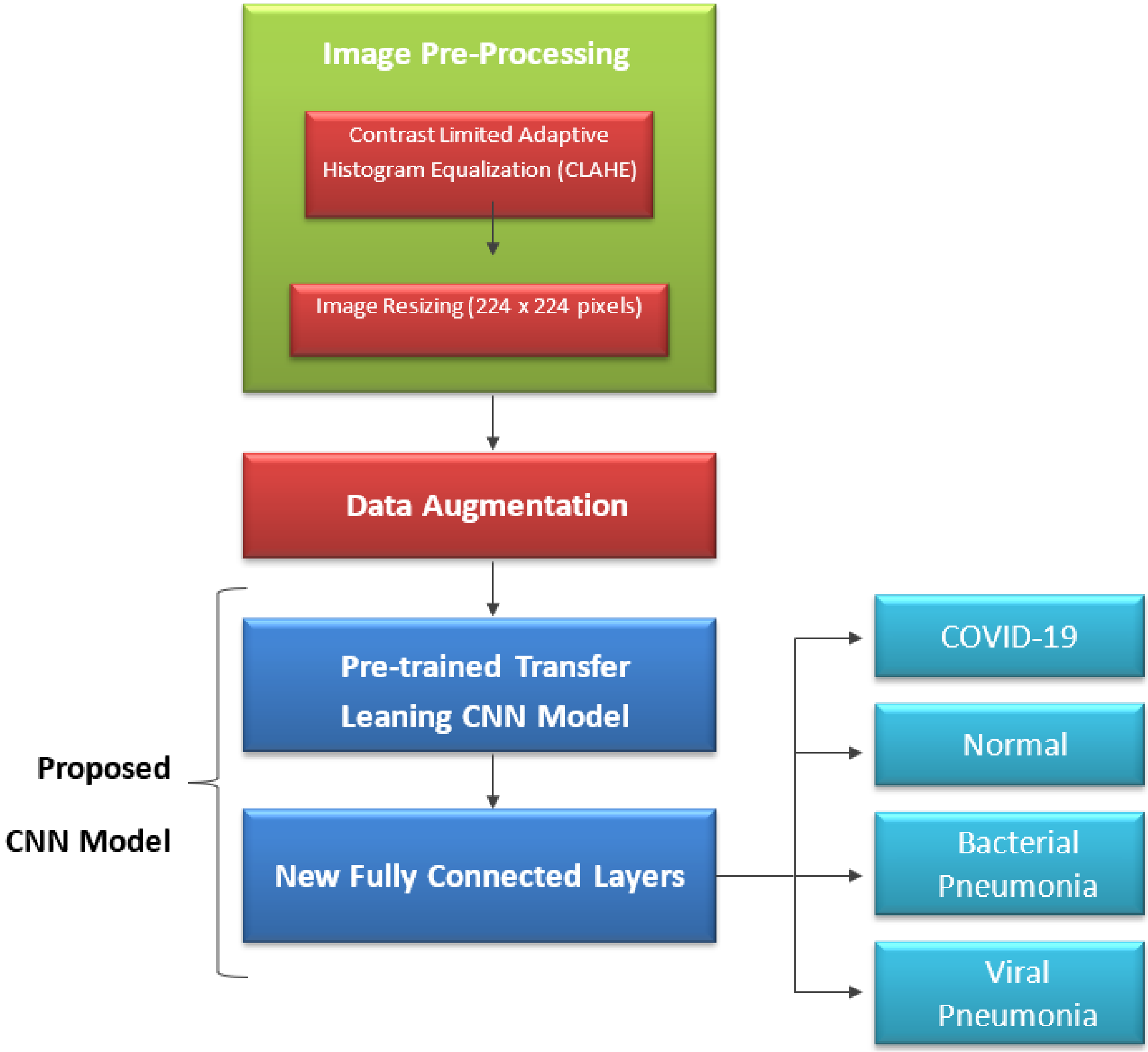

Figure 2 : Process Flow Chart [1]

3.2 Data Preprocessing methods

3.2.1 Contrast-Limited Adaptive Histogram Equalization

Contrast-Limited-Adaptive-Histogram-Equalization, or CLAHE, corrects over-exaggerated contrast in images.

Instead of utilising the whole picture, CLAHE works with smaller sections of it called tiles, and to get rid of false borders, nearby tiles are joined via bilinear interpolation.

When using CLAHE, we require two parameters: clipLimit, which controls the contrast limiting threshold, and tileGridSize, which controls the number of tiles in a row and column that are used to split an image. The clipLimit is 40 and the tileGridSize is 88 by default.

Figure 3 : CLAHE processed images

3.3 Data Augmentation

By creating additional data points from existing data, a group of techniques known as "data augmentation" can be used to artificially enhance the amount of data.

Data augmentation is used in the medical imaging domain to modify images and add diversity to datasets. The availability of tiny datasets for medical pictures is the primary driver of data augmentation interest in healthcare.

Augmentation	Value
Rescale	1/255
Height shift	20%
Width shift	20%
Shear	20%
Zoom	20%

Table 2 : Augmentation parameters [1]

Only a small number of patients have data that can be utilized to diagnose rare diseases.

By incorporating additional training data into the models, minimizing data scarcity for better models, eliminating data overfitting, and decreasing the expenses associated with data collection and labeling, we are employing data augmentation to increase the prediction accuracy of our models.

3.4 Transfer Learning with ConvNets

While putting a deep learning model through training for the accurate image categorization, we need to have a large amount of data. Thus, training the model becomes a significant challenge, especially in the medical domain where data is scarce.

The concept of transfer learning comes into picture is imperative in this context. Making the training process more effective employing data gathered from a pretrained network that may be moved to a new model for verification.

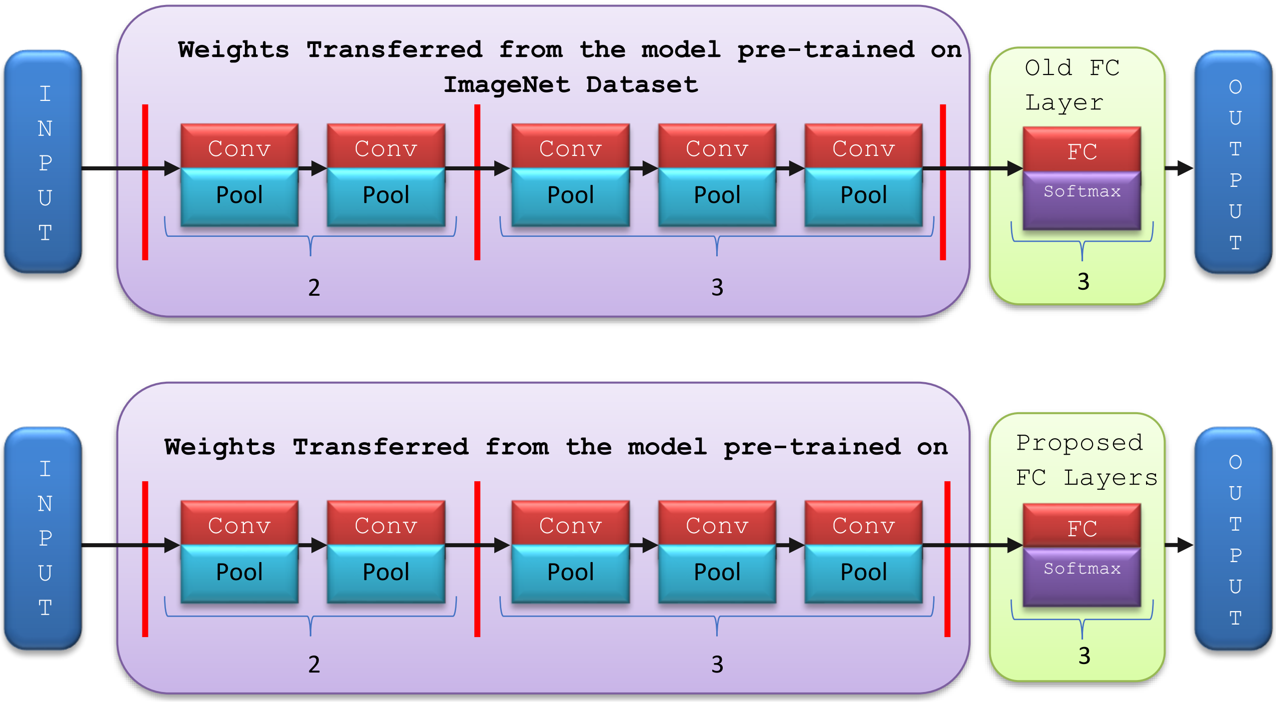

Figure 4 : Layered architecture of VGG-19 network with original and newly added layers [1]

The idea behind transfer learning for image classification is that if a model is trained on a sizable enough dataset with adequate generality, it will be able to represent the visual world as a whole. By training a big model on a big dataset, we can then use these learnt feature maps instead of starting from absolute zero.

There are two frequently utilised methods for putting transfer learning into practise:

Feature-Extraction: Obtaining valuable features from fresh samples by applying the representations that a previous network has learned. Simply build a new classifier on top of the pretrained model and train it from scratch to reuse the feature maps that were previously learned for the dataset. The complete model does not need to be (re)trained. There are existing elements in the underlying convolutional network that are generally helpful for classifying images. The final classification component of the pretrained model, however, is unique to the initial classification task and, as a result, exclusive to the set of classes that were used in the training of the model.

Fine-Tuning: The last layers of the base model as well as the newly added classifier layers are simultaneously trained while part of the top levels of a frozen model base are unfrozen. This allows us to "fine-tune" the higher-order feature representations of the fundamental model to make them more useful for the job at hand.

We use a pre-trained CNN model and fine tune it to classify 4 dissimilar classes. Normal, Covid, Viral Pneumonia and Bacterial Pneumonia. All model weights were borrowed from the models trained on the ImageNet dataset [19].

The 14,197,122 photos in the ImageNet database are annotated using the WordNet hierarchy. The dataset has been used since 2010 for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), a standard for image classification and object recognition.

Figure 2 demonstrates the fine-tuning procedure performed on the VGG19 architecture. The first image shows its Network architecture. Consisting of 16 layers of convolution (Conv) followed by 5 MaxPool Layers,3 FC (fully-connected) layers and 1 SoftMax layer.

A new randomly initialised and FC layer is added as a header for fine-tune, indicated in figure 2's last diagram. The layer has already trained a deep discriminant filter, and when the FC layer is reinitialized, it freezes the training of the convolutional layer. Once the fresh FC layer begins learning from the data set, the remaining layers are unfrozen and Network starts training gradually.

3.5 Experimental setup

The evaluation of eight pre-trained models, have been performed in this research work, namely MobileNetv2 [20], VGG16[21], ResNet50v2[22], Inceptionv3[23], NASNetMobile [24], DenseNet121[25], InceptionReNet50v2 [26] and Xception[27].

Models have been trained in Jupyter Notebooks (conda environment) using a TensorFlow.Keras framework on a PC with12th gen Intel i5-1240P (1.70 GHz) processor with 12 cores and 16 GB of RAM. Alternatively, we have also done another implementation in MATLAB using the Deep Learning library on a PC with Intel i5-8265U(1.80 GHz) processor with 8 GB of RAM

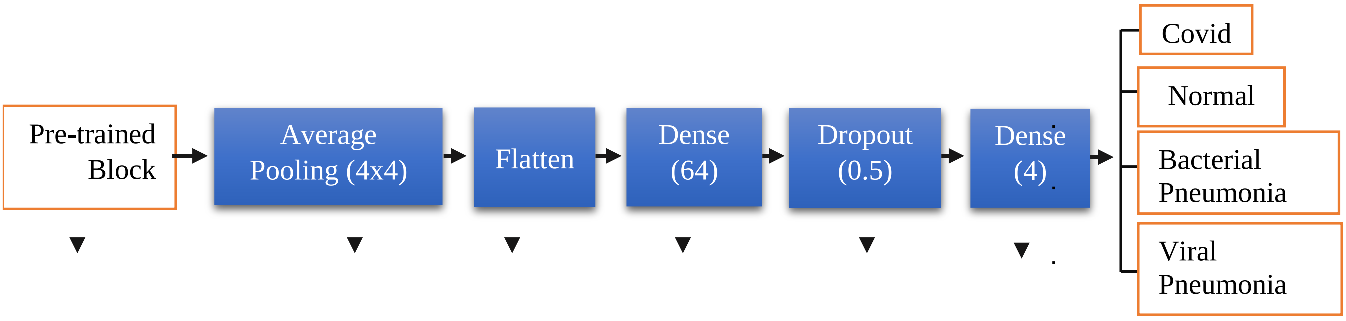

Figure 5 : Proposed New Fully Connected Head [1]

3.6 Hyper-parameters tuning

The batch size hyper-parameter of gradient descent determines how many training samples must be processed before the internal model parameters are updated, while the epochs parameter indicates how many iterations must be made over the full training dataset. Models have undergone 40 epochs of training, using 16 training batches and 128 testing batches. The learning rate hyper-parameter, which is important, governs how rapidly the model picks up new knowledge. It should neither be too much nor too little. In case, the rate of learning is very slow, the model may require a long duration to achieve the smallest possible loss. Also, in case the learning rate is very high, the network can exceed the low-loss region. The learning rate for this project has been set at 0.001. The Adam [28] optimization approach has been utilised for model compilation. Additionally, all of the convolutional layers have been activated using the ReLU [29] activation function, and all convolutional neural network models are finely tuned using a fresh FC head and dropouts. Also, we have implemented an Adaptive Learning rate and callbacks to ensure that the model is trained in the best possible manner.

3.7 Performance metrics

The values of the performance indicators were obtained and used to examine the outcomes using a confusion matrix. The actual count of labels and anticipated labels for each class is displayed in the confusion matrix. Here, the abbreviations TruNeg, FalNeg, TruPos and FalPos stand for True Negatives, False Negatives, True Positives, and False Positive results, respectively.

Accuracy: Accuracy is the model's capacity to categorize the inputs into accurate classes. Determined in proportion to the model's accurate predictions to all other forecasts.

$$\text{Accuracy} = \frac{\text{TruPos} + \text{FalPos}}{\text{TruPos} + \text{FalPos} + \text{FalNeg} + \text{TruNeg}} \quad (1)$$

Precision: Out of all the positive labels, this metric gives the proportion of classified positive labels to that of the actual positive labels.

$$\text{Precision} \quad = \quad \frac{\text{TruPos}}{\text{TruPos} + \text{FalPos}} \tag{2}$$

Sensitivity/Recall: he proportion of correctly predicted classes to the actual classes. Another synonym for sensitivity is recall.

$$\text{Recall} \quad = \quad \frac{\text{TruPos}}{\text{TruPos} + \text{FalNeg}} \tag{3}$$

Specificity: The fraction of real negative values that are classified as negative is known as specificity.

$$\text{Specificity} \quad = \quad \frac{\text{TruNeg}}{\text{TruNeg} + \text{FalPos}} \tag{4}$$

4. Results

4.1 Performance metrics on 1st dataset

Model	Labels	Precision	Sensitivity	Specificity	F1 score	Accuracy
Inceptionv3	COVID	0.98	1	1	0.99	**85.00%**
	Viral Pneumonia	0.73	0.65	0.84	0.59	
	Bacterial Pneumonia	0.55	0.49	0.83	0.47	
	Normal	0.71	0.98	0.99	0.82	
ResNet50v2	COVID	1	0.96	0.94	0.98	**84.50%**
	Viral Pneumonia	0.75	0.6	0.87	0.67	
	Bacterial Pneumonia	0.73	0.72	0.9	0.72	
	Normal	0.82	1	1	0.9	
Xception	COVID	1	0.98	0.99	0.98	**83.50%**
	Viral Pneumonia	0.93	0.42	0.82	0.58	
	Bacterial Pneumonia	0.72	0.84	0.97	0.77	
	Normal	0.75	1	1	0.85	
VGG19	COVID	1	0.91	0.96	0.95	**83.00%**
	Viral Pneumonia	0.81	0.46	0.83	0.59	
	Bacterial Pneumonia	0.68	0.68	0.89	0.68	
	Normal	0.68	0.98	1	0.8	
MobileNetv2	COVID	0.94	1	1	0.94	**82.50%**
	Viral Pneumonia	0.9	0.5	0.85	0.64	
	Bacterial Pneumonia	0.68	0.82	92.9	0.74	
	Normal	0.87	1	1	0.93	
InceptionResNetv2	COVID	1	0.98	1	0.99	**80.50%**
	Viral Pneumonia	0.41	0.73	0.83	0.52	
	Bacterial Pneumonia	0.68	0.71	0.89	0.69	
	Normal	1	0.68	1	0.81	
DenseNet121	COVID	0.95	0.98	0.99	0.96	**80.00%**
	Viral Pneumonia	0.77	0.54	0.87	0.63	
	Bacterial Pneumonia	0.81	0.64	0.89	0.71	
	Normal	0.66	1	1	0.79	
NASNetMobile	COVID	0.98	0.97	0.98	0.97	**79.50%**
	Viral Pneumonia	0.77	0.42	0.82	0.54	
	Bacterial Pneumonia	0.62	0.66	0.88	0.64	
	Normal	0.71	1	1	0.83	

Table 3 : Results of different models for dataset-1

4.2 Performance metrics for 2nd dataset

Model	Labels	Precision	Sensitivity	Specificity	F1 Score	Accuracy
DenseNet121	COVID	1	1	1	1	**98.00%**
	Normal	0.89	1	1	0.94	
	Pneumonia	0.91	0.93	0.96	0.92	
ResNet50v2	COVID	1	0.99	1	0.99	**97.33%**
	Normal	0.82	1	1	0.9	
	Pneumonia	0.91	0.89	0.93	0.9	
NASNetMobile	COVID	1	0.98	1	0.99	**97.33%**
	Normal	0.87	0.99	1	0.92	
	Pneumonia	0.97	0.84	0.92	0.9	
MobileNetv2	COVID	0.92	0.94	0.94	0.93	**96.67%**
	Normal	0.88	0.93	0.94	0.9	
	Pneumonia	1	0.86	0.93	0.92	
Inceptionv3	COVID	1	0.99	1	0.99	**96.67%**
	Normal	0.74	0.99	1	0.84	
	Pneumonia	0.91	0.77	0.9	0.83	
VGG19	COVID	1	0.91	0.97	0.95	**96.00%**
	Normal	0.81	0.99	1	0.89	
	Pneumonia	0.96	0.87	0.94	0.91	
InceptionResNetv2	COVID	1	1	1	1	**95.33%**
	Normal	0.83	0.97	1	0.89	
	Pneumonia	0.95	0.8	0.9	0.87	
Xception	COVID	0.97	0.91	0.9	0.94	**94.00%**
	Normal	0.89	0.9	0.9	0.89	
	Pneumonia	0.92	0.9	0.95	0.91	

Table 4 : Results of different models for dataset 2

Discussion

The results that we have obtained are quite consistent with those reported in the original paper by Aggarwal et. Al. [1]. Wherein they have reported a maximum accuracy of 97% and 81% for the second and first datasets respectively; as per our implementation, we have achieved very similar results with a maximum accuracy of 98% (DenseNet121) and 85% (Inceptionv3) for the second and first datasets respectively. Alternatively, our implementation in MATLAB had achieved a maximum accuracy of 95% (ResNet50) for the second dataset and 83% (ResNet50) for the first dataset.

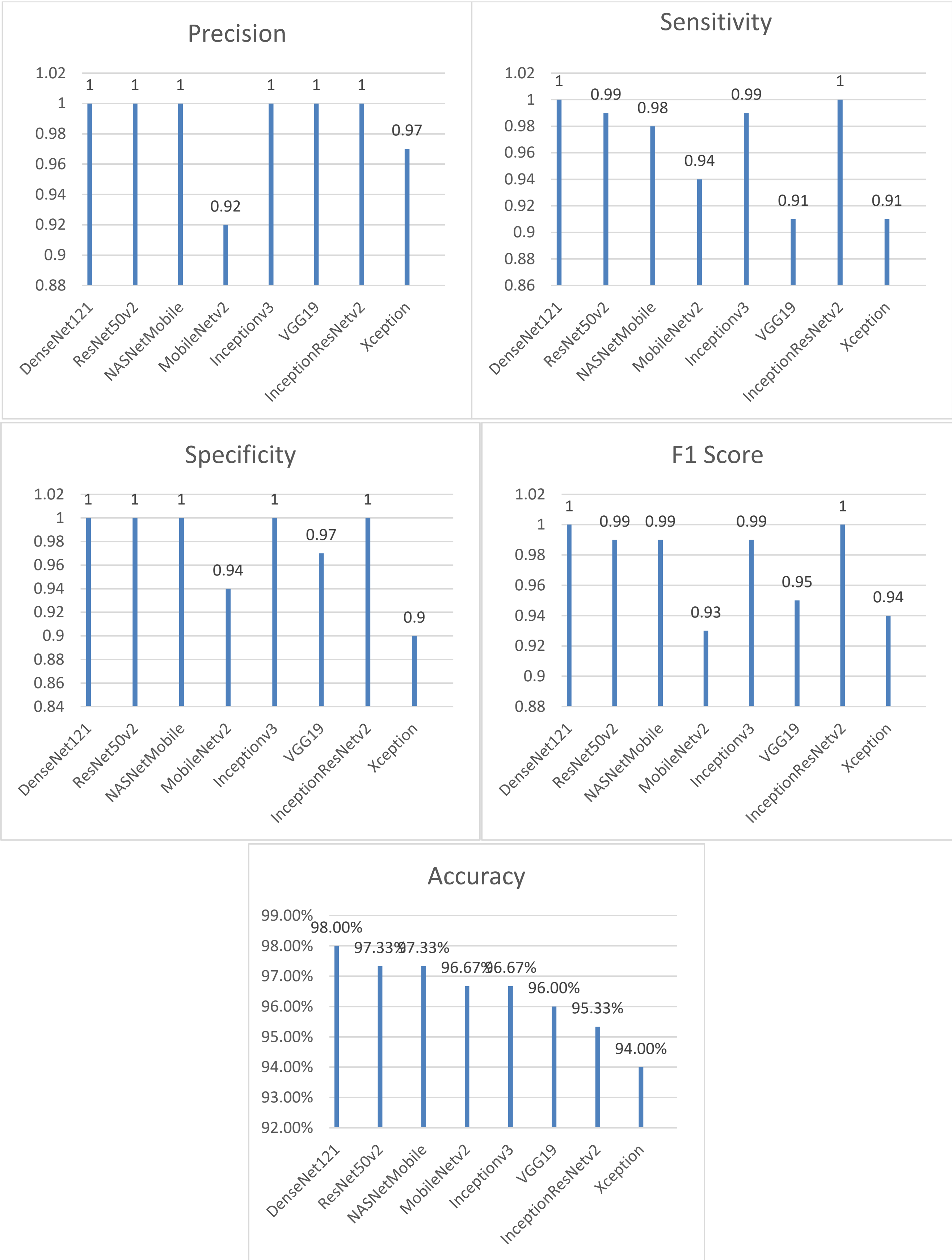

Figure 6: Plots of different models based on their efficacy on detecting COVID-19 based on the shown metrics [1]

5. Conclusion and Future Work

A deep transfer learning algorithm was proposed by Aggarwal et. Al. [1] to automatically detect the COVID-19 from chest X-rays by training it using X-ray images taken from both COVID-19 patients and people with normal chest X-rays. The study's excellent performance and efficacy promise to help doctors make decisions about their therapeutic practices. It also explains how the COVID-19 was automatically detected using transfer learning. As a result, an automated diagnosis approach is needed to quickly detect and diagnose COVID-19 from chest X-ray pictures. CNNs have proved to be particularly effective at doing so. Since COVID-19 shows symptoms just like Pneumonia, In order to categorize chest radiographs of humans infected with Pneumonia, COVID-19, and normal humans, eight most used convolutional neural networks have been utilized and used in this study. The minimal datasets used to train the deep learning models in this work made the results limited. In their implementation, they have attained maximum accuracies of 97% and 81% for the second and first datasets respectively; as per our implementation, we have achieved very similar results with a maximum accuracy of 98% and 85% for the second and first datasets respectively. For improved outcomes, the suggested model should also be tested on outside datasets. More picture data might be included in subsequent research to improve outcomes. More pictures can also be produced using synthetic image creation methods like GAN models. In addition, we can further improve the results of the four-class classification. Models prepared in this experiment cannot be made available directly without consultation from a radiologist, although certainly a workable solution is provided and an alternate solution is provided in order to accurately and promptly diagnose COVID-19.

In the future, we can try to improve the efficacies of the networks by using semantic segmentation to segment the lung images, which would allow the models to train on much more focused and relevant data.

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