A MINOR PROJECT REPORT
ON

COVID-19 Detection Using Chest X-ray Images

by

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Abstract

In medical practice, all decisions, as for example the diagnosis based on the classification of images, must be made reliably and effectively. The possibility of having automatic tools helping doctors in performing these important decisions is highly welcome. Artificial Intelligence techniques, and in particular Deep Learning methods, have proven very effective on these tasks, with excellent performance in terms of classification accuracy. The problem with such methods is that they represent black boxes, so they do not provide users with an explanation of the reasons for their decisions. Confidence from medical experts in clinical decisions can increase if they receive from Artificial Intelligence tools interpretable output under the form of, e.g., explanations in natural language or visualized information. In this paper, we propose a new general-purpose method that relies on interpretability ideas. This approach is tested on a set of chest X-ray images aiming at assessing the presence of COVID-19.

Keyword
COVID-19; deep learning; convolutional neural network; Ensemble-CNNs; X-ray scans

Introduction

Since the appearance of COVID-19 in the city of Wuhan, China, at the end of 2019, great efforts have been made to recognize this disease. Reverse Transcription Polymerase Chain Reaction (RT-PCR) is the definitive test for the recognition of COVID-19 disease. However,RT-PCR test is a time-consuming,laborious,and complicated manual process. In addition, test kits are only available in limited numbers worldwide. On the other hand, the rate of false negatives varies depending on how long the infection has been present. In the false-negative rate was 20% when testing was performed five days after symptoms began, but much higher (up to 100%) earlier in the infection. Chest X-ray scans show visual indexes associated with COVID-19. In addition, chestX-ray scan sare a fast,effective and affordable test to identify COVID-19 infection. Despite the availability of chest X-ray scans, an expert radiologist is needed to identify the COVID-19 infection. Because of the huge number of infections, the healthcare systems have already been over whelmed around the world. Artificial Intelligence (AI) systems can provide an alternative solution for the automatic diagnosis of COVID-19 infections and differentiate them from other diseases . Many Artificial Intelligence (AI) systems have proved their efficiency in medical images analysis, such as pneumonia detection semantic segmentation.

Many AI systems based on deep learning have been proposed and their performance has shown promising results in the diagnosis of COVID-19 infection from chest X-ray images. The ability of deep convolutional neural networks to extract relevant and high-level features directly from data makes them more powerful than Hand-crafted methods . Hand-crafted methods are based on extracting the features using designed models . Since the appearance of COVID-19, great efforts have been made to recognize COVID19 infection from X-ray scans. However, this field has not achieved great progress in the recognition of COVID-19 infection as a real application, and this is due to two main drawbacks. The first drawback is the limitation of COVID-19 X-ray scans. The second drawback is that there are no unified protocols, classes, and data. In the literature, each work defines its own protocol, classes, and data, and this makes comparison between different methods difficult. In this work, we aim to unify the efforts in this field. First, we created a great number of COVID-19X-rayscans. In addition,we defined two scenarios for differentiating COVID-19 scans from scans of other lung diseases in three-class and five class scenarios. We make our databases of COVID-19 X-ray scans publicly available to encourage other researchers to use them as a benchmark for their studies.

Motivation

As of now there are two common and popular testing methods available for detecting Covid-19. They are –

RT – PCR

This COVID-19 test detects the genetic material of the virus using a lab technique called reverse transcription-polymerase chain reaction (RT-PCR)

- Sensitivity : 72.1%
- Specificity : 98.7%

The results of this method is delivered comparatively slow to other testing methods but the accuracy is high.

AntiGen

This COVID-19 test detects certain proteins in the virus. Using a long nasal swab to get a fluid sample, some antigen tests can produce results in minutes

- Sensitivity : 60.5%
- Specificity : 99.5%

Here the results are delivered very quickly but a trade off with accuracy takes place.

This is where our motivation to do this project started. We started looking for methods which are both fast and accurate. Towards the end of this report we will discuss how we accomplished to devise a method to detect Covid- 19 which is both fast and accurate.

Related Work

Reference Paper

Problem Statement - COVID-19 Recognition Using Ensemble-CNNs in Two New Chest X-ray Databases

Publish Date - 3rd March, 2021

By -

- Edoardo Vantaggiato
- Emanuela Paladini
- Fares Bougourzi
- Cosimo Distante
- Abdenour Hadid
- Abdelmalik Taleb-Ahmed.

Link to the paper - https://www.mdpi.com/1424-8220/21/5/1742

About Dataset -

In this work, two scenarios are investigated to distinguish COVID-19 infection from other Lung diseases. In the first scenario, we defined three classes, which are:

• Healthy.

• COVID-19.

• Other pneumonia diseases.

In the second scenario, they identified four classes of Lung Diseases and Normal. The classes of the second scenario are:

• Normal.

• COVID-19.

• Viral Pneumonia.

• Bacterial Pneumonia.

• Lung Opacity No Pneumonia.

Models Used -

CNN Architectures

In their experiments, they used three of the most powerful pre-trained CNN models, which are: ResNeXt-50, Inception-v3 and DenseNet-161.

ResNeXt-50

The ResNeXt architecture inherited its structure from three CNN architectures: VGG, ResNet, and Inception. From the VGG architecture, ResNext leveraged repeating layers to build a deep architecture model. ResNeXt uses the idea of shortcut from the previous layer to the next layer from the ResNet architecture.

Inception-v3

Inception-v3 is the third version of the Google Inception architecture family. Since choosing the right kernel size is challenging for CNN architectures, Inception networks use filters with multiple sizes that operate on the same level, which makes the networks wider instead of deeper. In summary, Inception-v3 has several improvements over the previous versions, including:

1. Factorized convolutions;

2. Smaller convolutions;

3. Asymmetric convolutions;

4. Auxiliary classifier;

5. Grid size reduction.

DenseNet - 161

Densnet networks seek to solve the problem of CNNs when going deeper. This is because the path for information from the input layer until the output layer (and for the gradient in the opposite direction) becomes so big that they can be lost before reaching the other side. G. Huang et al proposed to connect each layer to every other layers in a feed-forward fashion to ensure maximum information flow between layers in the network. In Their Experiments, they used the DenseNet-161 pre-trained model.

Results -

The experimental results for the validation data of our proposed three-class COVID-19 database.

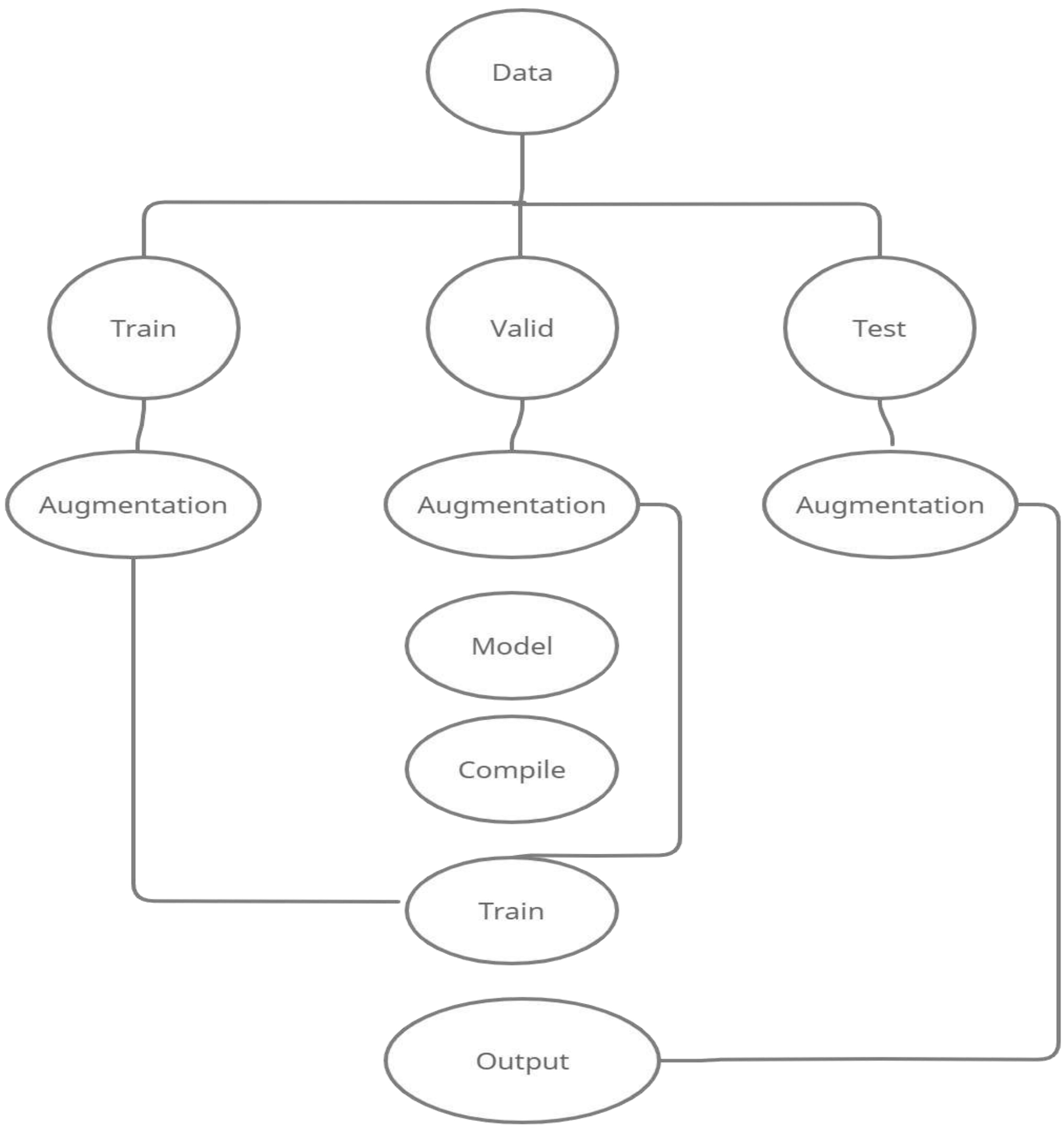
Model	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	AUC
ResNeXt-50	81.24 ± 3.42	83.96	83.60	86.40	83.63	0.8870
Inception-v3	80.55 ± 3.47	82.57	83.20	85.80	83.07	0.8950
DenseNet-161	82.20 ± 3.35	84.50	84.40	89.85	84.40	0.8963
Ensemble-CNNs	**93.2 ± 2.21**	**93.93**	**93.20**	**98.30**	**93.25**	**0.9575**

The experimental results for the testing data of our proposed three-class COVID-19 database.

Model	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	AUC
ResNeXt-50	79.94 ± 2.44	81.42	79.90	84.79	79.57	0.8617
Inception-v3	78.62 ± 2.50	79.35	78.65	84.66	78.31	0.8665
DenseNet-161	77.93 ± 2.53	80.43	77.51	84.47	77.93	0.8744
Ensemble-CNNs	**81.00 ± 2.39**	**82.99**	**82.96**	**85.24**	**81.49**	**0.8810**

Proposed Methods

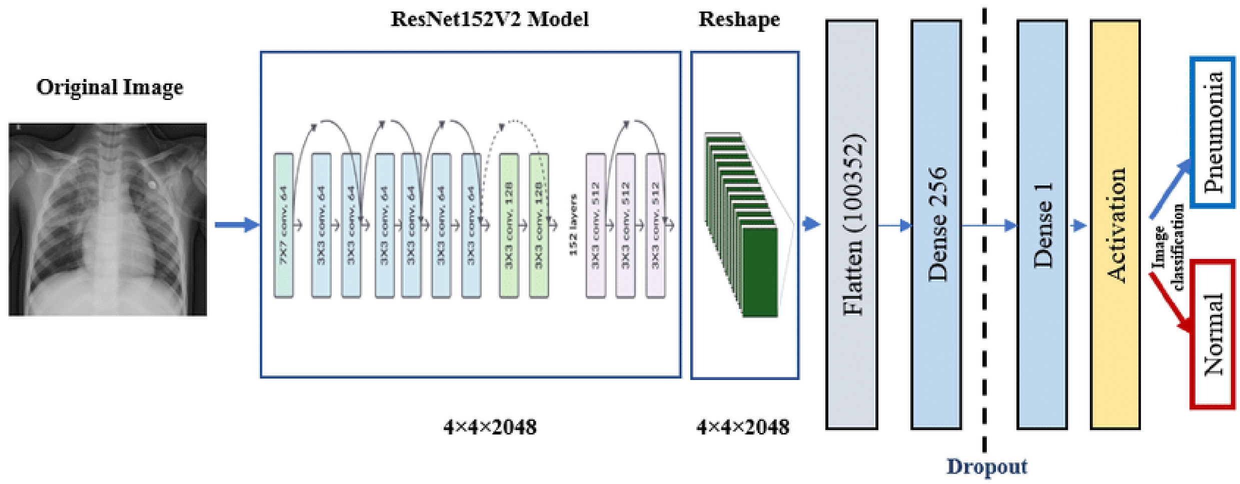
Workflow Diagram



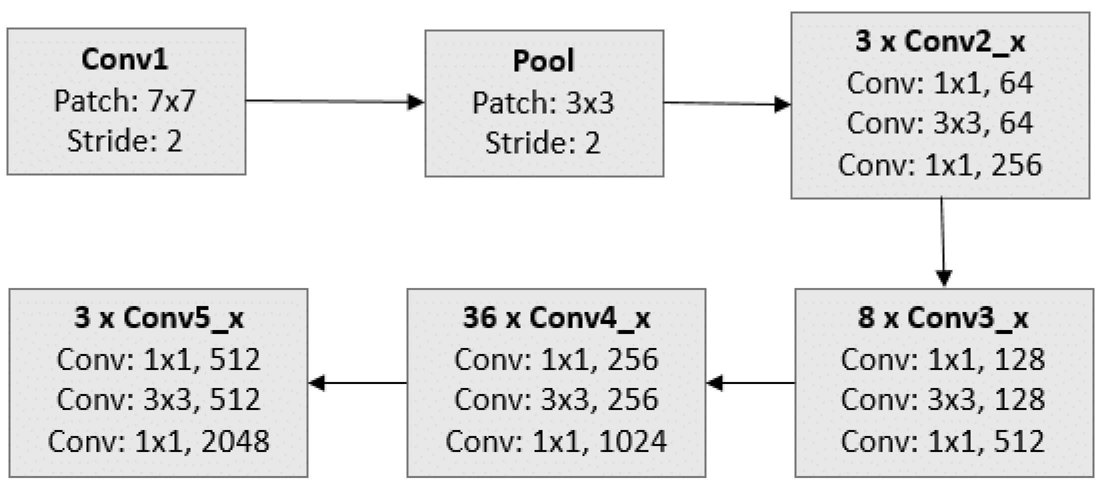
Our Models

1.ResNet152V2

Residual Network (ResNet) is a CNN architecture with hundreds or thousands of convolutional layers. Previous CNN structures decreased the efficacy of additional layers. ResNet contains a huge number of layers, with strong performance.The primary difference between ResNetV2 and the original (V1) is that V2 uses batch normalization before each weight layer. In the field of image recognition and localization tasks, ResNet has strong performance that demonstrates the importance of many visual recognition tasks.


ResNet152V2 Model
Reshape
Original Image
Flatten (100352)
Dense 256
Dense 1
Activation
Image classification
Pneumonia
Normal
4×4×2048
4×4×2048
Dropout

↓

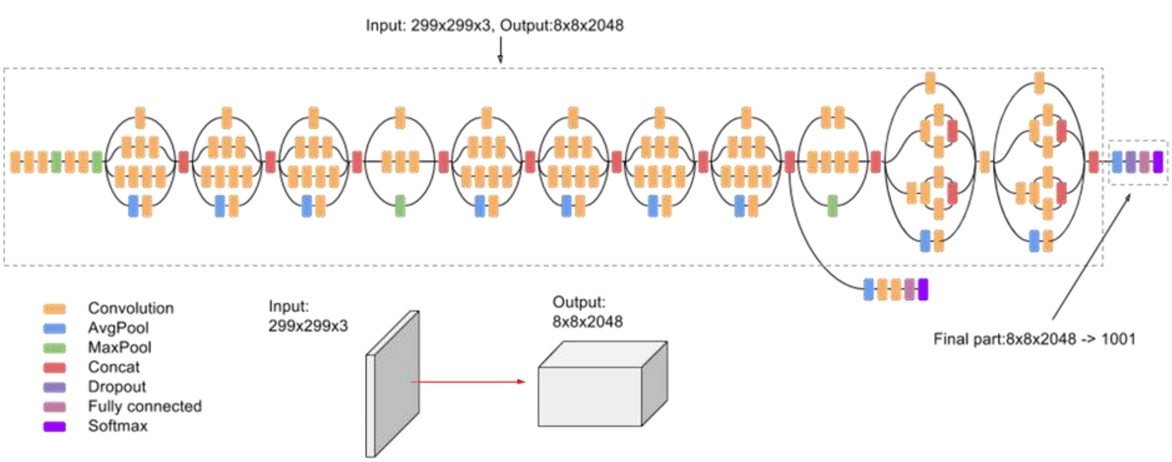

Conv1
Patch: 7x7
Stride: 2
Pool
Patch: 3x3
Stride: 2
3 x Conv2_x
Conv: 1x1, 64
Conv: 3x3, 64
Conv: 1x1, 256
8 x Conv3_x
Conv: 1x1, 128
Conv: 3x3, 128
Conv: 1x1, 512
36 x Conv4_x
Conv: 1x1, 256
Conv: 3x3, 256
Conv: 1x1, 1024
3 x Conv5_x
Conv: 1x1, 512
Conv: 3x3, 512
Conv: 1x1, 2048

Results:-

Classes	Accuracy	Sensitivity	Specificity	Recall	Precision
Bacterial	60.2	62.32	83.95	63.43	65.11
Covid 19	68.22	71.25	76.33	65.33	65.23
Viral	72.3	70.44	84.74	70.5	70.24
Lung Opacity	74.33	65.22	79.54	67.45	72.43
Normal	70.43	69.43	77.65	65.44	67.45
	60.1	67.73	80.44	66.43	68.1

2.InceptionV3

The Inception V3 is a deep learning model based on Convolutional Neural Networks, which is used for image classification. The inception V3 is a superior version of the basic model Inception V1 which was introduced as GoogLeNet in 2014. As the name suggests it was developed by a team at Google.



TYPE	PATCH / STRIDE SIZE	INPUT SIZE
Conv	3×3/2	299×299×3
Conv	3×3/1	149×149×32
Conv padded	3×3/1	147×147×32
Pool	3×3/2	147×147×64
Conv	3×3/1	73×73×64
Conv	3×3/2	71×71×80
Conv	3×3/1	35×35×192
3 × Inception	Module 1	35×35×288
5 × Inception	Module 2	17×17×768
2 × Inception	Module 3	8×8×1280
Pool	8 × 8	8 × 8 × 2048
Linear	Logits	1 × 1 × 2048

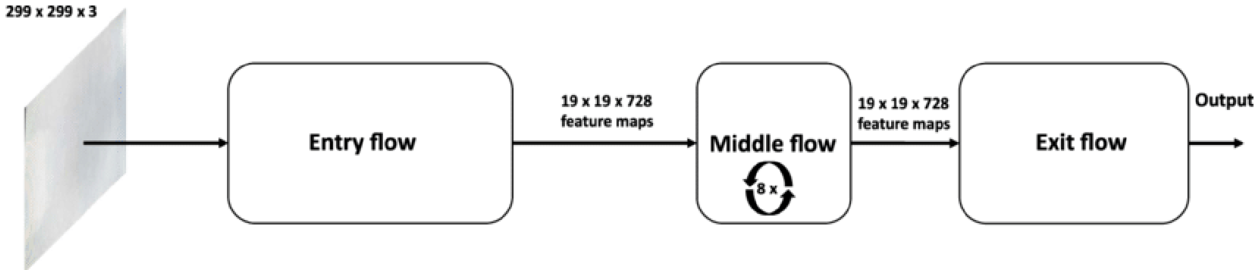
Softmax	Classifier	1 × 1 × 1000

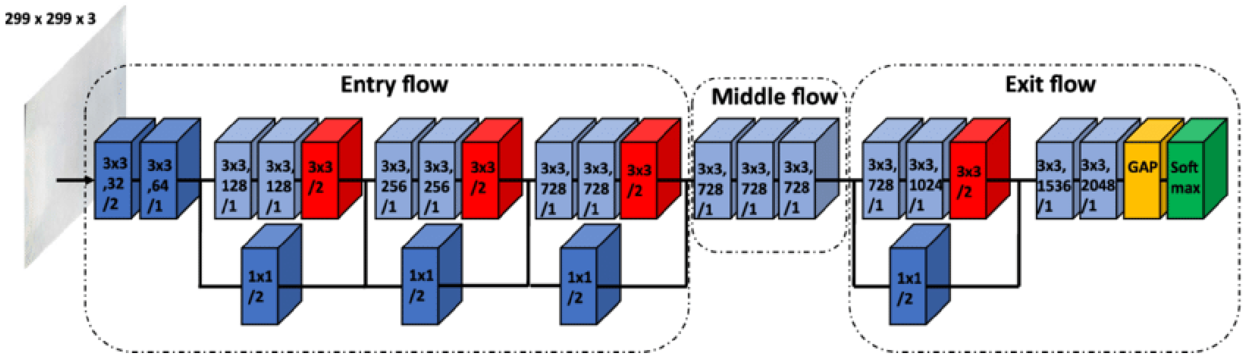
Results:-

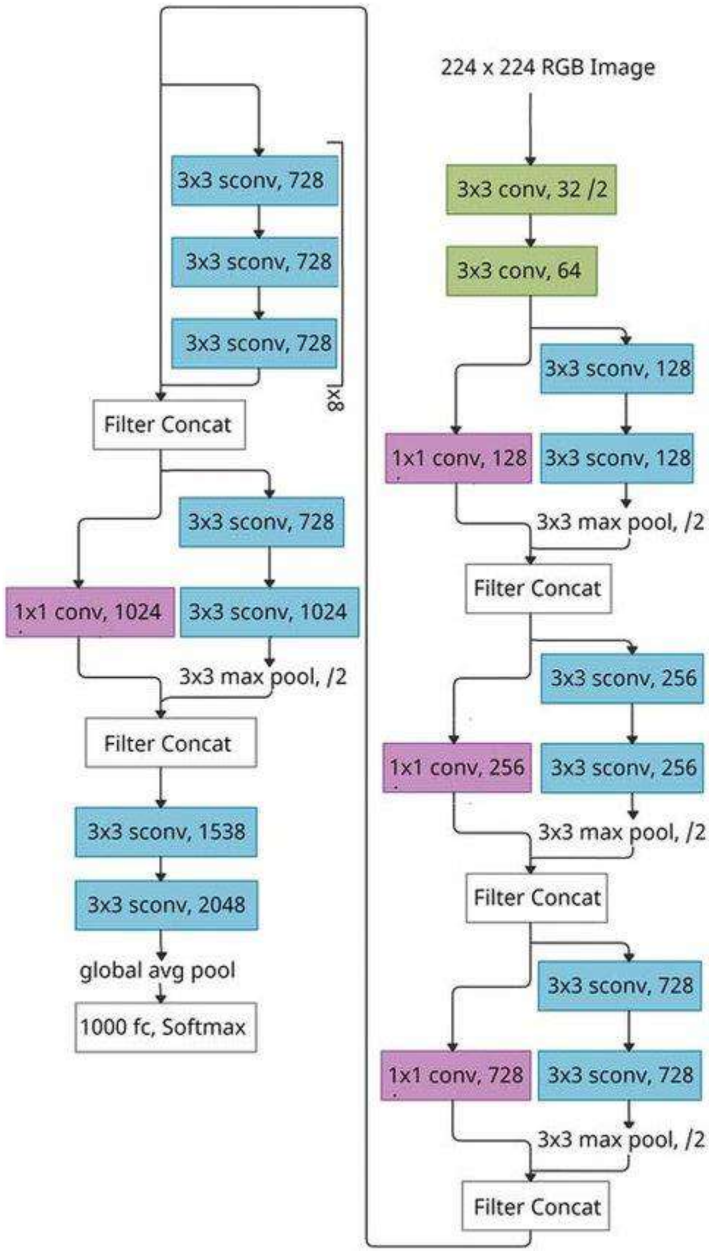
Classes	Accuracy	Sensitivity	Specificity	Recall	Precision
Bacterial	62.23	52.32	73.54	53.43	61.13
Covid 19	63.24	57.25	71.32	66.86	64.24
Viral	74.55	57.46	74.74	77.54	71.12
Lung Opacity	59.44	60.21	73.65	57.44	62.43
Normal	69.13	62.45	72.88	64.43	57.56
	65.71	57.93	73.22	63.94	63.3

3.Xception

Xception is a deep convolutional neural network architecture that involves Depthwise Separable Convolutions. This network was introduced Francois Chollet who works at Google.


299 x 299 x 3
Entry flow
19 x 19 x 728
feature maps
Middle flow
8 x
19 x 19 x 728
feature maps
Exit flow
Output


299 x 299 x 3
Entry flow
Middle flow
Exit flow
3x3 ,32 /2
3x3 ,64 /1
3x3, 128 /1
3x3, 128 /1
3x3 /2
1x1 /2
3x3, 256 /1
3x3, 256 /1
3x3 /2
1x1 /2
3x3, 728 /1
3x3, 728 /1
3x3 /2
1x1 /2
3x3, 728 /1
3x3, 728 /1
3x3, 728 /1
3x3, 728 /1
3x3, 1024 /1
3x3 /2
1x1 /2
3x3, 1536 /1
3x3, 2048 /1
GAP
Soft max



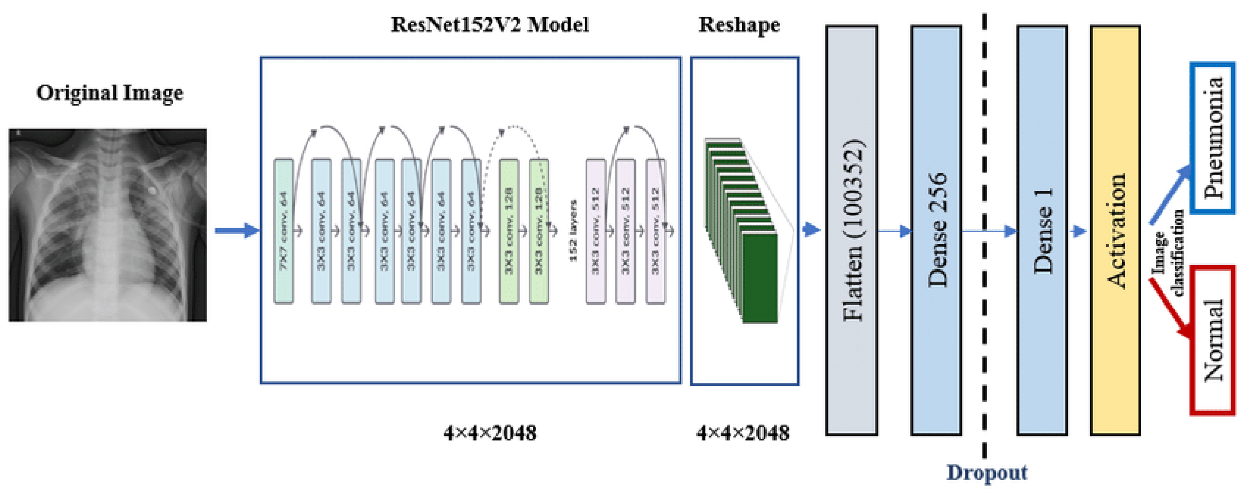
Results:-

Classes	Accuracy	Sensitivity	Specificity	Recall	Precision
Bacterial	52.43	51.11	68.88	53.21	51.13
Covid 19	53.14	47.77	71.11	56.46	60.92
Viral	54.66	51.33	64.43	71.62	65.18

Lung Opacity	59.51	50.32	73.66	67.91	60.34
Normal	59.17	52.21	68.91	66.41	63.71
	55.78	50.54	69.4	63.12	60.25

4.VGG-19

VGG-19 is a convolutional neural network that is 19 layers deep. It consists of 16 convolution layers, 3 Fully connected layer, 5 MaxPool layers and 1 SoftMax layer.The network has an image input size of 224-by-224.



ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Results:-

Classes	Accuracy	Sensitivity	Specificity	Recall	Precision
Bacterial	84.5	80	91.4	90.32	91.18
Covid 19	94.7	94.5	94.8	93.33	92.44
Viral	91.7	89.3	94.68	89.91	90.43

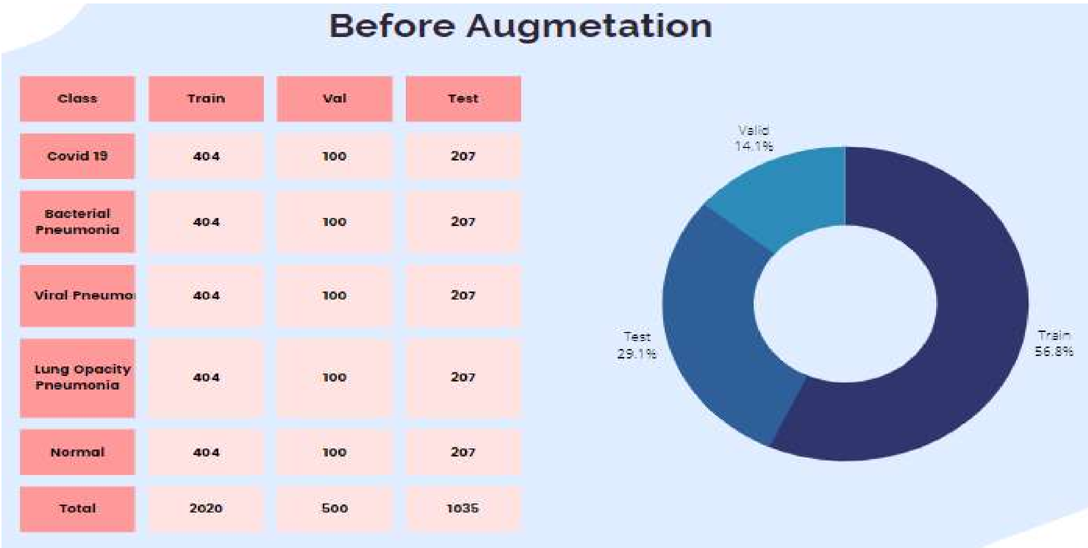
Lung Opacity	92.8	93.1	93.33	91.43	90.11
Normal	89.3	84.07	95.74	90.32	93.22
	90.63	88.2	94	91.06	91.47

Results

About Dataset

5-classes dataset – Original

Class	Train	Val	Test
Normal	404	10	207
Bacterial Pneuomonia	404	10	207
Viral Pneumonia	404	10	207
Covid 19	404	10	207
Lung Opacity	404	10	207
Total	2020	50	105

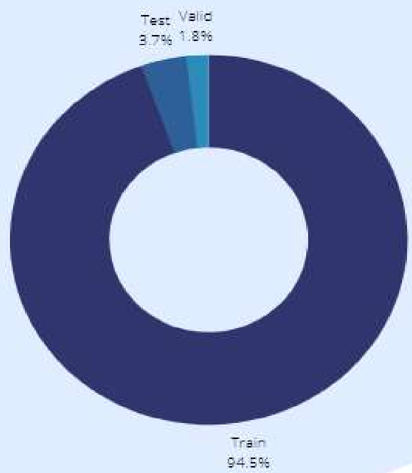


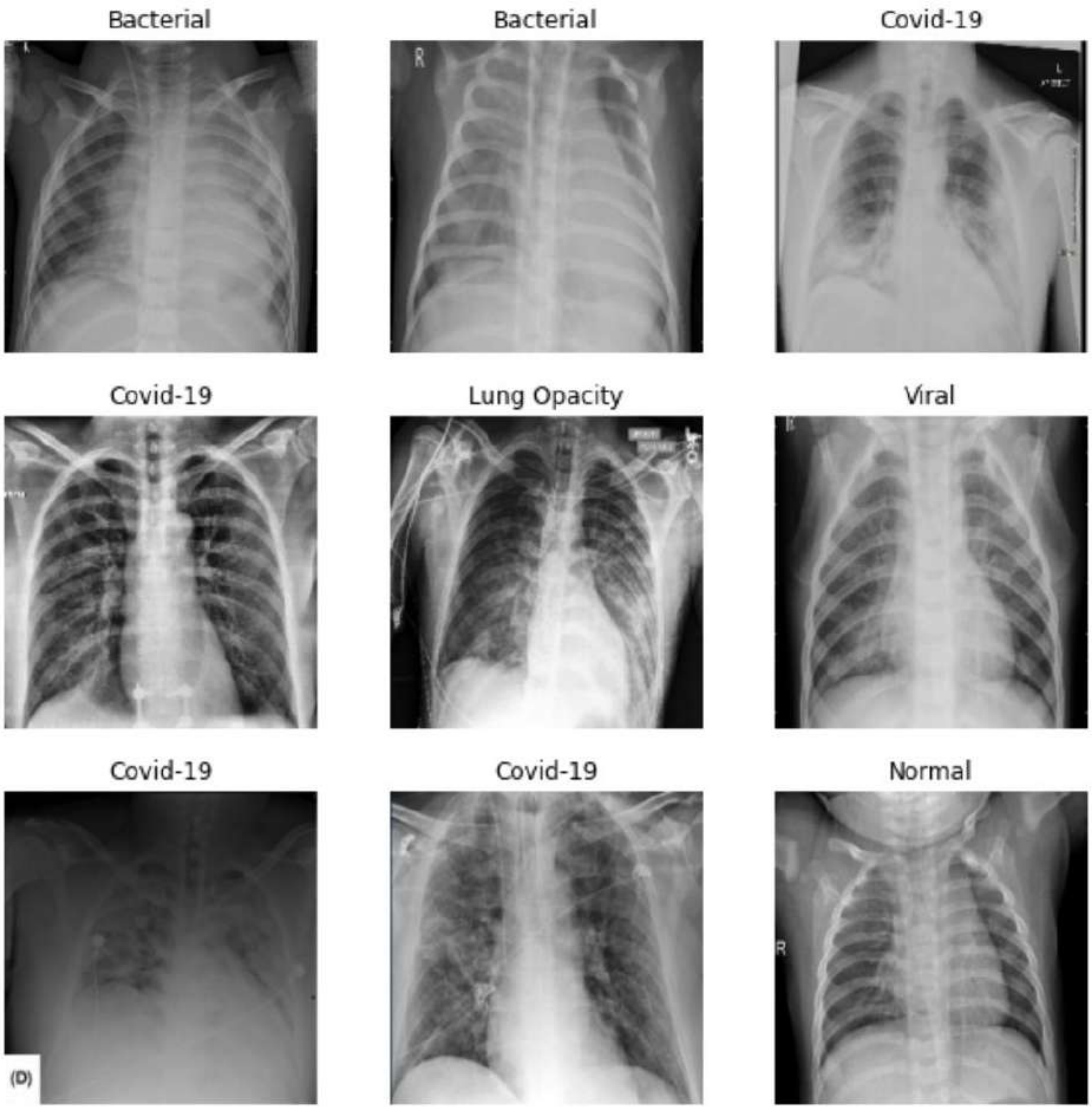
5-classes dataset – Original + Augmented

Class	**Train**	**Val**	**Test**
Normal	404+4848	10	207
Bacterial Pneuomonia	404+4848	10	207
Viral Pneumonia	404+4848	10	207
Covid 19	404+4848	10	207
Lung Opacity	404+4848	10	207
Total	2020+24240	50	105

After Augmetation

Class	Train	Val	Test
Covid 19	404+4848	100	207
Bacterial Pneumonia	404+4848	100	207
Viral Pneumonia	404+4848	100	207
Lung Opacity No Pneumonia	404+4848	100	207
Normal	404+4848	100	207
Total	2020+24240	500	1035



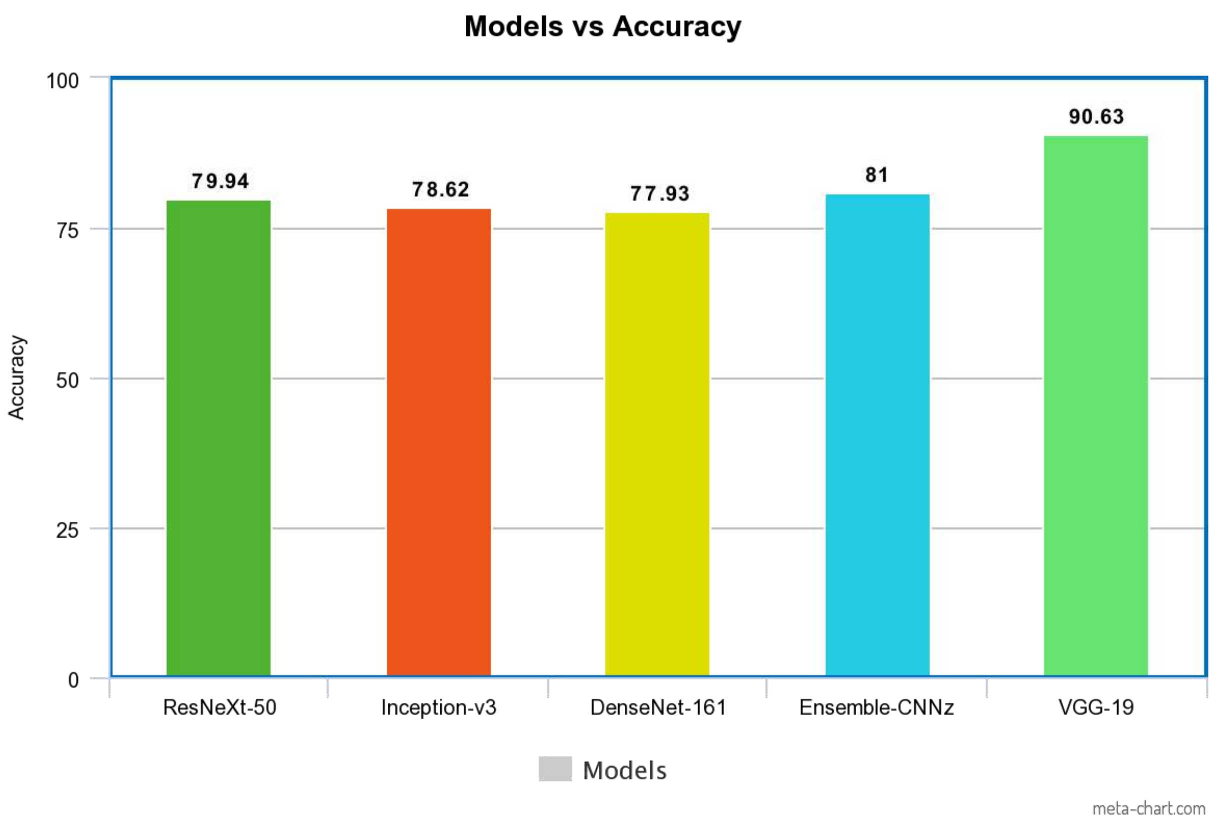

Bacterial
Bacterial
Covid-19
Covid-19
Lung Opacity
Viral
Covid-19
Covid-19
Normal
(D)

Comparison with existing models

We evaluated our model on the following evaluation metrics and the results are as follows –

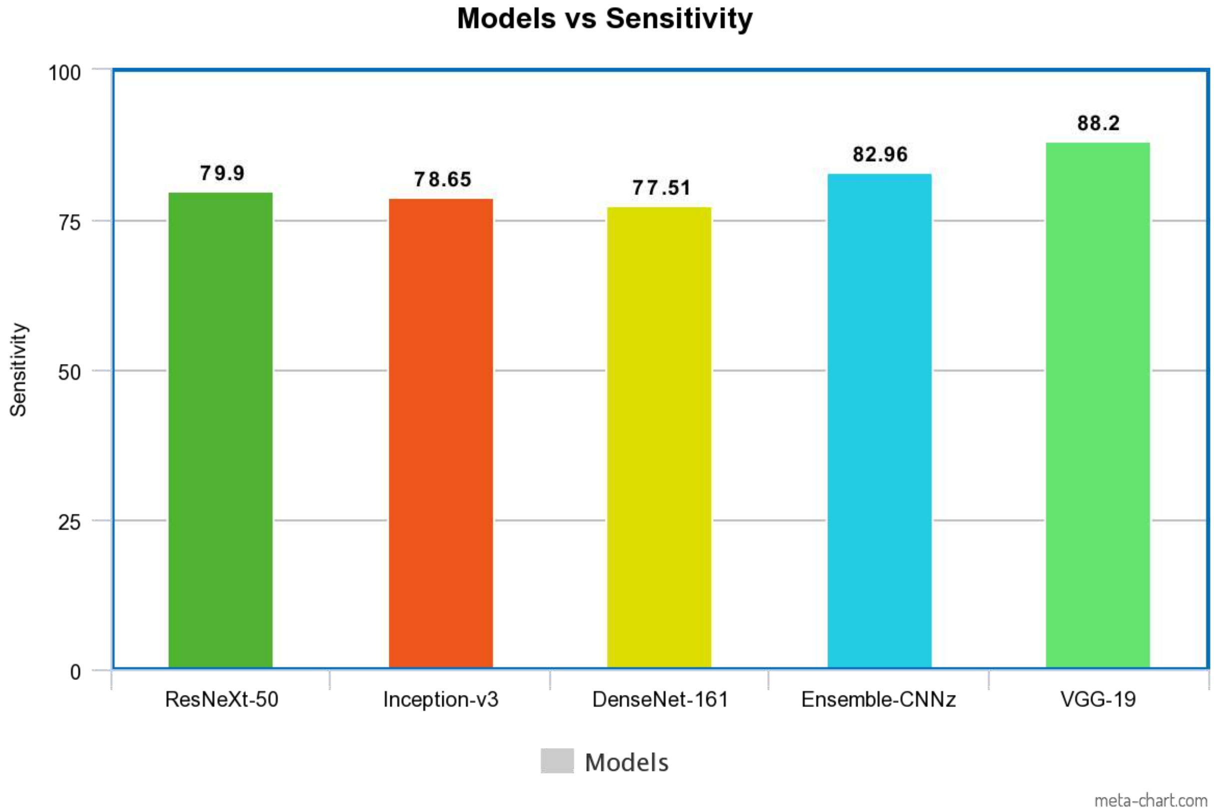
Accuracy

Accuracy is how close or far off a given set of measurements (observations or readings) are to their true value



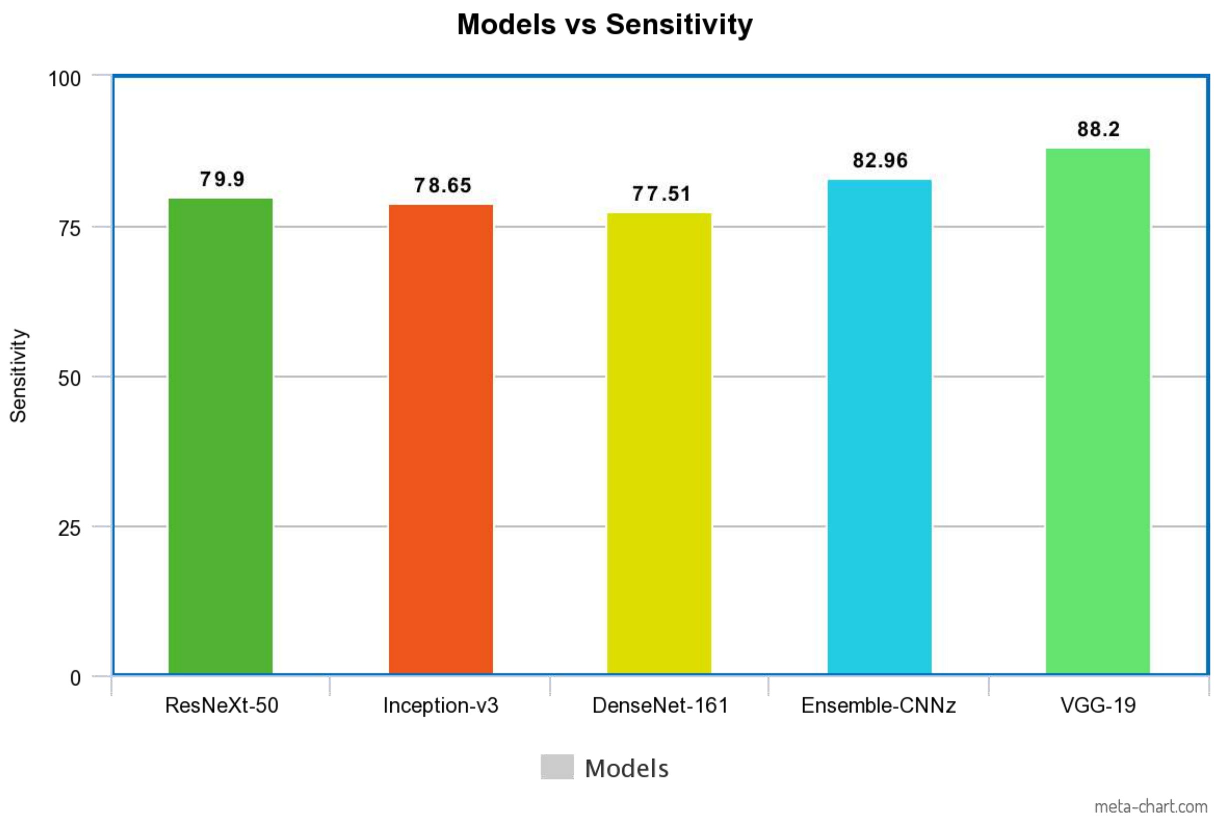
Sensitivity

(True Positive Rate) refers to the probability of a positive test, conditioned on truly being positive.



Specificity

(True Negative Rate) refers to the probability of a negative test, conditioned on truly being negative.



Confusion Matrix –

Limitations and Future Work

Limitations -

- Limited Access to X-Ray Machines in Rural India.
- Development of new infrastructure in Medical Science for using this method. This can be time-consuming.
- This model can only classify a patient as +ve or -ve. It can't say which part of the lungs is severely impacted.
- The second drawback is that there are no unified protocols, classes, and data. In the literature, each work defines its own protocol, classes, and data, and this makes comparison between different methods difficult.

Future work –

One of the limitations of this work was the imbalance of data in the datasets used for training and testing. In general, balanced data set with an equal number of normal and COVID-19 X-ray images makes the model building more comfortable, and the developed model can provide better prediction accuracy. Furthermore, the classification algorithm finds it easier to learn from a balanced dataset. Naturally, in any open source database,
the number of normal images would be higher than the COVID-19-positive images. As the images used in this study were taken from open-source databases, the imbalance in the training and testing data sets was obvious. However, the ratio between the number of normal and COVID-19 images was maintained Comparison among existing methods in the COVID-19 detection.

In comparison, the data sets in this study with a ratio of 1.57 make it only slightly imbalanced datasets. Therefore, it can be said that the imbalanced data are not the only factor that could affect the prediction accuracy; other factors, such as data set size, filtering technique, feature extraction technique, and the machine-learning algorithm used, should also be taken into consideration.

However, the performance of our proposed method could be further improved by the following two techniques. First, our method does not utilize offline data augmentation techniques in the experiment. Thus, the use of extensive augmentation techniques such as GAN or Convolution Auto-encoder before training could improve the performance further. This also helps to increase the number of CXR images, which results in mitigating the overfitting problem during the training step. Second, the use of other pre-trained deep learning models having a smaller filter size could improve the performance of CXR images. This is because a smaller filter size helps extract more discriminating ROIs of CXR images.

Conclusions

In this paper, we proposed a novel deep learning model using attention module on top of VGG-19 to classify the COVID-19 CXR images. We evaluated our method on three COVID-19 CXR datasets. The evaluation results indicate that our method is not only efficient in terms of classification accuracy but also in sensitivity and specificity. From this result, we can conclude that our proposed method is more appropriate for COVID-19 CXR image classification.

Implementable -
Cane be easily implemented in current scenario and results are compatible with current variant.
Best Performance -
The evaluation results indicate that our method is not only efficient in terms of classification accuracy but also in sensitivity and specificity.
Fast and Accurate -
It is faster than antigen method and more accurate than antigen method.

Reference

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