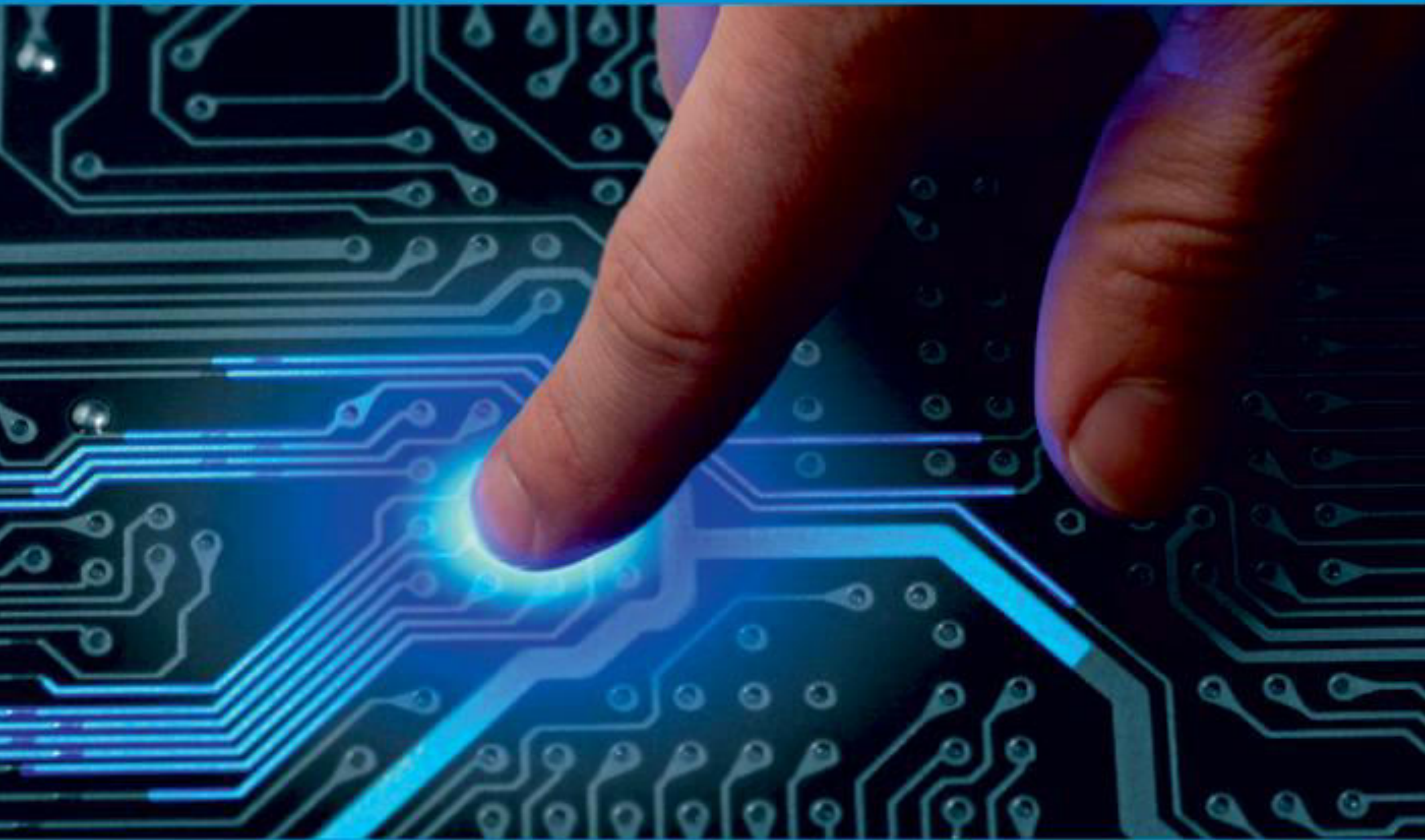
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 10, Issue 5, May 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.165

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 5, May 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1005247 |

COVID-19 Detection Model Based On Deep Learning

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ABSTRACT: The coronavirus pandemic has affected millions of people globally and led to thousands of casualties in the world. Since it is an airborne disease, any person misdiagnosed with Non-COVID can be a potential carrier of the disease inthe society. Therefore, any technological advancement allowing to accelerate the screening of the COVID-19 infection with high accuracy can be crucially helpful to healthcare professionals and the society.

Coronavirus is a respiratory disease and hence its effects can be seen in lungs. X-ray imaging of lungs is an easily accessible tool that can help in diagnosing COVID-19 cases. But since the images of various viral cases of pneumonia are similar, it is difficult for radiologists to differentiate between COVID-19 cases and other lung infections of pneumonia. Hence, we are trying to use Machine Learning algorithms to better distinguish between cases of COVID-19 and other infections.

KEYWORDS: VGG-16, RESNET-50, CNN

I. INTRODUCTION

Coronavirus disease (COVID-19) is a serious and contagious disease that has spread around the world since December 2019. COVID- 19 presentation, which began with the reporting of unknowncauses of pneumonia in Wuhan, Hubei province of China on December 31, 2019, has rapidly become a pandemic. The disease is named COVID-19 and the virus is termed SARS-CoV-2. This new virus spread from Wuhan to much of China in 30 days.

The United States of America, where the first seven cases were reported on January 20, 2020, reached over 300,000 by the 5th of April 2020. Most coronaviruses affect animals, but they can also be transmitted to humans because of their zoonotic nature. Severe acute respiratory syndrome Coronavirus (SARS-CoV) and the Middle East respiratory syndrome Coronavirus (MERS-CoV) have caused severe respiratory disease and death in humans. The typical clinical features of COVID-19 include fever, cough, sore throat, headache, fatigue, muscle pain, and shortness of breath.

The most common test technique currently used for COVID-19 diagnosis is a real-time reverse transcription-polymerase chain reac- tion (RT-PCR). Chest radiological imaging such as computed tomogra- phy (CT) and X-ray have vital roles in early diagnosis and treatment of this disease. Due to the low RT-PCR sensitivity of 60%–70%, even ifnegative results are obtained, symptoms can be detected by examining radiological images of patients. It is stated that CT is a sensitive method to detect COVID-19 pneumonia, and can be considered as a screening tool with RT-PRC. CT findings are observed over a long interval after the onset of symptoms,

and patients usually have a normalCT in the first 0–2 days. In a study on lung CT of patients who survived COVID-19 pneumonia, the most significant lung disease is observed ten days after the onset of symptoms.

II. PROJECT STATEMENT

The goal of this project is to introduce the concept of transfer learning as a way to classify chest x-rays to identifyCOVID-19 infection in the lungs. Since in transfer learning, we use models that are pre trained on large dataset, they will produce better results.

We will be comparing different models used for Transfer Learning: deep learning model based on the ResNet-50 andVGG-16 convolutional neural network architectures, which are pre trained to recognize objects from a million of imagesand then the pretrained models will be used to detect abnormality in chest X-ray images. The aim will be to get an optimum model by tweaking the hyperparameters of the model to get the lower recall rate. Hence the Metric for comparison between different models will Recall as we aim to minimize false negatives in the classification.

III. DATA DESCRIPTION

We are using a radiography image dataset from Kaggle(https://www.kaggle.com/tawsifurrahman/covid19-radiography- database).

The dataset of X-ray images used in this project is collectedby a team of researchers from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh along with their collaborators from Pakistan and Malaysia in collaboration with medical doctors. They have created a database of chest X-ray images for COVID-19 positive cases along with Normal and Viral Pneumonia images and Non lung infection. This COVID-19, normal, and other lung infection dataset is released in stages. This is the 2nd update (latest) dataset which is being used in the project. Following are the number of images in the dataset availablefor each category :

COVID-19 positive cases: 3616, Normal: 10,192,

Lung Opacity (Non-COVID lung infection): 6012, Viral Pneumonia images : 1345

Healthy and Lung Opacity samples compose 80% of the dataset. The data is unbalanced with almost 50% of samples belonging to *"NORMAL"* class. The model will probably be biased towards these examples. Therefore, it will be better to use Precision/Recall or F1 score as a metricas accuracy can be misleading in case of Unbalanced dataset.

IV. DATA PRE PROCESSING & EXPLORATION

We began our exploratory data analysis by reading images and tagging them with the correct labels. X-ray images were tagged as Covid-19, Lung Opacity, Normal or Pneumonia. We then used sns to plot a bar graph representing the number of images representing each of these 4 labels. It was concluded that we had 10191 normal cases, 6012 lung opacity cases, 3616 Covid cases and 1345 Viral pneumoniacases.

It was concluded that there was a serious problem of classimbalance. We used random oversampling of classes with lower samples to deal with the problem of class imbalance.

We then used OpenCV to load these images and match them with their labels. OpenCV-Python is a library of Python bindings designed to solve computer vision problems.

This method helps load images from the specified file. To represents a sample of the data set along with their Keras is used to build and train Deep Learning models in this project. Keras is an API built on top of TensorFlow. Keras follows best practices for reducing cognitive load: it offers consistent & simple APIs, it minimizes the number ofuser actions required for common use cases, and it provides clear & actionable error messages. It also has extensive documentation and developer guides. It is one of the most used Deep learning frameworks and also one of the most user friendly Deep learning APIs.

PyTorch is also used for Deep Learning models in the project. PyTorch is an open source deep learning frameworkdeveloped by Facebook AI’s research lab. It provides a Python package for high-level features like tensor computation (like NumPy) with strong GPU acceleration

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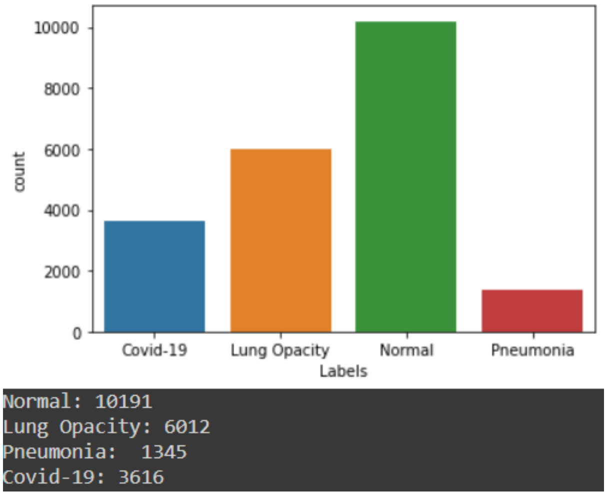
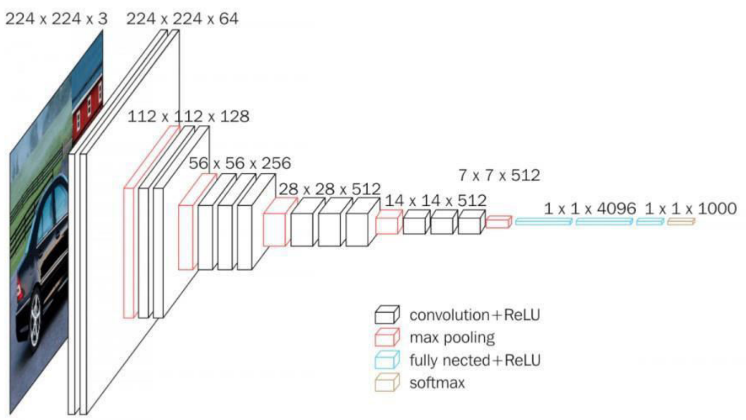


Fig 1. Distribution Of Dataset

V. VGG-16

VGG16 is a convolutional neural network model pre-trained over ImageNet which is a dataset of over 14 million images belonging to 1000 classes. It was proposed by K. Simonyan and A. Zisserman from the University of Oxford inthe paper “Very Deep Convolutional Networks for Large-Scale Image Recognition”. VGG-16 achieves 92.7%top-5 test accuracy in ImageNet. It is better in performanceas compared to AlexNet by replacing large kernel filters with multiple 3×3 kernel filters one after another. VGG16 was trained on NVIDIA Titan Black GPU.



This model is identified for its simplicity, using only 3×3 kernel sized convolutional layers stacked on top of each other in increasing depth. Spatial hierarchy is maintained byperforming max pooling over a 2×2 pixel window, with stride These stacks of convolutional layers are then followed bythree fully-connected dense layers each consisting of 4,096nodes which are then further followed by a softmax classifier. Softmax Layer gives the probability of occurrenceof each class.

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VI. RESNET-50

ResNet50 is a variant of the Residual Network model whichhas 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has 3.8 x 10^9 Floating points operations. ResNet was introduced in 2012 at the ILSVRC2012 classification contest.

The model is identified for training very deep neural networks and still has achieved great performance. The problem with training a very deep neural network, one with hundreds or thousands of layers, is that they suffer from theproblem of Vanishing Gradient which leads to an increase intraining error. The problem of Vanishing Gradient is addressed and corrected by the ResNet model by introducing shortcutconnections that simply perform identity mappings.

In the model, the layers fit a residual mapping denoted as H(x) and the nonlinear layers fit another mapping F(x):=H(x)−x so the original mapping becomes H(x):=F(x)+x[2]. There were no additional parameters added to the model which is one of the benefits. The idea behind the skipping connection is that during training, if the residual network learns the identity mapping were optimal weights, weights of the multiple nonlinear layers can be pushed to 0 by solver. This implies that no corrections will be required, our $F(x)$ is essentially set to 0, and the shortcut path can be used to perform an identity mapping.

VII. CNN MODEL

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 299, 299, 32)	320
batch_normalization (BatchNo	(None, 299, 299, 32)	128
conv2d_1 (Conv2D)	(None, 299, 299, 64)	18496
batch_normalization_1 (Batch	(None, 299, 299, 64)	256
average_pooling2d (AveragePo	(None, 149, 149, 64)	0
dropout (Dropout)	(None, 149, 149, 64)	0
conv2d_2 (Conv2D)	(None, 149, 149, 64)	36928
batch_normalization_2 (Batch	(None, 149, 149, 64)	256
conv2d_3 (Conv2D)	(None, 149, 149, 64)	36928
batch_normalization_3 (Batch	(None, 149, 149, 64)	256
average_pooling2d_1 (Average	(None, 74, 74, 64)	0
dropout_1 (Dropout)	(None, 74, 74, 64)	0
conv2d_4 (Conv2D)	(None, 74, 74, 64)	36928
batch_normalization_4 (Batch	(None, 74, 74, 64)	256
average_pooling2d_2 (Average	(None, 37, 37, 64)	0
dropout_2 (Dropout)	(None, 37, 37, 64)	0
conv2d_5 (Conv2D)	(None, 37, 37, 64)	36928
batch_normalization_5 (Batch	(None, 37, 37, 64)	256
conv2d_6 (Conv2D)	(None, 37, 37, 64)	36928
batch_normalization_6 (Batch	(None, 37, 37, 64)	256
average_pooling2d_3 (Average	(None, 18, 18, 64)	0
dropout_3 (Dropout)	(None, 18, 18, 64)	0
flatten (Flatten)	(None, 20736)	0
batch_normalization_7 (Batch	(None, 20736)	82944
dense (Dense)	(None, 128)	2654336
activation (Activation)	(None, 128)	0
dropout_4 (Dropout)	(None, 128)	0
batch_normalization_8 (Batch	(None, 128)	512
dense_1 (Dense)	(None, 4)	516

Total params: 2,943,428
Trainable params: 2,900,868
Non-trainable params: 42,560

Fig. CNN Model Architecture

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|| Volume 10, Issue 5, May 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1005247 |

VIII. MODEL EVALUATION

VGG-16

Following are the results from the VGG-16 model on our testing set. The graph in Fig 2 shows the gradual decrease in losses over the span of 25 epochs. We saw training losses going as low as 0.51 and validation losses on testingset as low as 0.368.

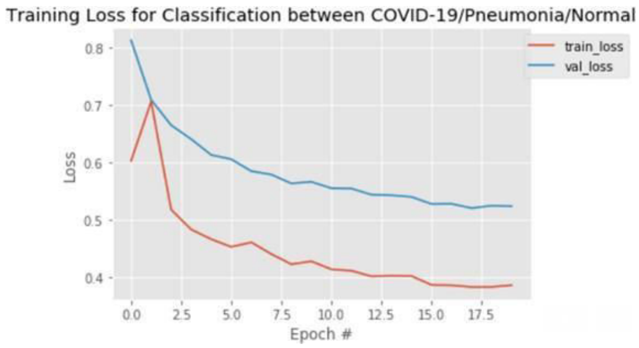

Fig 2: VGG-16 losses

The VGG-16 model also showed promising results when evaluated for accuracy. We saw training accuracy of 89% and validation accuracy of 90.5%. These are represented in Fig 3

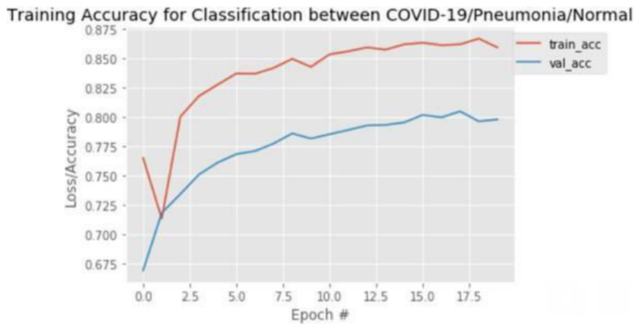

Fig 3: VGG-16 accuracy

The overall results are given in Fig 4. We observed an average value for precision, recall and F-1 score of 0.82, 0.82 and 0.81 respectively.

	precision	recall	f1-score	support
COVID	0.78	0.59	0.68	723
Lung_Opacity	0.86	0.73	0.79	1202
Normal	0.79	0.95	0.86	2039
Viral Pneumonia	0.95	0.80	0.86	269
avg / total	0.82	0.82	0.81	4233

Fig 4: VGG-16 results

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ResNet-50

Following are the results from the ResNet-50 model on our testing set. The graph in Fig 5 shows the gradual decrease in losses over the span of 25 epochs. We saw training losses going as low as 0.26 and validation losses on testingset as low as 0.225.

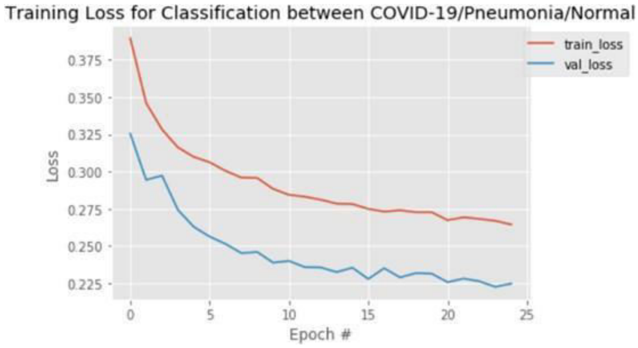

Fig 5: ResNet-50 losses

The VGG-16 model also showed promising results when evaluated for accuracy. We saw training accuracy of 88% and validation accuracy of 90.65%. These are represented in Fig 6

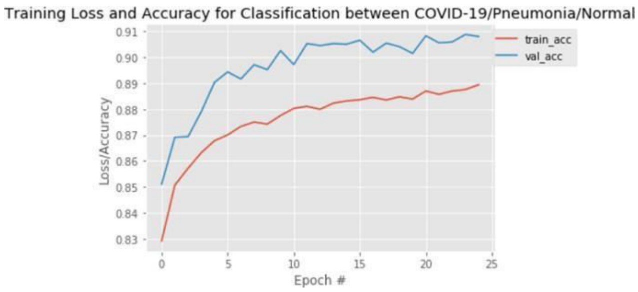

Fig 6: ResNet-50 accuracy

The overall results are given in Fig 7. We observed an average value for precision, recall and F-1 score of 0.86, 0.86 and 0.86 respectively.

	precision	recall	f1-score	support
COVID	0.94	0.76	0.84	723
Lung_Opacity	0.80	0.83	0.81	1202
Normal	0.86	0.91	0.88	2039
Viral Pneumonia	0.94	0.92	0.93	269
avg / total	0.86	0.86	0.86	4233

Fig 7: ResNet-50 results

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CNN Model

Following are the results from the CNN model on our testingset. The graph in Fig 8 shows the gradual decrease in losses over the span of "" epochs. We saw training losses going as low as 0.25 and validation losses on testing set as low as 0.60.

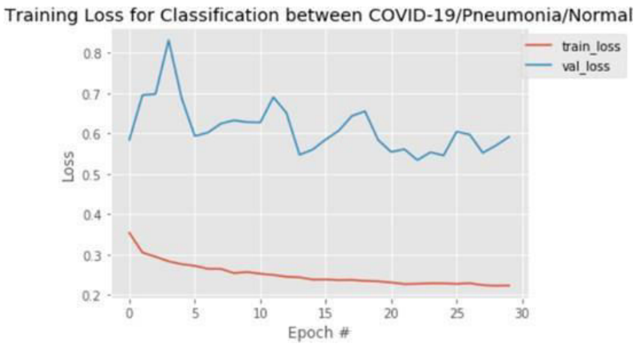

Fig 8: CNN Model losses

The CNN model showed poor results when evaluated for accuracy. We saw training accuracy of 92% and validation accuracy of just 65%. This was suspected to be a result of over-fitting on training data. We concluded this to be a resultof class imbalance. We felt oversampling the dataset did notprovide enough of a solution to the class imbalance problem. These are represented in Fig 9.

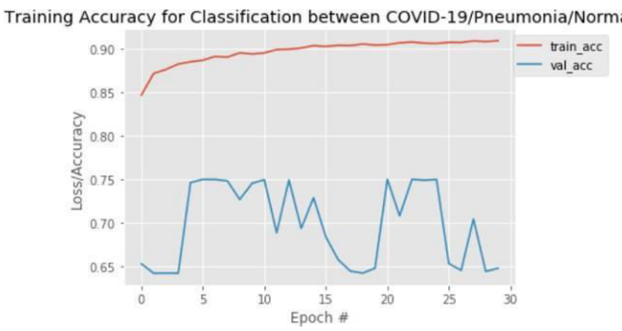

Fig 9: CNN Model accuracy

The overall results are given in Fig 10. We observed significantly lower average values for precision, recall andF-1 score of 0.81, 0.74 and 0.77 respectively.

	precision	recall	f1-score	support
COVID	0.73	0.55	0.63	723
Lung_Opacity	0.83	0.70	0.76	1202
Normal	0.79	0.96	0.87	2039
Viral Pneumonia	0.94	0.75	0.83	269
avg / total	0.81	0.74	0.77	4233

Fig 10: CNN Model results

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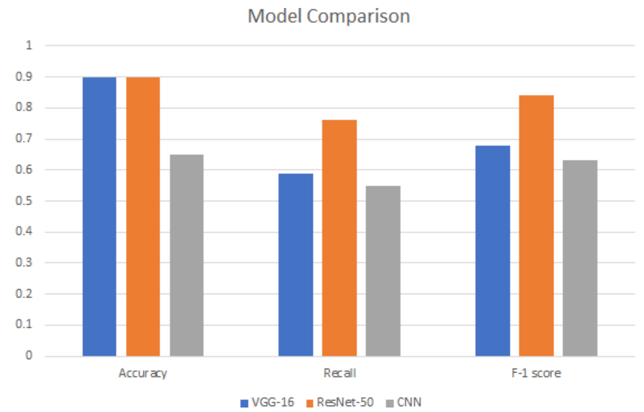
IX. REAL WORLD INSIGHTS

COVID-19 is spreading rapidly in many countries. And with new variants of COVID spreading, humans are at a disadvantage on limiting the casualties due to it. It is hard topredict the effect on lungs from the new variant. Only by studying new cases, we'll be able to generalize the effects. Deep Learning is a very effective mechanism for that.
Especially since the dataset is insufficient in these cases, pretrained models will perform better in this scenario. And as more data is collected i.e X-ray images of more COVID affected patients, more accurate the results can be. The project can be further extended to classify different variantsof COVID-19 as more data is available on them.

X. LESSONS LEARNED

Transfer Learning gives better performance in case of a task where the dataset is small. We observed in our experiment as we compared two Transfer Learning models:ResNet50 and VGG16 pretrained on ImageNet and, a Convolutional Neural Network trained only on X-ray dataset that both the Transfer Learning Models performed better than the CNN. Also, in case of deep learning networks, Skipping Connection architecture as adopted by ResNet improves the accuracy of the model. Recall is a better metric to measure performance in case of a task where False Negatives should be minimized. We observed that ResNet gave the highest recall rate and F1 score as well.



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