Covid-19 Radiography Classification Using CNN

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Abstract

Project goal:

For classifying the COVID-19 phenomenon based on the image classifiers, which in this term project the Convolutional Neural Network(CNN) model had been used.

Approach:

We tuned the neural networks pre-trained using CNN. In this case, the convolutional network for classification and detection includes VGG16, Inception, and ResNet. VGG16 is a convolutional neural network model that achieves high test accuracy in ImageNet. Inception is a convolutional neural network for assisting in image analysis and object detection and got its start as a module for Googlenet. ResNet is a CNN of a kind that builds on constructs known from pyramidal cells in the cerebral cortex.

Results:

We are able to reach a high test accuracy on the test dataset. CNN models showed reliable results in the classification problem of COVID - 19. Overall the accuracy is close to 90%.

Keywords:

COVID-19, Neural Networks, Radiography Classification, CNN, VGG16, Inception, ResNet

1. Introduction

From 2020 to 2021, COVID - 19 has been a wild pandemic that is raging on a global scale, influencing both developed and developing countries globally. The pandemic pronouncement also stressed the deep worries of the alarming rate of spread and severity of COVID-19. It is the principal recorded pandemic brought about by any coronavirus. It is characterized as a worldwide wellbeing emergency of its time and it has spread everywhere throughout the world. Legislatures of various nations are forcing fringe limitations, flight limitations, social distancing, and expanding consciousness of Organization. By 2021, this virus has infected more than 40,000,000 people and caused more than one million deaths around the world. (Hopkins, 2020).

For testing the Covid-19, the most common approach are two types of diagnostic tests – molecular (RT-PCR) tests that detect the virus's genetic material, and antigen tests that detect specific proteins on the surface of the virus. Samples are typically collected with a nasal or throat swab, or saliva collected by spitting into a tube. But these methods are expensive and may contribute to spreading the virus if the control environment is not fixed enough. The other diagnosis methods of Covid -19 also include clinical symptoms investigation, epidemiological history, and positive radiographic images computed tomography (CT).

Most of the COVID-19 cases have comparable highlights on radiographic pictures including reciprocal, multi-focal, ground-glass opacities with a fringe or back dissemination, primarily in the lower projections, in the early stage, and pulmonary consolidation in the late-stage. Therefore, we have been motivated to use neural network approaches to help in the detection of the disease from the X-ray images from the patient's chest. The dataset is from *COVID-19 RADIOGRAPHY DATABASE* (Winner of the COVID-19 Dataset Award by Kaggle Community). Over 219 COVID-19 detected cases, 1341 normal cases, and 1345 viral pneumonia chest X-ray (CXR) images had been released and used in the CNN model in this case.

Our approach in classifying the Covid - 19 is the Convolutional Neural Network(CNN), including VGG16, Inception, and ResNet.

2. Background

In the previous works, many of the researchers had applied deep learning models in the classification problem of detecting the Covid -19 based on the patients' chest X-ray images. SADMAN SAKIB and TAHRAT TAZRIN propose a viable and efficient deep learning-based chest radiograph classification (DL-CRC) framework to distinguish the COVID-19 cases with high accuracy from other abnormal (e.g., pneumonia) and normal cases. (Sakib, 2020) Furthermore, they justify their customized CNN model by extensively comparing it with widely adopted CNN architectures in the literature, namely ResNet, Inception-ResNet v2, and DenseNet that represent depth-based, multi-path-based, and hybrid CNN paradigms. The results showed good confidence in implementing their model in the specific classification problem. Pedro R. A. S. Bassi and Romis Attux had developed an image classifier from Dense Convolutional Networks and transfer learning to classify chest X-ray images. They had fine-tuned neural networks pre-trained on ImageNet and applied a twice-transfer learning approach, using NIH ChestX-ray14 dataset as an intermediate step. (Bassi, 2021) Asif, S. et al. had been working on developing a deep CNN that uses radiological imaging to automatically detect the Covid - 19 phenomena. Their model is based on Inception V3 and the accuracy of the model is more than 97% percent in training datasets and 93% invalidation datasets.

Figure 2.1 Covid - 19 detected patient's radiography image
(source from *COVID-19 RADIOGRAPHY DATABASE*)

Based on the previous works, we find detecting the Covid – 19 using the CNN model would be interesting to explore. Therefore, we had applied the VGG16, Inception, as well as ResNet in classifying the Covdi - 19 X-ray infected patients' images and normal patient images.

3. Approach

3.1. VGG16

VGG16 is a convolutional neural network (CNN) architecture that was used to win the 2014 ILSVR (Imagenet) competition. It is considered as one of the outstanding visual model architectures so far. The most unique thing about VGG16 is that they don't use a lot of hyperparameters, but instead focus on a convolutional layer with a 3x3 filter with a step size of 1, and always use the same padding and maxpool with a 2x2 filter with a step size of 2. Floor. It follows this arrangement. The convolutional layer and the max-pooling layer are consistent throughout the architecture. In the end it has 2 FCs (Fully Connected Layer)

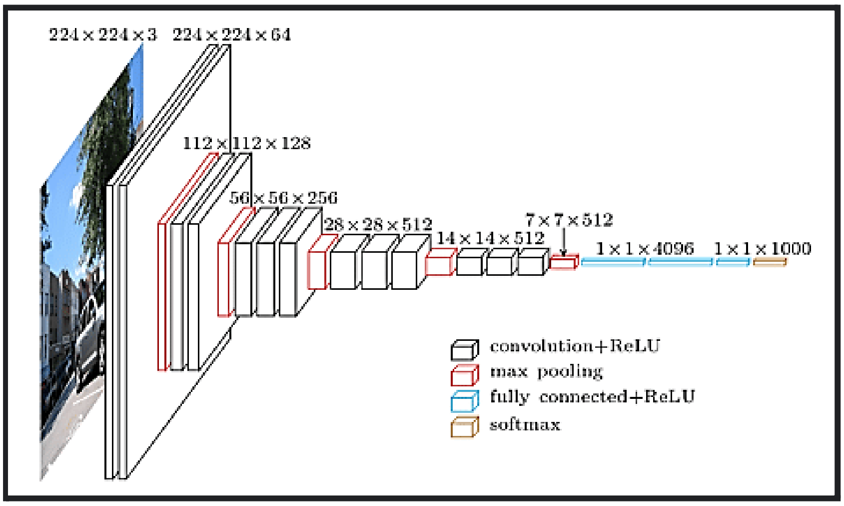


Figure 3.1 Architecture of VGG16(*source from research gate*)

3.2. Inception

The Inception network is a deep neural network whose architecture design consists of repeated components called Inception modules. Inception Modules are merged into Convolutional Neural Networks (CNN) as a way to reduce computational overhead. Since neural networks process a large number of images, the content of characteristic images (also called salient parts) varies greatly, so it needs to be designed appropriately. Using the Inception model has plenty of benefits. First, the model would benefit from high-performance gains on convolutional neural networks. Second, it will increase the effective utilization of computing resources with minimal computing load to achieve high-performance output of the Inception network. Third, by using different convolution filter sizes, it is possible to extract features from input data of different scales.

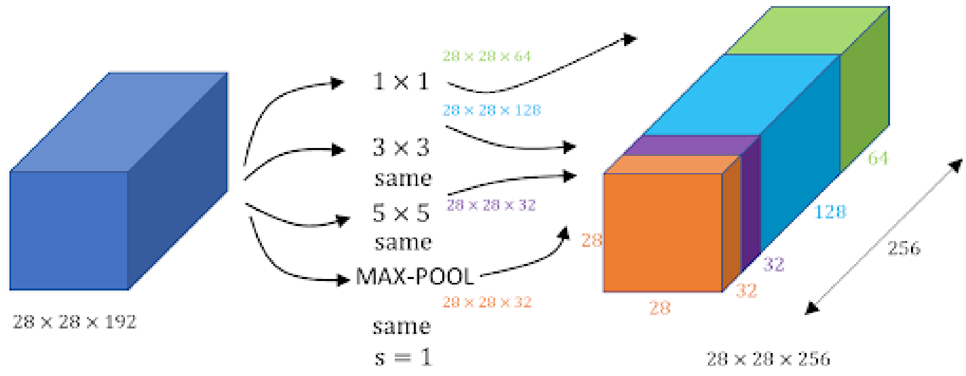


Figure 3.2 Architecture of Inception

3.3. ResNet

ResNet is an architecture that relies on microarchitecture modules. ResNet is an artificial neural network (ANN), which is based on the known structure of the pyramidal cells of the cerebral cortex. Residual neural networks do this by making use of shortcuts that skip connections or skip certain layers. The typical ResNet model is implemented by two-layer or three-layer hopping, which includes non-linearity (ReLU) and batch normalization between the two. The ResNet model can easily train networks with a large number of layers without increasing the training error rate. Meanwhile, the ResNet model uses identity mapping to help solve the vanishing gradient problem.

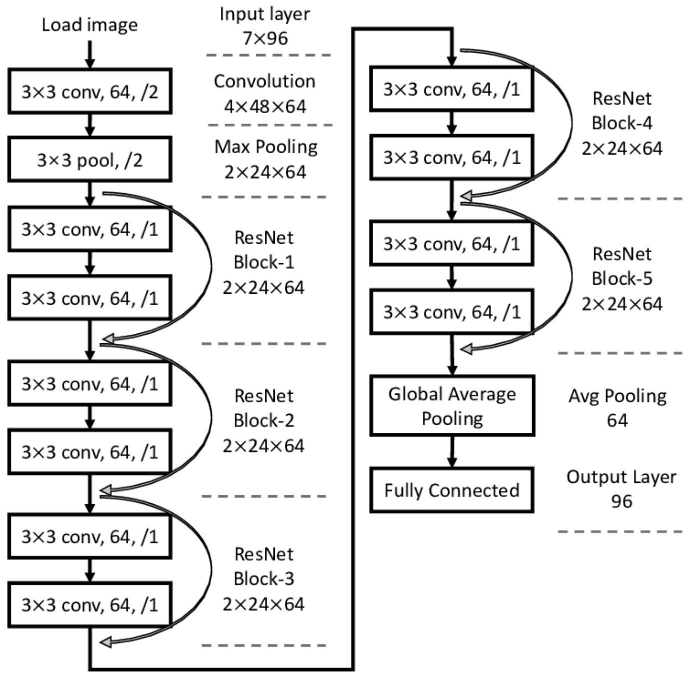


Figure 3.3 Architecture of ResNet

3.4. Evaluation

In this study, Accuracy is our main evaluation metric to evaluate the performance of the model. Accuracy is the proportion of true results among the total number of cases examined.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN)$$

where
TP is the true positive.
TN is the true negative.
FP is the false positive.
FN is the false negative.

In order to do an in-depth analysis of our results, in addition to printing the Accuracy number, we display the Confusion Matrix and calculate the precision, recall and f1-score.

$$precision = TP/(TP + FP)$$
$$recall = TP/(TP + FN)$$
$$F1\, score = 2 * recall * precision/(recall + precision)$$

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. Recall is the ratio of correctly predicted positive observations to the all observations in actual class.F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account, it is useful especially if you have an uneven class distribution.

4. Experimental Results

4.1. Data Preprocessing

From the Kaggle website, we got two types of dataset. One is an image dataset which is filled by COVID-19 patients' chest X ray plots, Lung-Opacity X ray plots, Viral Pneumonia patients' chest X ray plots and normal people chest X ray plots. The other one is a numeric dataset which is filled by the size of image, and the label of image. In our project, we spent more time on images preprocessing. First of all, we copied all images to a new folder. Then, we count and visualize the number of images in each category. When we finished checking the image dataset, we started to split raw images data into train, validation and test dataset and then stored them in folders respectively. In each of these three folders, we created two new folders storing COVID and Normal images. For the train dataset, we randomly chose 3900 images of COVID and Normal. In the validation dataset, we randomly chose 500 images from COVID and Normal folders. And, for the test dataset, we randomly chose 300 images of them. After that we began to build three models which are VGG16, Inception and Resnet.

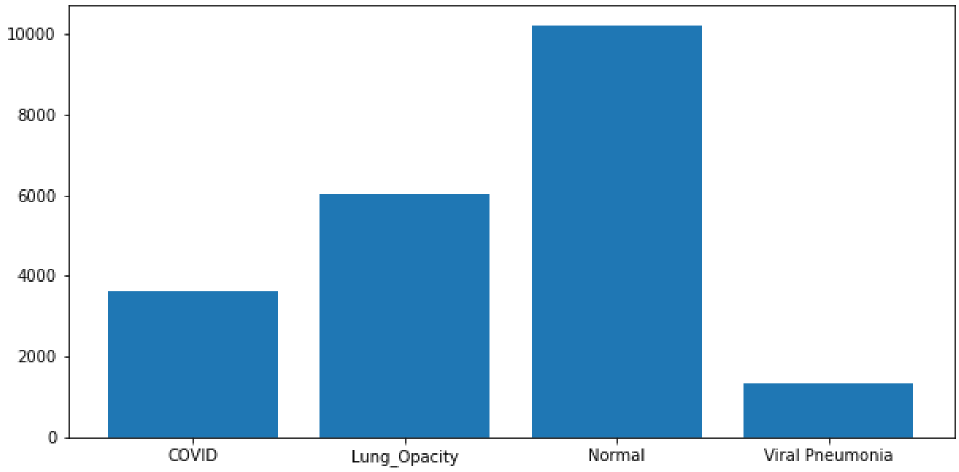
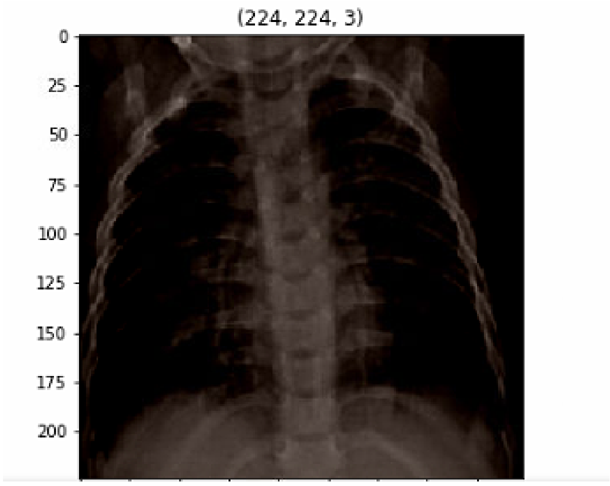


Figure 4.1 the visualization of image dataset

4.2. Input Pipine

Due to the fact that it is an image classification problem, we decided to introduce Convolutional Neural Network model to solve it. There are many pretrained Convolutional Neural Network models which are ready for transfer learning in tensorflow. In this project, we only use three classic models with relatively high accuracy : VGG16, ResNet50 and InceptionV3. We use keras Imagedatagenerator as data input pipeline and use flow_from_directory to change image size to (224, 224,3) and generate batches of augmented data.



4.3. Training Process

In our training process, we'd like to go with 8 epochs with 10 steps per epoch and we achieved accuracy 90% with VGG16, 94% with ResNet50 and 80% with Inception.

VGG16

```
Epoch 3/8
10/10 [==============================] - 113s 12s/step - loss: 0.5368 - accuracy: 0.7437 - val_loss: 0.3448 - val_accuracy
0.8442
Epoch 4/8
10/10 [==============================] - 114s 12s/step - loss: 0.4711 - accuracy: 0.7719 - val_loss: 0.3607 - val_accuracy
0.8413
Epoch 5/8
10/10 [==============================] - 115s 12s/step - loss: 0.4571 - accuracy: 0.7625 - val_loss: 0.5135 - val_accuracy
0.7381
Epoch 6/8
10/10 [==============================] - 114s 12s/step - loss: 0.4364 - accuracy: 0.8125 - val_loss: 0.4410 - val_accuracy
0.8016
Epoch 7/8
10/10 [==============================] - 115s 12s/step - loss: 0.3639 - accuracy: 0.8406 - val_loss: 0.2972 - val_accuracy
0.8790
Epoch 8/8
10/10 [==============================] - 114s 12s/step - loss: 0.3065 - accuracy: 0.8813 - val_loss: 0.2677 - val_accuracy
0.8978
```

ResNet50

```
Epoch 4/8
10/10 [==============================] - 55s 6s/step - loss: 2.0505 - accuracy: 0.8781 - val_loss: 0.8518 - val_accuracy: 0.933
5
Epoch 5/8
10/10 [==============================] - 55s 6s/step - loss: 1.3481 - accuracy: 0.9125 - val_loss: 0.6098 - val_accuracy: 0.928
6
Epoch 6/8
10/10 [==============================] - 56s 6s/step - loss: 0.5904 - accuracy: 0.9094 - val_loss: 0.4507 - val_accuracy: 0.921
6
Epoch 7/8
10/10 [==============================] - 56s 6s/step - loss: 0.2518 - accuracy: 0.9344 - val_loss: 0.2909 - val_accuracy: 0.936
5
Epoch 8/8
10/10 [==============================] - 56s 6s/step - loss: 0.4322 - accuracy: 0.9219 - val_loss: 0.2338 - val_accuracy: 0.940
5
```

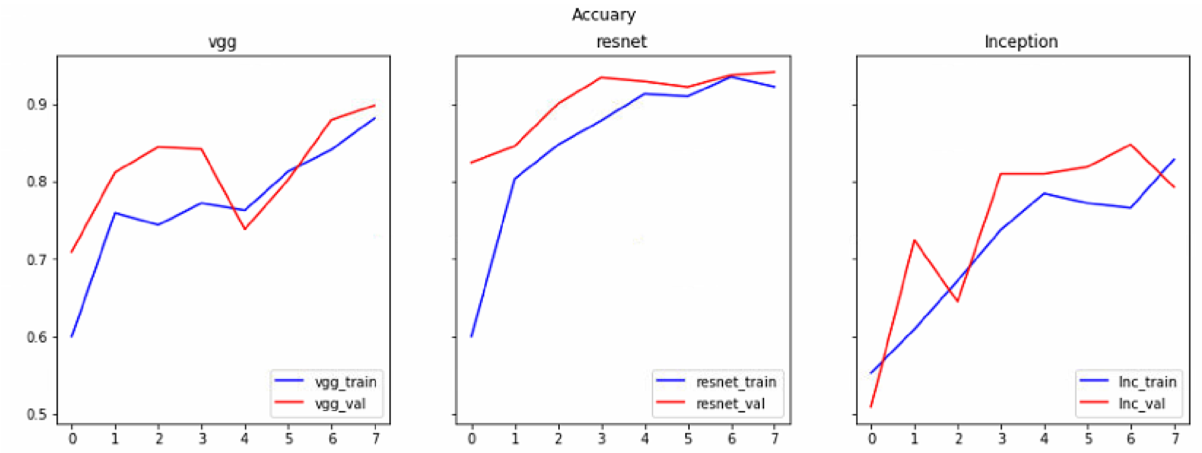
Inception

```
Epoch 4/8
10/10 [==============================] - 29s 3s/step - loss: 0.5235 - accuracy: 0.7375 - val_loss: 0.4316 - val_accuracy: 0.809
5
Epoch 5/8
10/10 [==============================] - 29s 3s/step - loss: 0.4519 - accuracy: 0.7844 - val_loss: 0.4110 - val_accuracy: 0.809
5
Epoch 6/8
10/10 [==============================] - 29s 3s/step - loss: 0.4633 - accuracy: 0.7719 - val_loss: 0.3979 - val_accuracy: 0.818
5
Epoch 7/8
10/10 [==============================] - 29s 3s/step - loss: 0.4602 - accuracy: 0.7656 - val_loss: 0.3829 - val_accuracy: 0.847
2
Epoch 8/8
10/10 [==============================] - 29s 3s/step - loss: 0.3918 - accuracy: 0.8281 - val_loss: 0.4380 - val_accuracy: 0.792
7
```

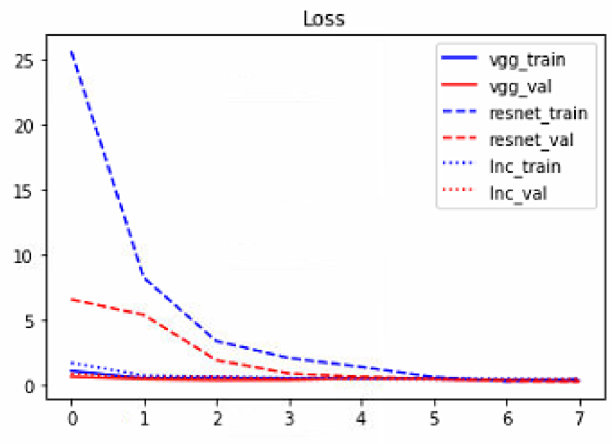
4.4. Evaluation

4.4.1. Accuarcy

We plotted the accuracy and loss for better comparison. ResNet50 achieved the best accuracy both in training and validation datasets.



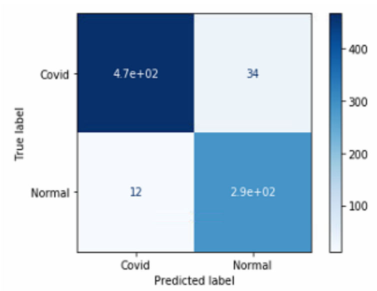
4.4.2. Loss



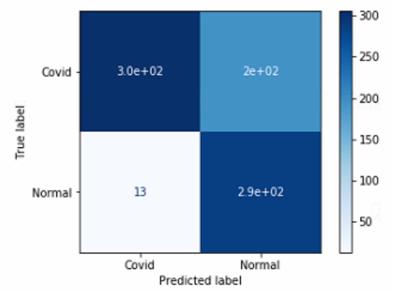
4.4.3. Confusion Matrix

confusion matrix shows the results we are getting from VGG16 and ResNet50 are good, but it is still necessary to improve it since the cost of misclassifying covid-19 to normal is huge.

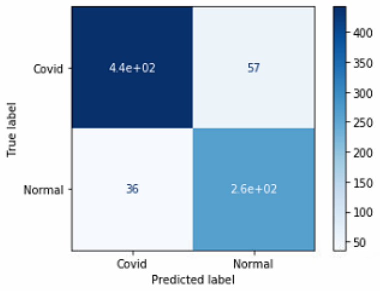
VGG16



ResNet50



Inception



4.4.4. Other Evaluations Metrics

VGG16:

	precision	recall	f1-score	support
Covid	0.92	0.89	0.91	500
Normal	0.82	0.88	0.85	300
accuracy			0.88	800
macro avg	0.87	0.88	0.88	800
weighted avg	0.89	0.88	0.88	800

ResNet50:

	precision	recall	f1-score	support
Covid	0.97	0.93	0.95	500
Normal	0.89	0.96	0.93	300
accuracy			0.94	800
macro avg	0.93	0.95	0.94	800
weighted avg	0.94	0.94	0.94	800

Inception:

	precision	recall	f1-score	support
Covid	0.96	0.61	0.75	500
Normal	0.60	0.96	0.73	300
accuracy			0.74	800
macro avg	0.78	0.78	0.74	800
weighted avg	0.82	0.74	0.74	800

4.4.5. Prediction

To further relate with our current situation, we did two test experiments to help us test the accuracy of classification in the real world. One is we randomly chose a COVID image from the folder and put it into models. Then, we found that the chance of the image being COVID is 64.62% in the Vgg16 model. From the Resnet model, the chance of the image being COVID is 94.18%. And, in the Inception model, the chance of the image being COVID is 69.99%. The other experiments used the Delta Variant virus image. We collected the chest X ray plots from the patients who suffered from Delta variant virus. We did the same steps like the last experiment. Then, we see that the Resnet model is still better than the other two models. But, all of them classified the pictures very well.

Table 4.1 COVID TEST

Covid test Image	Vgg16	Resnet	Inception
Covid	64.62%	94.18%	69.99%
Normal	20.77%	20.51%	51.29%

Table 4.2 DELTA VARIANT TEST

Delta Variant Image	Vgg16	Resnet	Inception
Covid	79.10%	95.24%	83.31%
Normal	22.62%	9.61%	37.86%

4.4.6. Discussion

From our models summary, all of these three models have pretty good accuracy. But, the Resnet model is more suitable for image classification. According to the test experiments, the Resnet has the highest accuracy. In the future, we think when we deal with some problem about image classification, we will choose Resnet first. Or, this model is more suitable to deal with COVID-19 classification questions.

5. Conclusion

The COVID-19 has been going on for two years. During this period, we experienced too much. We took online classes and wore masks the whole year. Even though we have vaccines now, we still need to be more careful. The virus doesn't disappear and it is still changing. From the original virus to Delta variant, and now, it changes to a new type, Omicron variant. Thus, our project is concentrated on COVID-19 image classification. We used thousands of images to build three kinds of models and used them to help us identify which one has the probability of COVID or not. And, to connect with the current situation, we collected Delta variant images from Youtube website. Combined with original virus test result and Delta variant test result, we can find that the Resnet model has the highest accuracy which means this model is more suitable for image classification. Thus, we inferred that, in the future, when we meet some problems about image classification, we can use the Resnet model first. Hopefully we won't use these models to predict COVID-19 or do COVID-19 image classification anymore.

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