Covid-19 Classification using CNNs

Data Science for Management – LM91

Introduction

AI-enabled Medical Image Analysis (MIA) Workshop is devoted to medical image analysis, with emphasis on radiological quantitative image analysis for diagnosis of diseases. The focus is on Artificial Intelligence (AI), Machine and Deep Learning (ML, DL) approaches that target effective and adaptive diagnosis; there is also a particular interest in approaches that enforce trustworthiness and automatically generate explanations, or justifications of the decision making process.

COV19D Competition is based on a database of chest CT scan series that is manually annotated with respect to Covid-19/non-Covid-19 diagnosis.

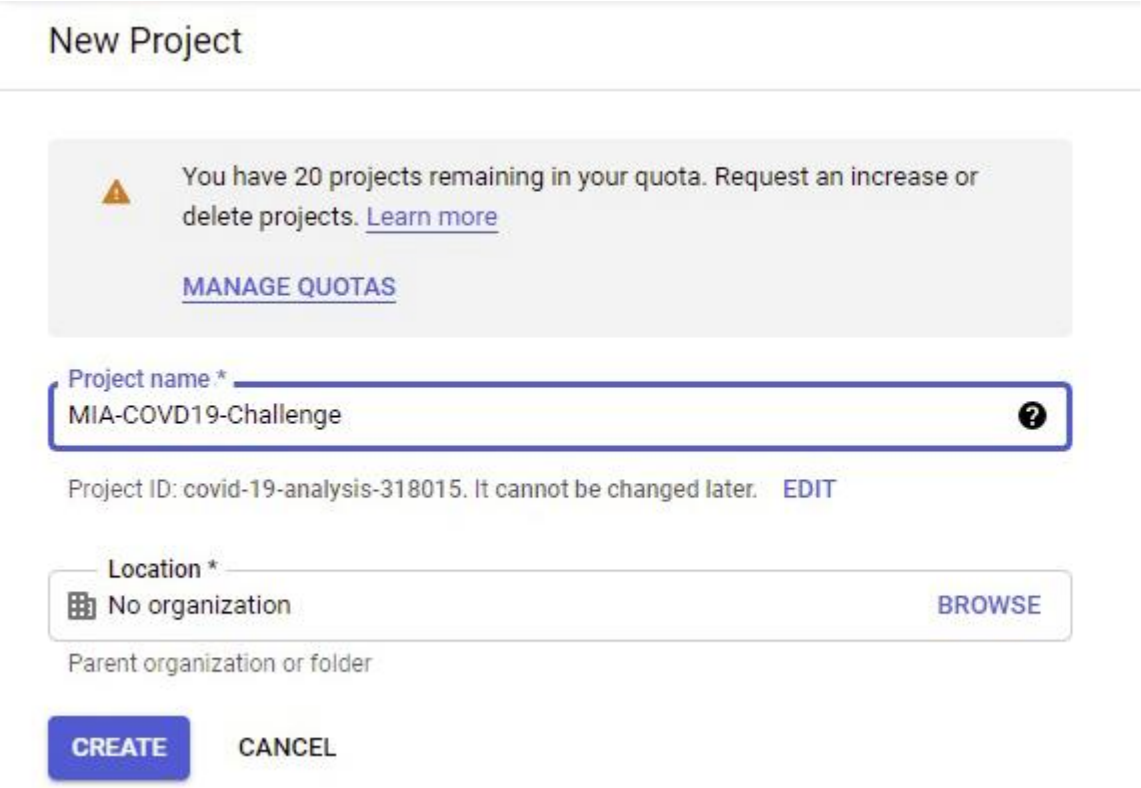
The aim of this Computer Vision project is to build a classifier using some models CNNs on PyTorch to classify ct scans of covid and non-covid patients.

The Workflow

The workflow

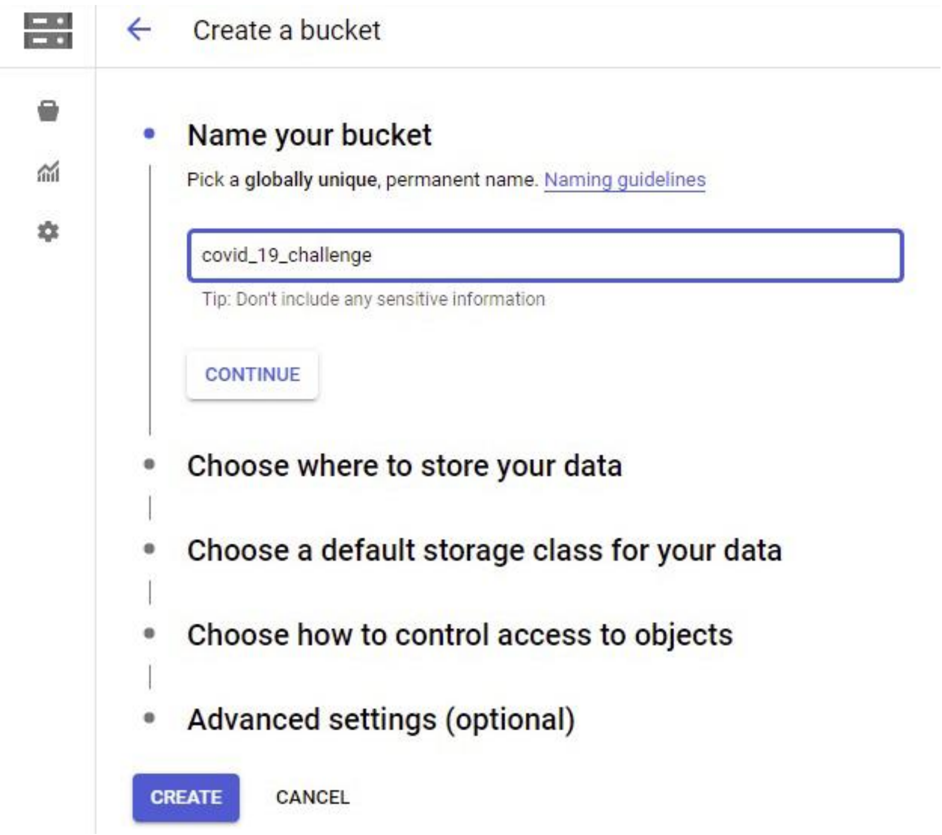
Here we describe the cloud workflow to upload to perform the classification

The workflow – Google Cloud Platform



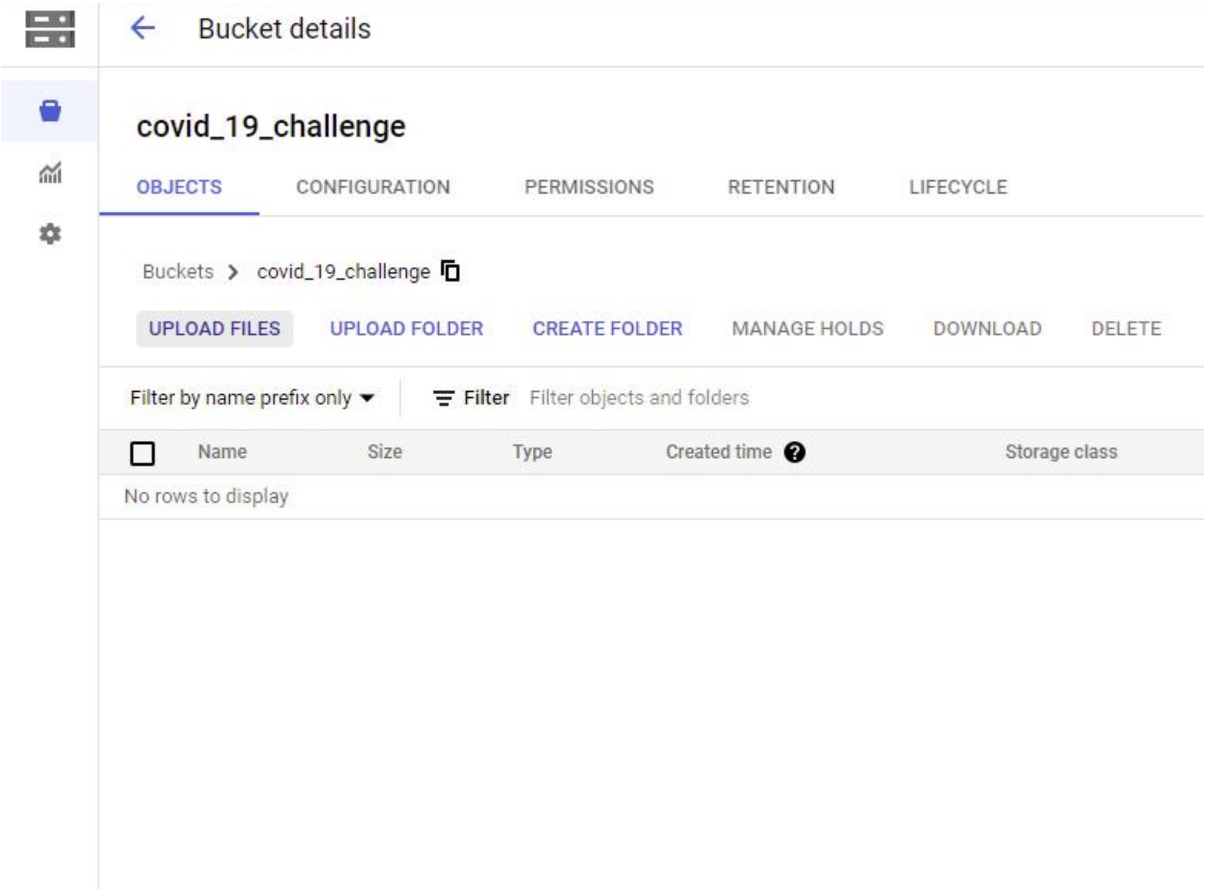
In Google Cloud create a new project naming it ''MIA-COVD19-Challenge''

The workflow – Google Cloud Storage



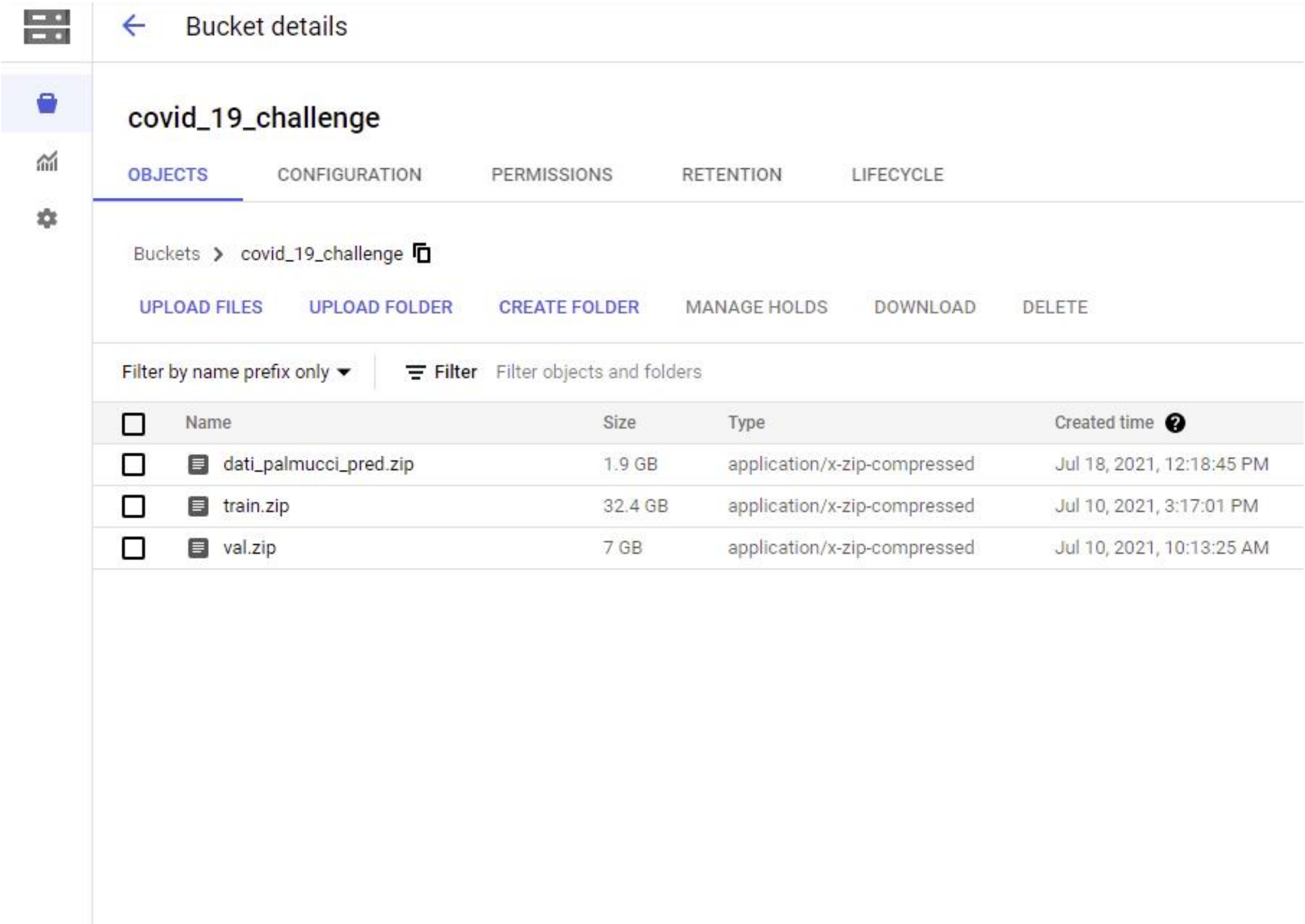
1. In Google Cloud Storage create a new bucket and naming it ‘covid_19_challenge’’
2. Leave everything default and click on CREATE to create the bucket

The workflow – Google Cloud Storage



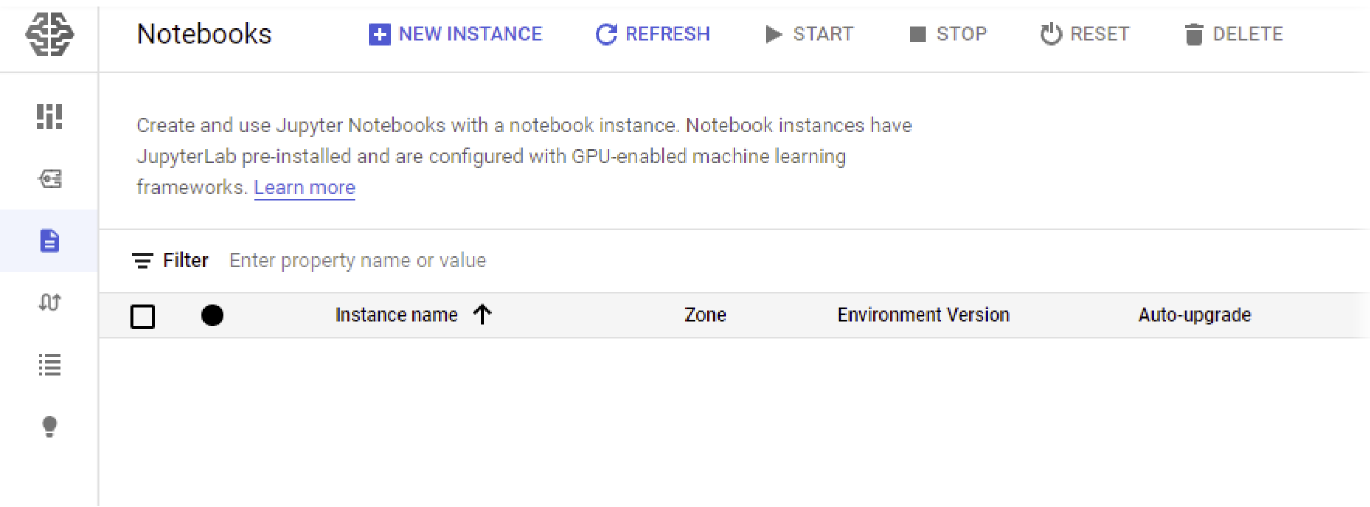
1. In Google Cloud Storage create a new bucket and naming it ‘covid_19_challenge’’
2. Leave everything default and click on CREATE to create the bucket
3. Click on UPLOAD FILES and select the files of the dataset

The workflow – Google Cloud Storage



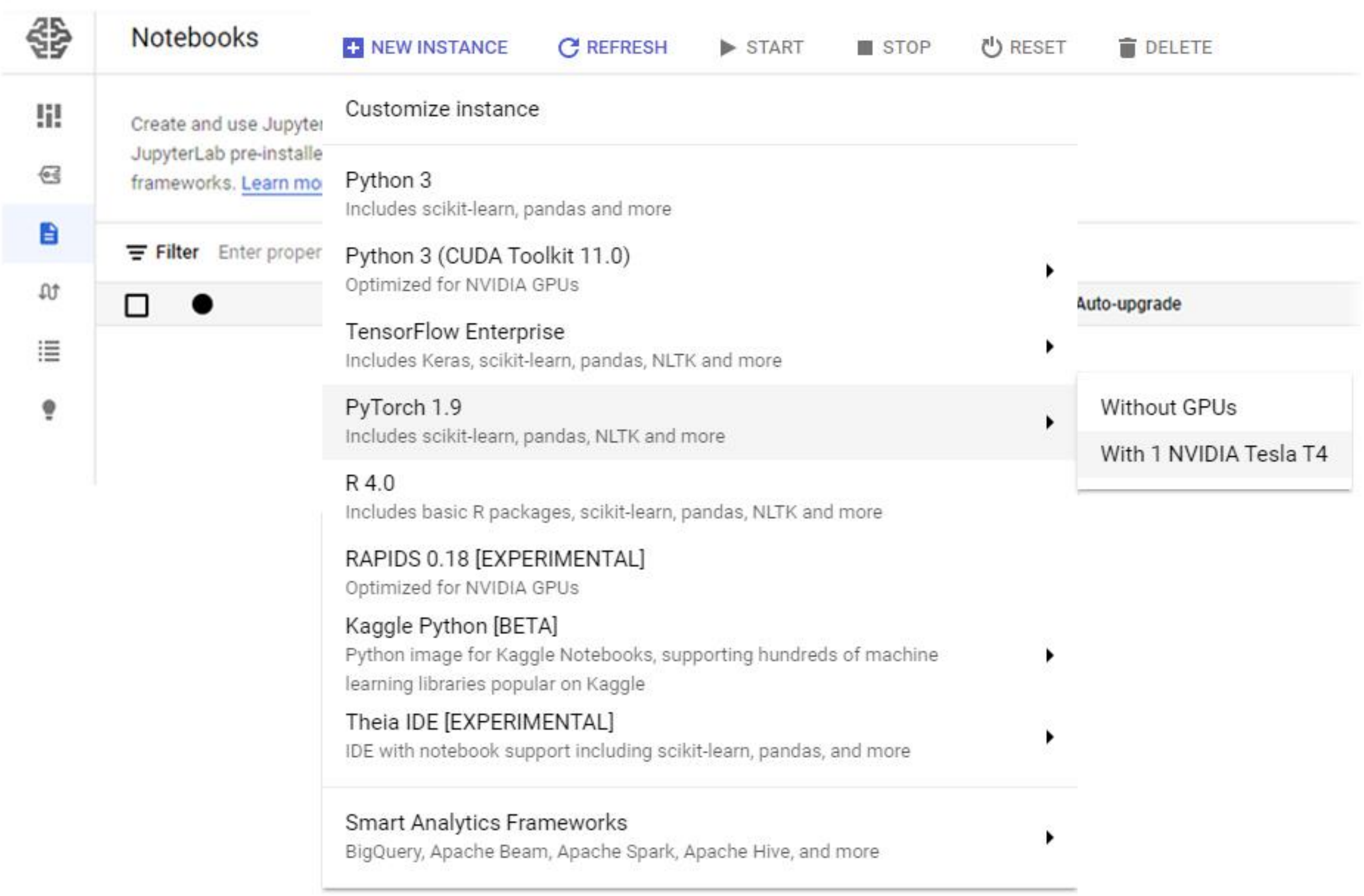
1. In Google Cloud Storage create a new bucket and naming it ‘covid_19_challenge’’
2. Leave everything default and click on CREATE to create the bucket
3. Click on UPLOAD FILES and select the files of the dataset
4. And wait until files are uploaded to the Bucket

The workflow – Google AI Platform (Notebooks)



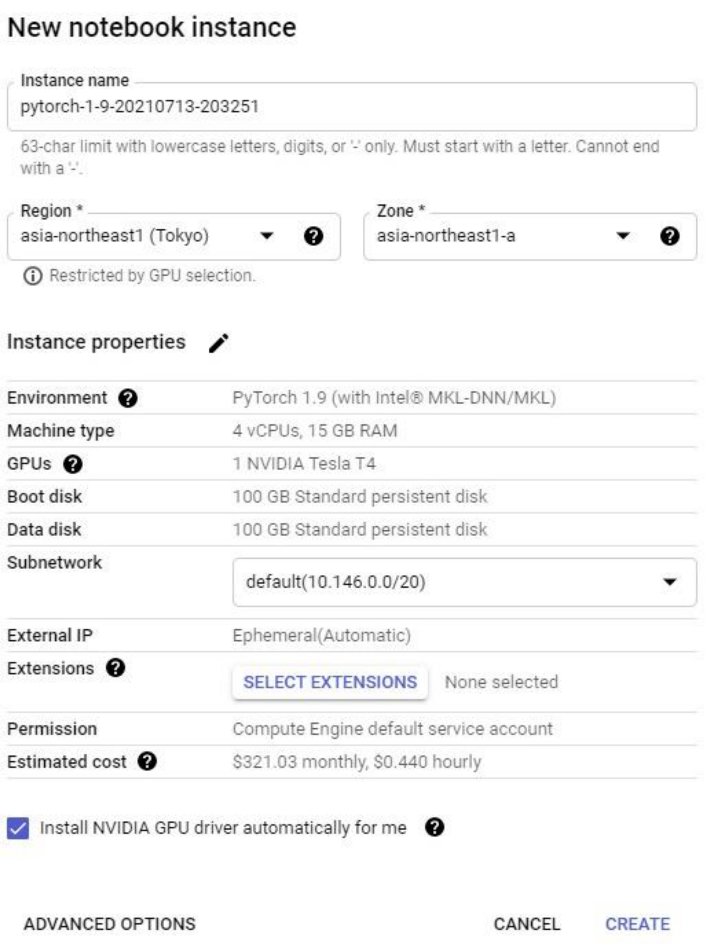
1. Create a NEW INSTANCE

The workflow – Google AI Platform (Notebooks)



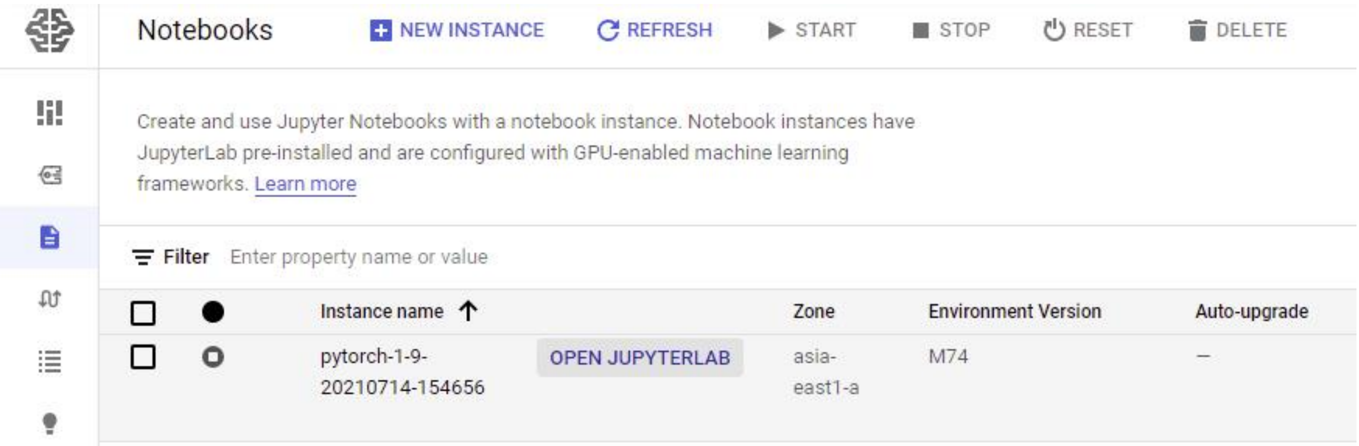
1. Create a NEW INSTANCE
2. Select PyTorch 1.9 With 1 NVIDIA Tesla T4

The workflow – Google AI Platform (Notebooks)



1. Create a NEW INSTANCE
2. Select PyTorch 1.9 With 1 NVIDIA Tesla T4
3. Find a Region and Zone with the instance properties required
4. Click on CREATE

The workflow – Google AI Platform (Notebooks)



1. Create a NEW INSTANCE
2. Select PyTorch 1.9 With 1 NVIDIA Tesla T4
3. Find a Region and Zone with the instance properties required
4. Click on CREATE
5. When the VM is ready on click on OPEN JUPYTERLAB

The dataset

The analysis of the dataset

The dataset consists of ct scans of 1926 patients, split in:

- **Training set**

  687 Covid patients with 153.680 ct scan slices

  865 Non-covid patients with 181.991 ct scan slices

- **Validation set**

  165 Covid patients with 35.002 ct scan slices

  209 Non-covid patients with 40.516 ct scan slices

Please note: Test set will be created using the 10% of the training set

The analysis of the dataset

After the analysis we found that 14 slices in ct_scan_34 in the validation set (covid) and 1 slice in ct_scan_263 in the training set (covid) are black:

Also, there are two files "._9.jpg" and "._92.jpg" in ct_scan_9 in the validation set (non covid) that create problems during the training process.

The analysis of the dataset

At the end we have:

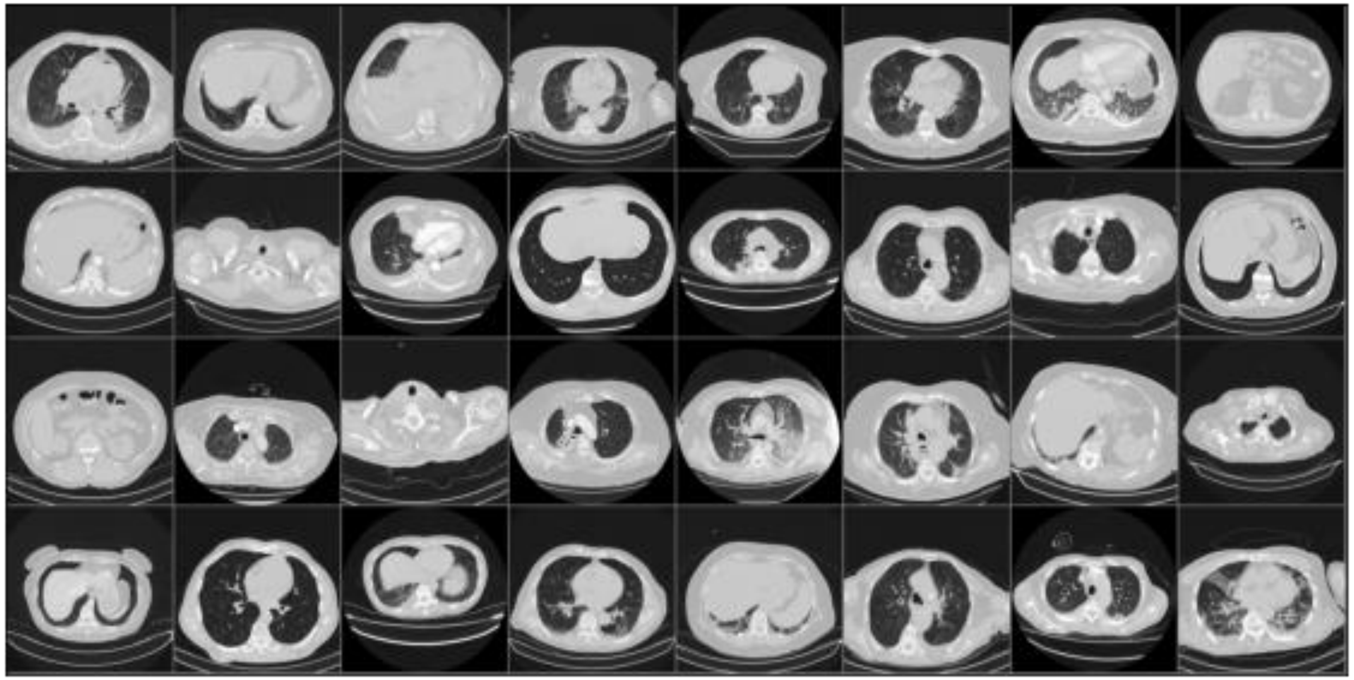
	Set	Class	Number of Patients	Number of slices	Average number of slices
0	train	covid	687	153680	224
1	train	non-covid	865	181991	210
2	val	covid	165	35002	212
3	val	non-covid	209	40516	194

And we decided to create the test set as the 10% of the training set, and we obtain:

- Number of training samples: 302103
- Number of validation samples: 75518
- Number of test samples: 33568

The analysis of the dataset

Image sample (after the preprocessing and loaded in the batch)



Classification

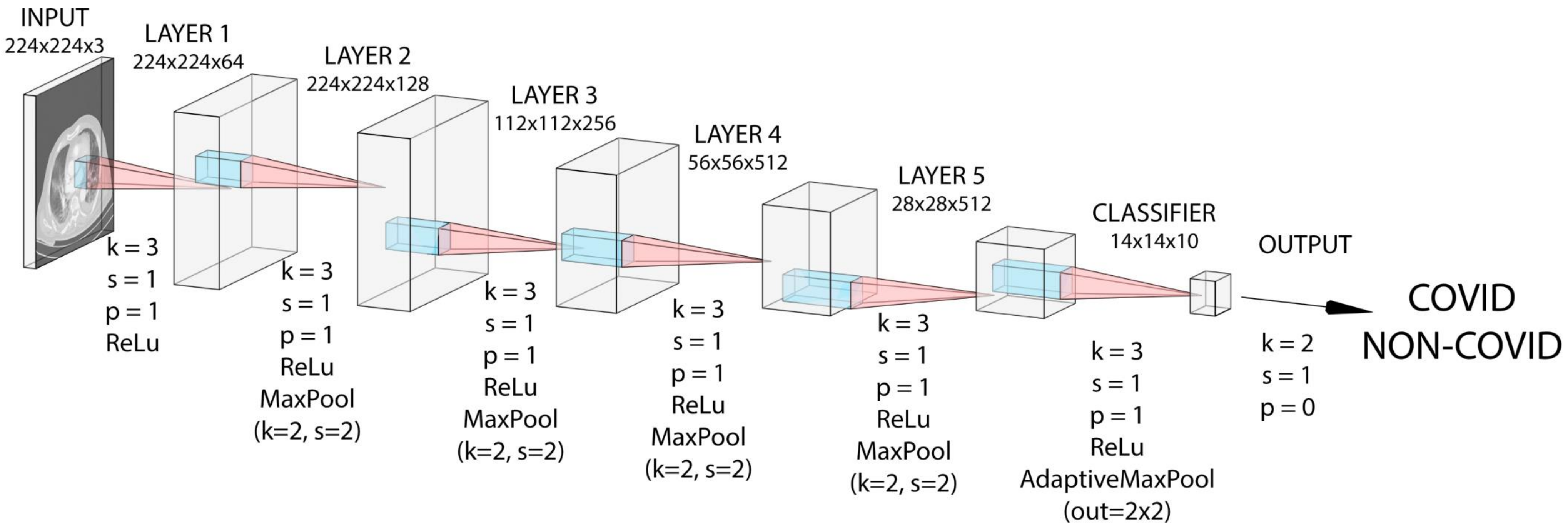
Settings

The dataset is transformed and loaded with:

- Resize of 224x224
- Normalization with mean and std of 0.5
- Batch size of 32 (only for FCN, then 64)
- Cross Entropy for the loss
- Adam with learning rate of 0.0001
- 5 Epochs for training
- Comparison of FCN vs VGG19, ResNet-152 and DenseNet-161 (Pre-trained)

FCN Architecture

- 5 layer, with kernel size 3x3, padding and striding 1.
- The number of channels is doubled at each layer, starting from 64 to 512.
- The activation function used is ReLu with Max pooling of size 2x2 and striding 2.
- Due to the lack of final dense layer as classifier we used a convolutional layer of 512, kernel size 2x2, padding 0 and striding 1, that will be able to classify images in the 2 predefined classes.



FCN Architecture – Results

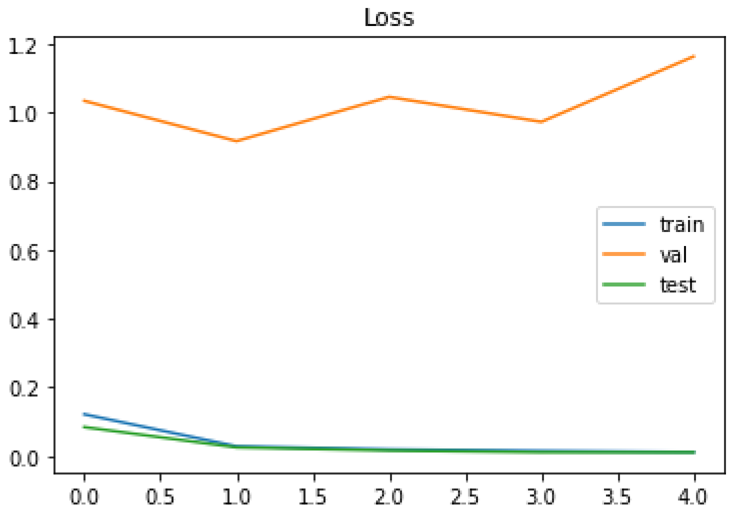
Epoch 1: Training Loss=0.1219, Training Accuracy=0.9495, Validation Loss=1.0336, Validation Accuracy=0.8058, Test Loss=0.0846, Test Accuracy=0.9691

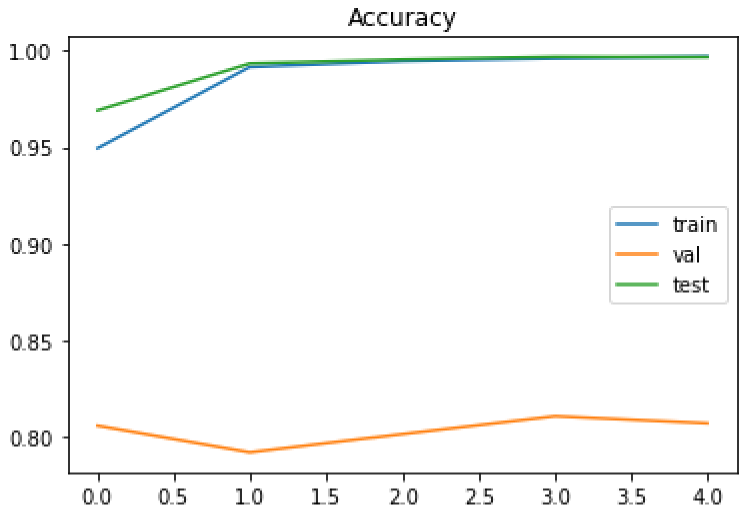
Epoch 2: Training Loss=0.0286, Training Accuracy=0.9916, Validation Loss=0.9163, Validation Accuracy=0.7920, Test Loss=0.0254, Test Accuracy=0.9934

Epoch 3: Training Loss=0.0196, Training Accuracy=0.9947, Validation Loss=1.0451, Validation Accuracy=0.8015, Test Loss=0.0164, Test Accuracy=0.9955

Epoch 4: Training Loss=0.0152, Training Accuracy=0.9961, Validation Loss=0.9725, Validation Accuracy=0.8108, Test Loss=0.0113, Test Accuracy=0.9969

Epoch 5: Training Loss=0.0117, Training Accuracy=0.9971, Validation Loss=1.1629, Validation Accuracy=0.8071, Test Loss=0.0111, Test Accuracy=0.9968

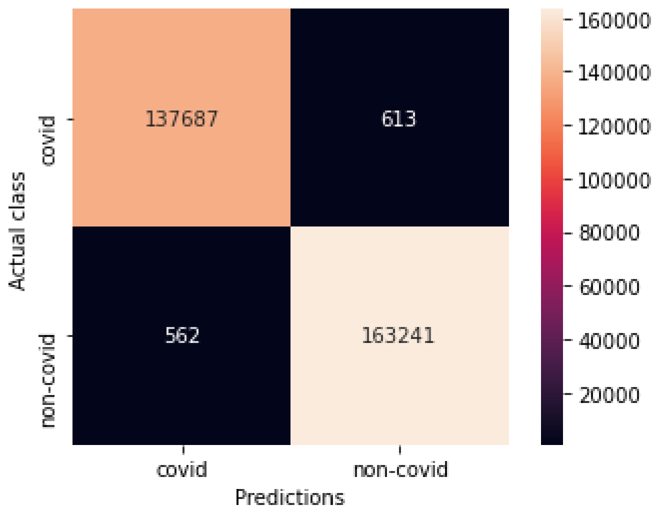




FCN Architecture – Results (Best model)

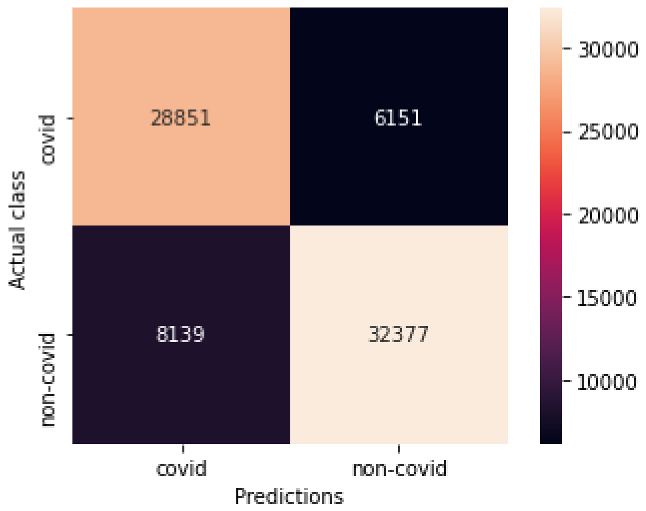
Epoch 4: Training Loss=0.0152, Training Accuracy=0.9961, Validation Loss=0.9725, Validation Accuracy=0.8108, Test Loss=0.0113, Test Accuracy=0.9969

Confusion Matrix train set



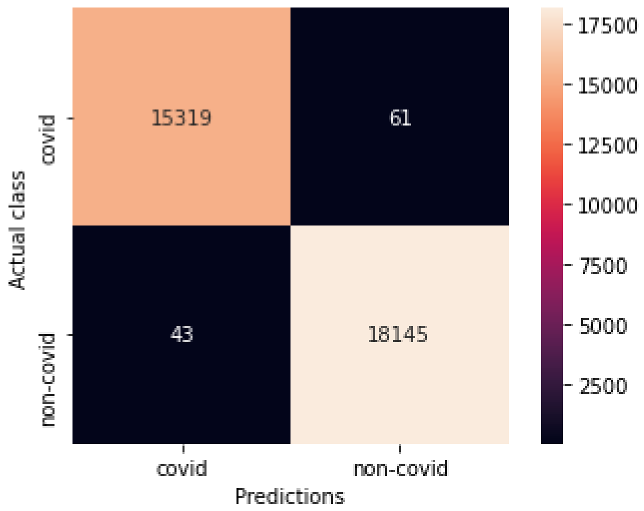
	precision	recall	f1-score	support
covid	1.00	1.00	1.00	138300
non-covid	1.00	1.00	1.00	163803
accuracy			1.00	302103
macro avg	1.00	1.00	1.00	302103
weighted avg	1.00	1.00	1.00	302103

Confusion Matrix val set



	precision	recall	f1-score	support
covid	0.78	0.82	0.80	35002
non-covid	0.84	0.80	0.82	40516
accuracy			0.81	75518
macro avg	0.81	0.81	0.81	75518
weighted avg	0.81	0.81	0.81	75518

Confusion Matrix test set

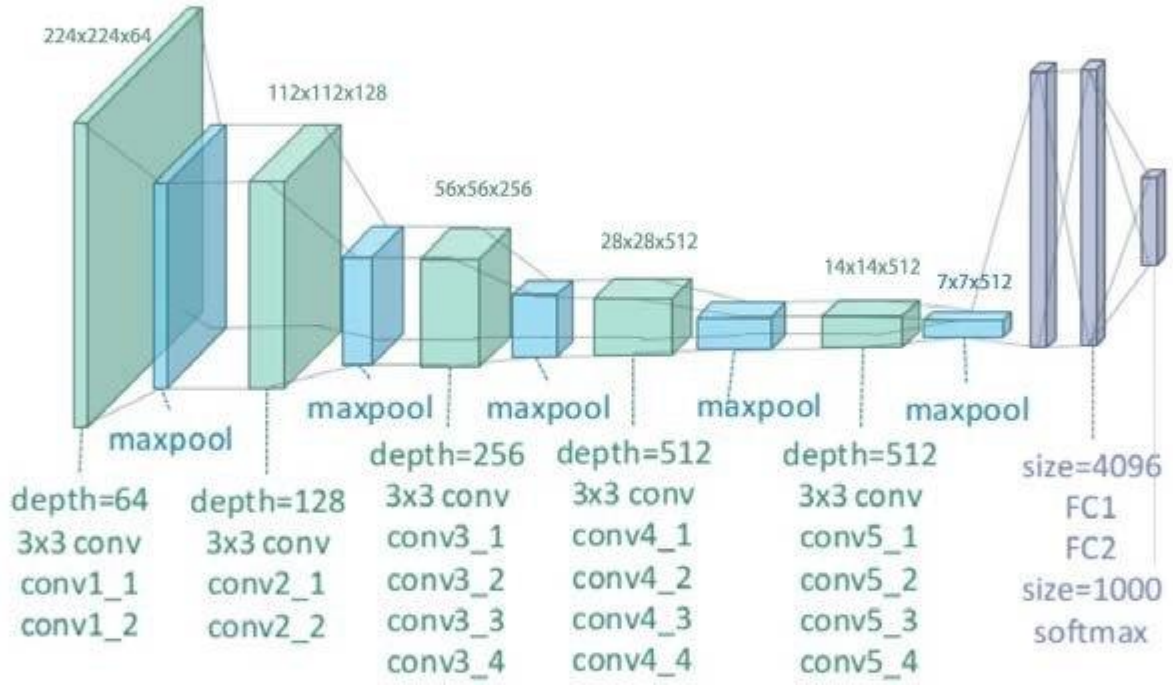


	precision	recall	f1-score	support
covid	1.00	1.00	1.00	15380
non-covid	1.00	1.00	1.00	18188
accuracy			1.00	33568
macro avg	1.00	1.00	1.00	33568
weighted avg	1.00	1.00	1.00	33568

VGG19 Architecture

VGG stands for Visual Geometry Group from Oxford. It is composed by 19 convolutional layers with a 3 x 3 Kernel, max pool kernel of size 2x2 size with stride 2, and 3 fully connected layers used for classification.

It has a total of about 143 million parameters.



VGG19 Architecture – Results

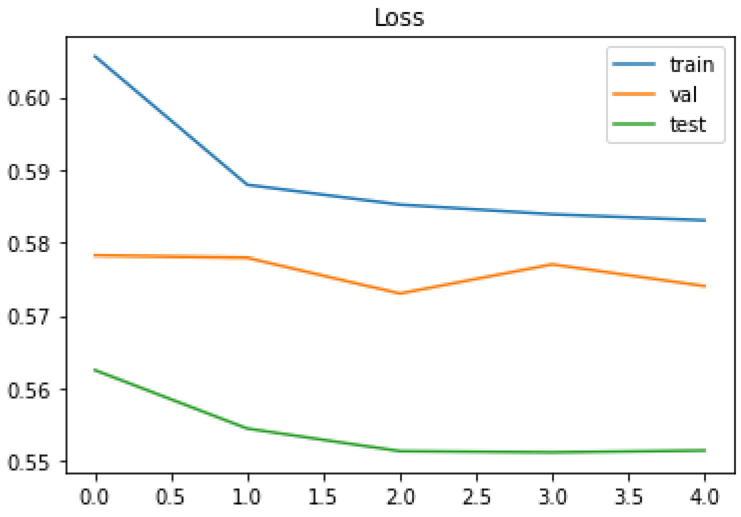
Epoch 1: Training Loss=0.6056, Training Accuracy=0.6771, Validation Loss=0.5782, Validation Accuracy=0.7077, Test Loss=0.5625, Test Accuracy=0.7207

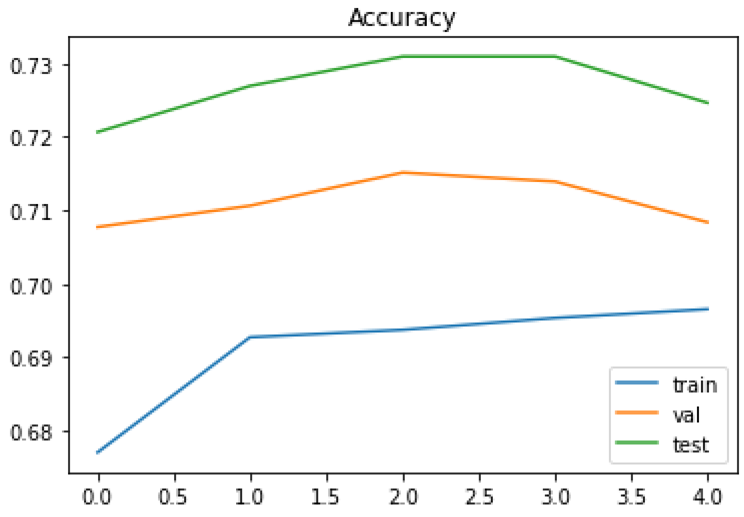
Epoch 2: Training Loss=0.5880, Training Accuracy=0.6927, Validation Loss=0.5779, Validation Accuracy=0.7106, Test Loss=0.5545, Test Accuracy=0.7269

Epoch 3: Training Loss=0.5852, Training Accuracy=0.6938, Validation Loss=0.5730, Validation Accuracy=0.7151, Test Loss=0.5513, Test Accuracy=0.7310

Epoch 4: Training Loss=0.5839, Training Accuracy=0.6954, Validation Loss=0.5771, Validation Accuracy=0.7139, Test Loss=0.5512, Test Accuracy=0.7310

Epoch 5: Training Loss=0.5831, Training Accuracy=0.6966, Validation Loss=0.5741, Validation Accuracy=0.7084, Test Loss=0.5514, Test Accuracy=0.7246

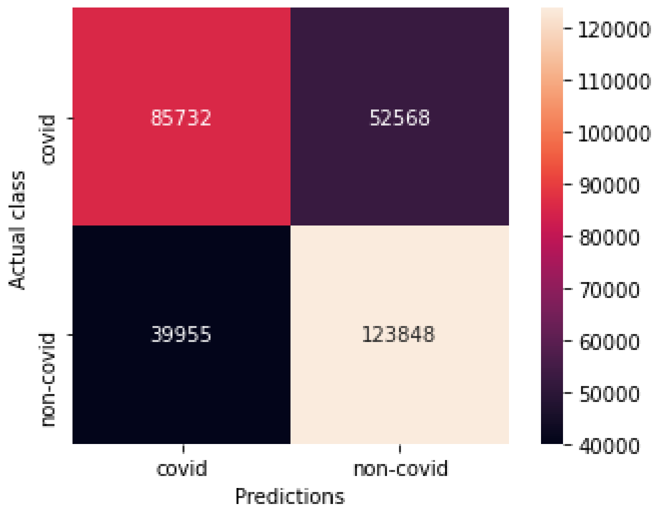




VGG19 Architecture – Results (Best model)

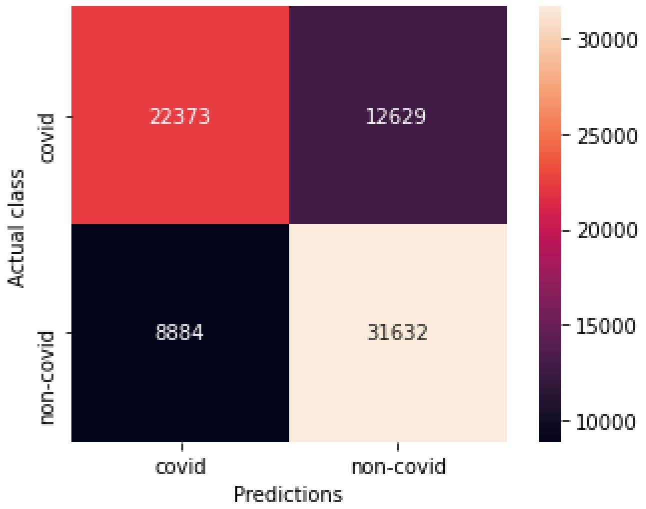
Epoch 3: Training Loss=0.5852, Training Accuracy=0.6938, Validation Loss=0.5730, Validation Accuracy=0.7151, Test Loss=0.5513, Test Accuracy=0.7310

Confusion Matrix train set



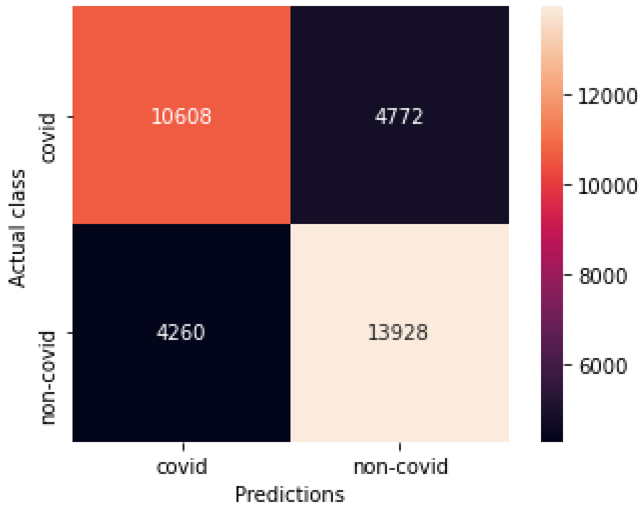
	precision	recall	f1-score	support
covid	0.68	0.62	0.65	138300
non-covid	0.70	0.76	0.73	163803
accuracy			0.69	302103
macro avg	0.69	0.69	0.69	302103
weighted avg	0.69	0.69	0.69	302103

Confusion Matrix val set



	precision	recall	f1-score	support
covid	0.72	0.64	0.68	35002
non-covid	0.71	0.78	0.75	40516
accuracy			0.72	75518
macro avg	0.72	0.71	0.71	75518
weighted avg	0.72	0.72	0.71	75518

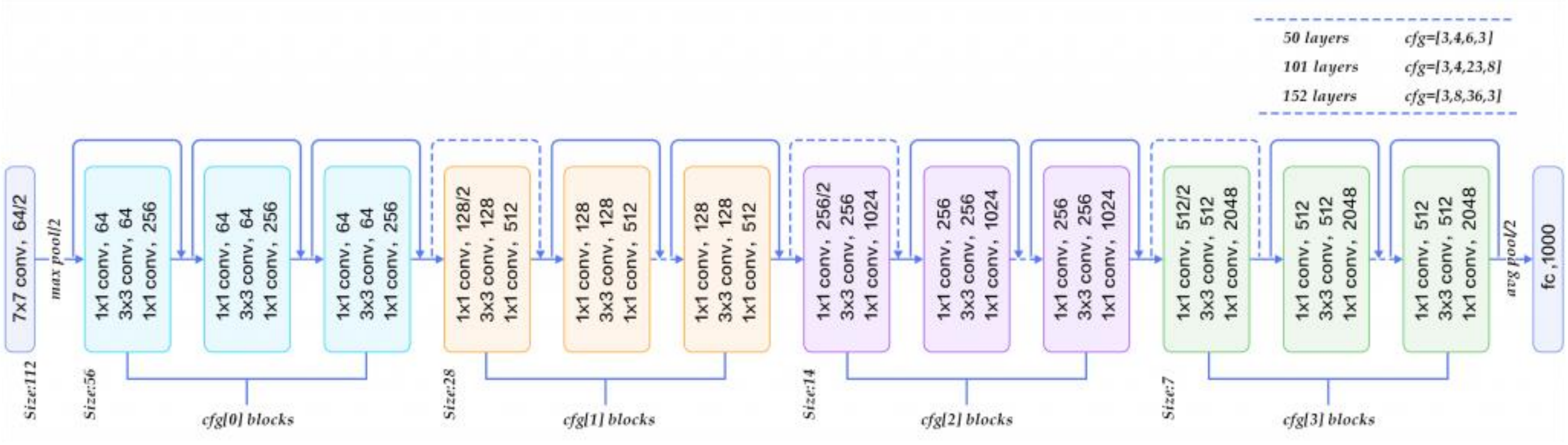
Confusion Matrix test set



	precision	recall	f1-score	support
covid	0.71	0.69	0.70	15380
non-covid	0.74	0.77	0.76	18188
accuracy			0.73	33568
macro avg	0.73	0.73	0.73	33568
weighted avg	0.73	0.73	0.73	33568

ResNet-152 Architecture

To avoid the problem of vanishing/exploding gradients ResNet uses the so Residual Block which is a residual mapping layer copied from the shallower layer. All convolutional layers apply the same convolutional window of size 3 × 3, the number of filters increases following the depth of networks, from 64 to 2048. There is only one max-pooling layer with pooling size 3 × 3, and a stride of 2 is applied after the first layer. The average pooling layer is applied to replace fully connected layers at the end of the architecture. It has 60 million of parameters.



ResNet-152 Architecture – Results

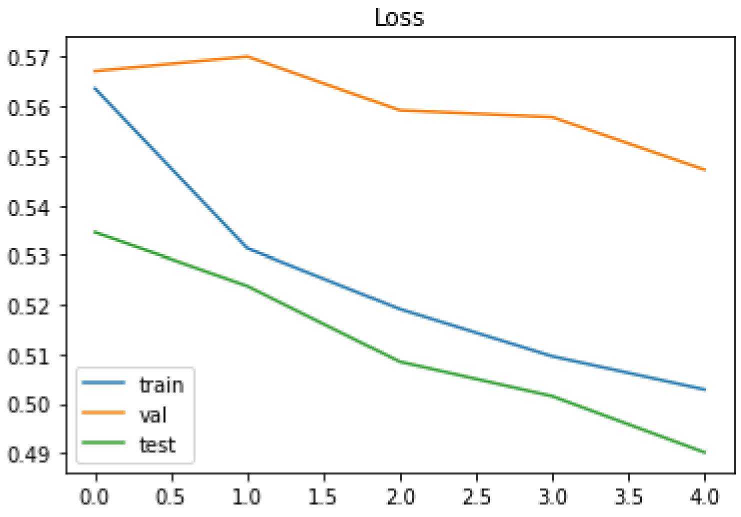
Epoch 1: Training Loss=0.5636, Training Accuracy=0.7139, Validation Loss=0.5671, Validation Accuracy=0.7171, Test Loss=0.5346, Test Accuracy=0.7363

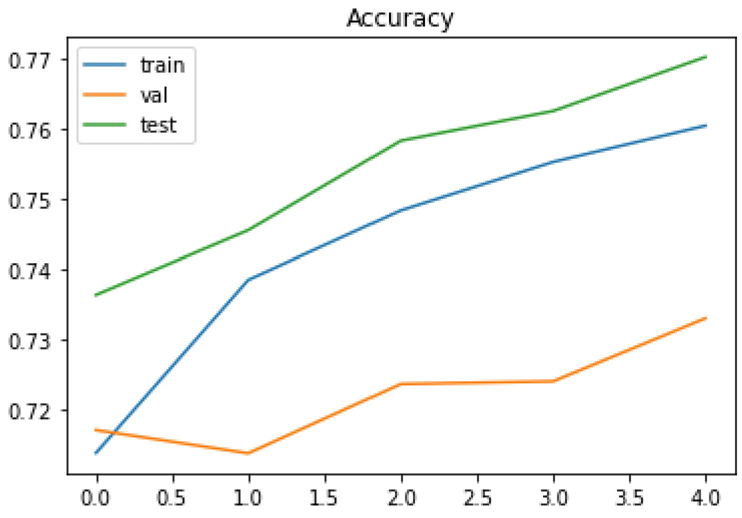
Epoch 2: Training Loss=0.5314, Training Accuracy=0.7385, Validation Loss=0.5701, Validation Accuracy=0.7138, Test Loss=0.5238, Test Accuracy=0.7455

Epoch 3: Training Loss=0.5191, Training Accuracy=0.7483, Validation Loss=0.5592, Validation Accuracy=0.7237, Test Loss=0.5085, Test Accuracy=0.7582

Epoch 4: Training Loss=0.5096, Training Accuracy=0.7552, Validation Loss=0.5578, Validation Accuracy=0.7240, Test Loss=0.5015, Test Accuracy=0.7624

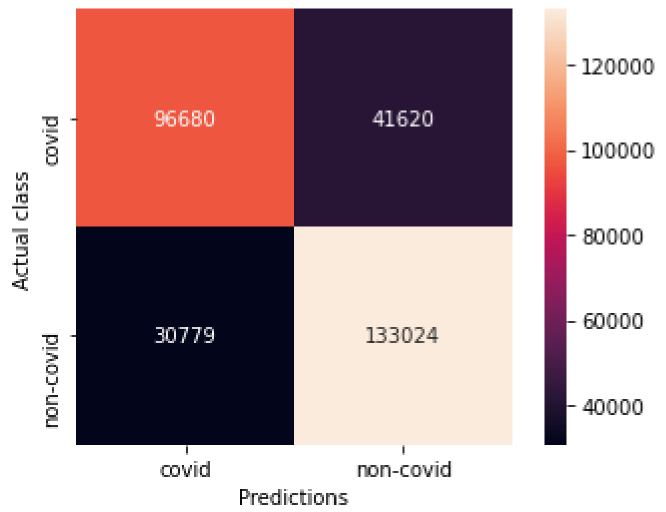
Epoch 5: Training Loss=0.5029, Training Accuracy=0.7603, Validation Loss=0.5472, Validation Accuracy=0.7330, Test Loss=0.4902, Test Accuracy=0.7701



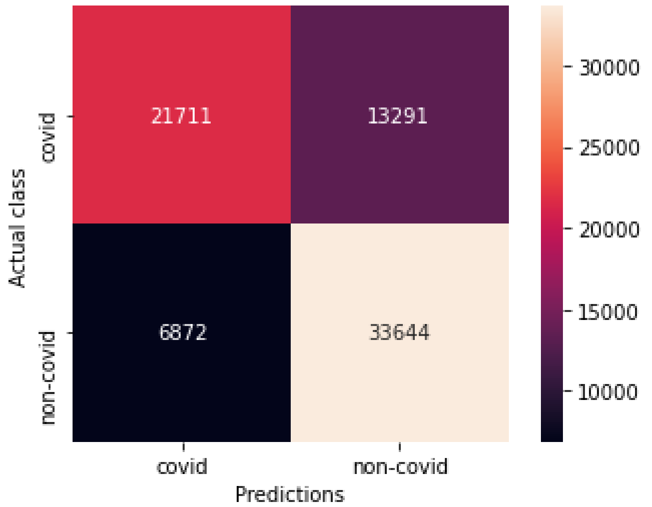


ResNet-152 Architecture – Results (Best model)

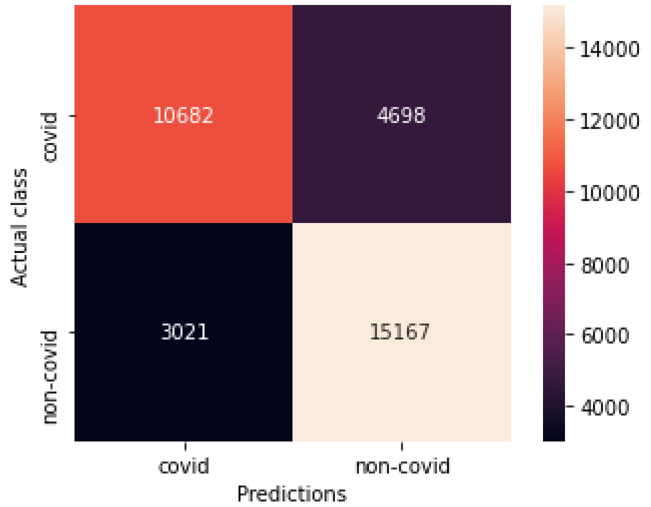
Epoch 5: Training Loss=0.5029, Training Accuracy=0.7603, Validation Loss=0.5472, Validation Accuracy=0.7330, Test Loss=0.4902, Test Accuracy=0.7701



	precision	recall	f1-score	support
covid	0.76	0.70	0.73	138300
non-covid	0.76	0.81	0.79	163803
accuracy			0.76	302103
macro avg	0.76	0.76	0.76	302103
weighted avg	0.76	0.76	0.76	302103



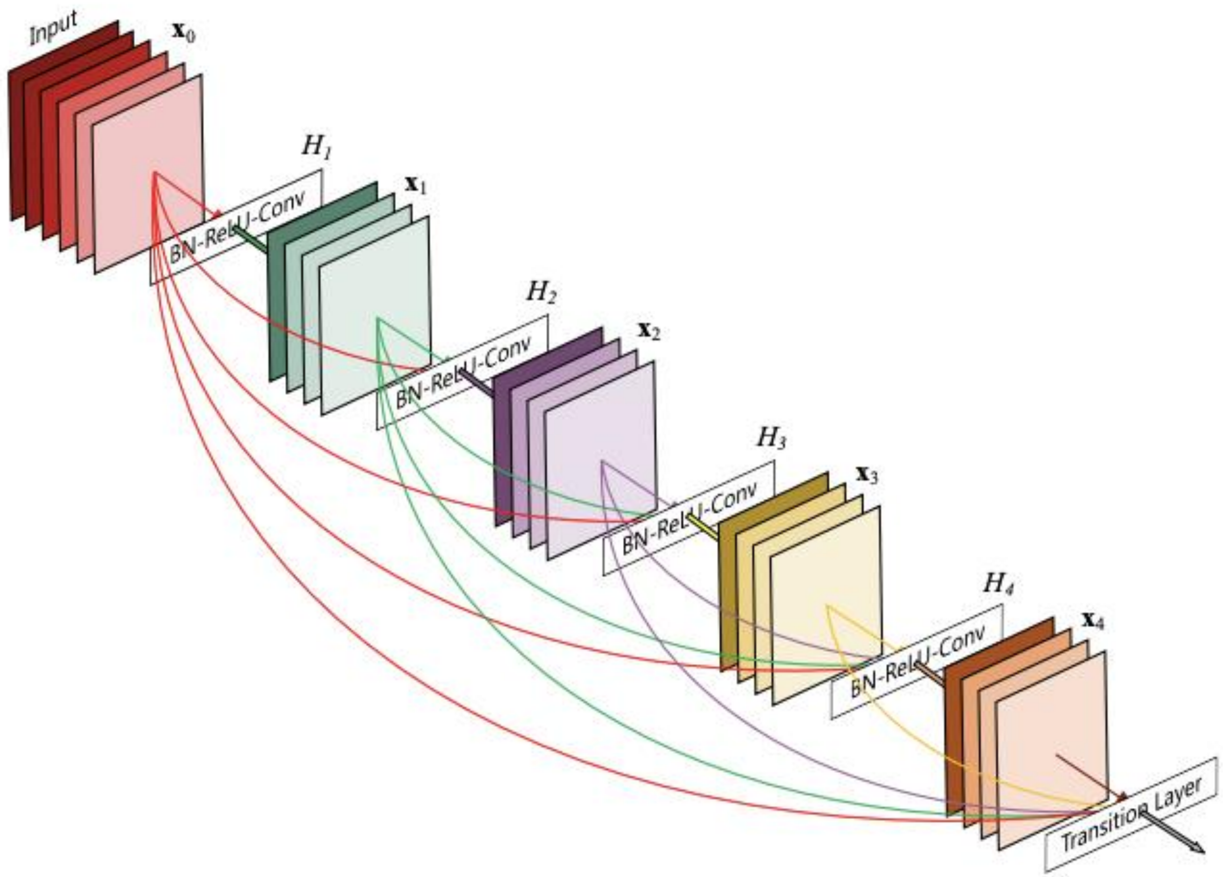
	precision	recall	f1-score	support
covid	0.76	0.62	0.68	35002
non-covid	0.72	0.83	0.77	40516
accuracy			0.73	75518
macro avg	0.74	0.73	0.73	75518
weighted avg	0.74	0.73	0.73	75518



	precision	recall	f1-score	support
covid	0.78	0.69	0.73	15380
non-covid	0.76	0.83	0.80	18188
accuracy			0.77	33568
macro avg	0.77	0.76	0.77	33568
weighted avg	0.77	0.77	0.77	33568

DenseNet-161 Architecture

Quite differently from ResNet, in DenseNet for each layer the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs into all subsequent layers. This alleviates the vanishing-gradient problem, strengthen feature propagation, encourage feature reuse, and substantially reduce the number of parameters. It is composed by a 7x7 convolutional layer with stride 2, then max pool 3x3 with stride 2, and then a series of dense blocks and transition layers. The classification layer is created by a 7x7 global average pool with a 1000D fully connected. It has 29 million of parameters.



DenseNet-161 Architecture – Results

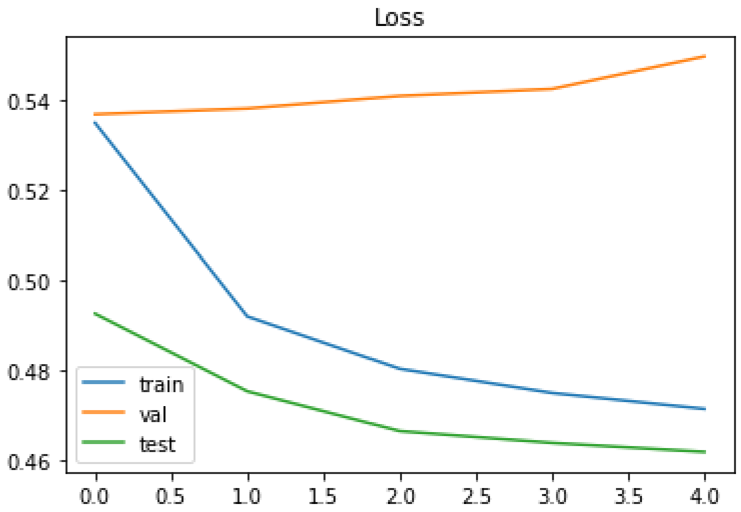
Epoch 1: Training Loss=0.5348, Training Accuracy=0.7375, Validation Loss=0.5367, Validation Accuracy=0.7381, Test Loss=0.4925, Test Accuracy=0.7699

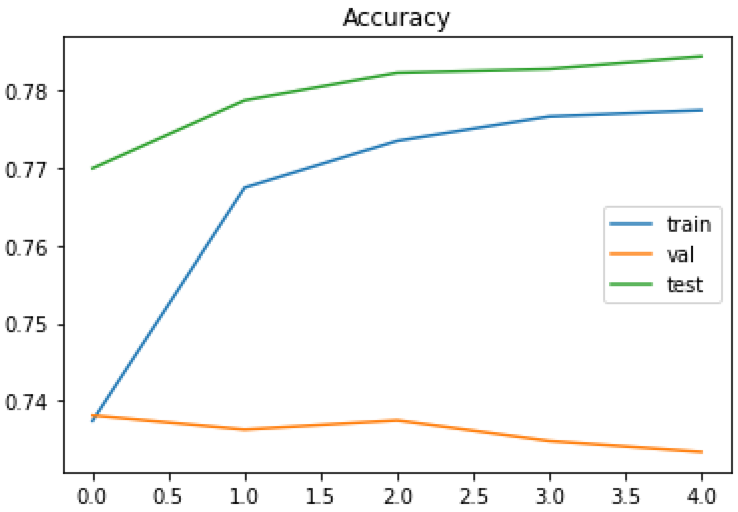
Epoch 2: Training Loss=0.4919, Training Accuracy=0.7674, Validation Loss=0.5380, Validation Accuracy=0.7363, Test Loss=0.4753, Test Accuracy=0.7787

Epoch 3: Training Loss=0.4802, Training Accuracy=0.7734, Validation Loss=0.5408, Validation Accuracy=0.7375, Test Loss=0.4664, Test Accuracy=0.7822

Epoch 4: Training Loss=0.4749, Training Accuracy=0.7766, Validation Loss=0.5423, Validation Accuracy=0.7348, Test Loss=0.4638, Test Accuracy=0.7827

Epoch 5: Training Loss=0.4713, Training Accuracy=0.7774, Validation Loss=0.5495, Validation Accuracy=0.7334, Test Loss=0.4618, Test Accuracy=0.7843

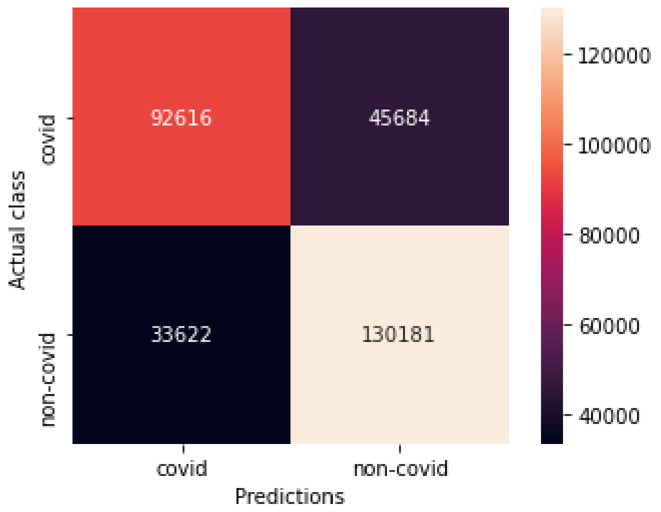




DenseNet-161 Architecture – Results (Best model)

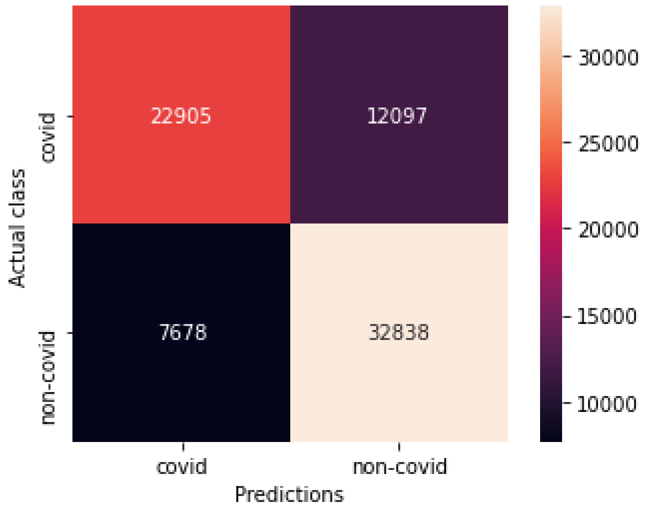
Epoch 1: Training Loss=0.5348, Training Accuracy=0.7375, Validation Loss=0.5367, Validation Accuracy=0.7381, Test Loss=0.4925, Test Accuracy=0.7699

Confusion Matrix train set



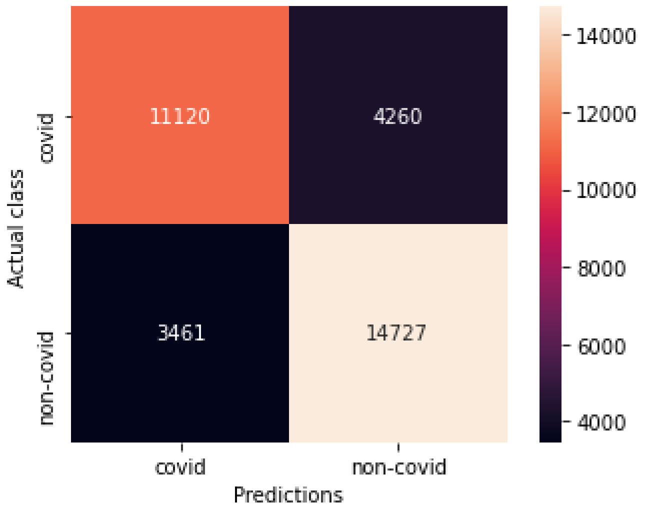
	precision	recall	f1-score	support
covid	0.73	0.67	0.70	138300
non-covid	0.73	0.79	0.77	163803
accuracy			0.74	302103
macro avg	0.74	0.73	0.73	302103
weighted avg	0.74	0.74	0.74	302103

Confusion Matrix val set



	precision	recall	f1-score	support
covid	0.75	0.65	0.70	35002
non-covid	0.73	0.81	0.77	40516
accuracy			0.74	75518
macro avg	0.74	0.73	0.73	75518
weighted avg	0.74	0.74	0.74	75518

Confusion Matrix test set



	precision	recall	f1-score	support
covid	0.76	0.72	0.74	15380
non-covid	0.78	0.81	0.79	18188
accuracy			0.77	33568
macro avg	0.77	0.77	0.77	33568
weighted avg	0.77	0.77	0.77	33568

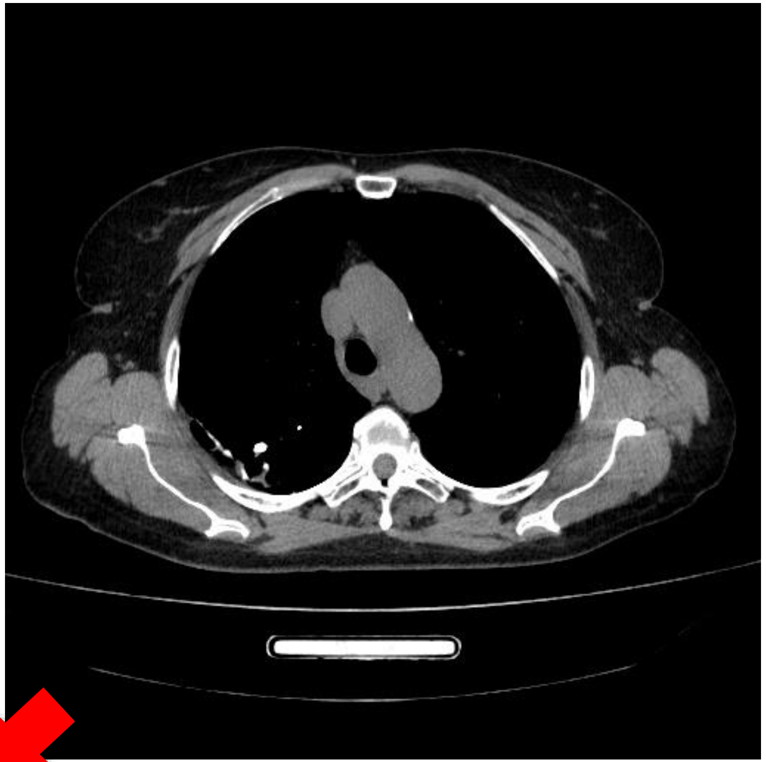
Comparison between architectures

Model	Epoch	Train Accuracy	Val Accuracy	Test Accuracy
My model FCN	4	0.996111	0.810769	0.996902
DenseNet-161	1	0.737452	0.738148	0.769911
ResNet-152	5	0.760347	0.733011	0.770119
VGG19	3	0.693755	0.715129	0.730952

Inference

The analysis of the Inference dataset

Data inconsistencies (same patient but different ct scans)



ct_scan_2 slice 100.jpg

ct_scan_3 slice 100.jpg

Inference on the Inference set

Prediction set consists in:

- Number of patients: 49
- Total number of slices: 14635
- Average number of slices per patient: 299

Patient: “ct_scan_21”
Number of Covid slices: 63/166
Number of Non-Covid slices: 103/166

Slice: 3.jpg - covid