# data\_aug\_adam\_val\_95\_28

October 7, 2021

### 1 Covid Classifier Model

### 1.0.1 Goals

Classify: - Normal CXR - Viral Pneumonia CXR - COVID CXR

### 1.1 Create Directories for Dataset

Separate the data to use later as generators.

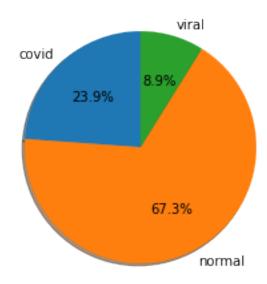
```
[]: # Matriz de confusion, cambiar learnings rates (learning rates dinamicos),
     → dropouts 0.3 & 0.2, Batch Normalization
     # K-Fold o avg de modelos
     import os
     BASE PATH = '/home/hivini/learn/research/new-covid'
     ORIGINAL_DATASET_DIR = os.path.join(BASE_PATH, 'COVID-19_Radiography_Dataset')
     ORIGINAL VIRAL DIR = os.path.join(ORIGINAL DATASET DIR, 'Viral Pneumonia')
     ORIGINAL_COVID_DIR = os.path.join(ORIGINAL_DATASET_DIR, 'COVID')
     ORIGINAL_NORMAL_DIR = os.path.join(ORIGINAL_DATASET_DIR, 'Normal')
     DATASET_DIR = os.path.join(BASE_PATH, 'small_dataset')
     TRAIN_DIR = os.path.join(DATASET_DIR, 'train')
     VALIDATION_DIR = os.path.join(DATASET_DIR, 'validation')
     TEST_DIR = os.path.join(DATASET_DIR, 'test')
     TRAIN_VIRAL_DIR = os.path.join(TRAIN_DIR, 'viral_pneumonia')
     TRAIN_COVID_DIR = os.path.join(TRAIN_DIR, 'covid')
     TRAIN_NORMAL_DIR = os.path.join(TRAIN_DIR, 'normal')
     VALIDATION_VIRAL_DIR = os.path.join(VALIDATION_DIR, 'viral_pneumonia')
     VALIDATION_COVID_DIR = os.path.join(VALIDATION_DIR, 'covid')
     VALIDATION_NORMAL_DIR = os.path.join(VALIDATION_DIR, 'normal')
     TEST_VIRAL_DIR = os.path.join(TEST_DIR, 'viral_pneumonia')
     TEST_COVID_DIR = os.path.join(TEST_DIR, 'covid')
     TEST NORMAL DIR = os.path.join(TEST DIR, 'normal')
     def createDir(path: str) -> None:
         if not os.path.exists(path):
             os.mkdir(path)
```

```
createDir(DATASET_DIR)
createDir(TRAIN_DIR)
createDir(VALIDATION_DIR)
createDir(TEST_DIR)
createDir(TRAIN_VIRAL_DIR)
createDir(TRAIN_COVID_DIR)
createDir(TRAIN_NORMAL_DIR)
createDir(VALIDATION_VIRAL_DIR)
createDir(VALIDATION_COVID_DIR)
createDir(VALIDATION_NORMAL_DIR)
createDir(TEST_VIRAL_DIR)
createDir(TEST_VIRAL_DIR)
createDir(TEST_COVID_DIR)
createDir(TEST_NORMAL_DIR)
```

```
[]: import numpy as np
     import shutil
     def generate_sets(source: str):
         allFiles = os.listdir(source)
         np.random.shuffle(allFiles)
         return np.split(np.array(allFiles), [int(len(allFiles)*0.7),__
      →int(len(allFiles)*0.85)])
     def saveAndSeparateFiles(src_dir: str, train_dir: str, val_dir: str, test_dir):
         train_fnames, val_fnames, test_fnames = generate_sets(src_dir)
         for fname in train_fnames:
             src = os.path.join(src_dir, fname)
             dst = os.path.join(train_dir, fname)
             shutil.copyfile(src, dst)
         for fname in val_fnames:
             src = os.path.join(src_dir, fname)
             dst = os.path.join(val_dir, fname)
             shutil.copyfile(src, dst)
         for fname in test_fnames:
             src = os.path.join(src_dir, fname)
             dst = os.path.join(test_dir, fname)
             shutil.copyfile(src, dst)
     create = False
     if create:
         saveAndSeparateFiles(ORIGINAL_NORMAL_DIR, TRAIN_NORMAL_DIR,
                             VALIDATION_NORMAL_DIR, TEST_NORMAL_DIR)
```

## 1.2 Counting our images

2021-10-07 20:14:24.777820: I tensorflow/stream\_executor/platform/default/dso\_loader.cc:49] Successfully opened dynamic library libcudart.so.10.1



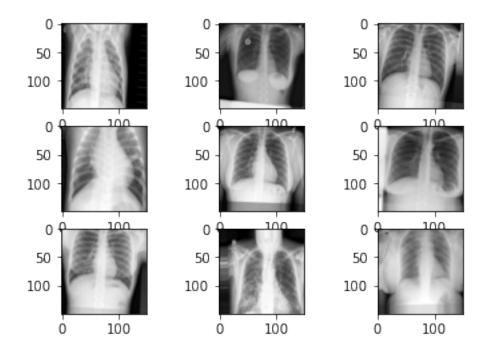
#### 1.3 Create our Covnet Model

In this case we are doing a multi class classification, our total clases are 3: - Viral CXR - Covid CXR - Normal CXR

Our neural network will output neurons as 3 classes that will calculate the probability of being one using the softmax function.

```
[]: from keras.preprocessing.image import ImageDataGenerator
     train_datagen = ImageDataGenerator(
        rescale=1./255,
        featurewise_center=False, # set input mean to 0 over the dataset
        samplewise_center=False, # set each sample mean to 0
        featurewise_std_normalization=False, # divide inputs by std of the dataset
        samplewise_std_normalization=False, # divide each input by its std
        zca_whitening=False, # apply ZCA whitening
         # randomly rotate images in the range (degrees, 0 to 180)
        rotation_range=10,
        zoom_range=0.1, # Randomly zoom image
         # randomly shift images horizontally (fraction of total width)
        width shift range=0.1,
         # randomly shift images vertically (fraction of total height)
        height_shift_range=0.1,
        horizontal_flip=False, # randomly flip images
        vertical_flip=False # randomly flip images
     )
     # train_datagen = ImageDataGenerator(rescale=1./255)
     test_datagen = ImageDataGenerator(rescale=1./255)
     evaluate_datagen = ImageDataGenerator(rescale=1./255)
     train_generator = train_datagen.flow_from_directory(
        TRAIN_DIR,
        target_size=(150, 150),
        batch size=32,
         class_mode='categorical',
         color mode='grayscale'
     )
     print(train_generator.class_indices)
     validation_generator = test_datagen.flow_from_directory(
        VALIDATION_DIR,
        target_size=(150, 150),
        batch_size=32,
        class_mode='categorical',
         color_mode='grayscale'
```

```
print(validation_generator.class_indices)
     test_generator = evaluate_datagen.flow_from_directory(
         TEST_DIR,
         target_size=(150, 150),
         batch_size=32,
         class_mode='categorical',
         color_mode='grayscale'
    print(test_generator.class_indices)
    Found 10606 images belonging to 3 classes.
    {'covid': 0, 'normal': 1, 'viral_pneumonia': 2}
    Found 2273 images belonging to 3 classes.
    {'covid': 0, 'normal': 1, 'viral_pneumonia': 2}
    Found 2274 images belonging to 3 classes.
    {'covid': 0, 'normal': 1, 'viral_pneumonia': 2}
[]: for X_batch, y_batch in train_generator:
             # create a grid of 3x3 images
             for i in range(0, 9):
                    plt.subplot(330 + 1 + i)
                     plt.imshow(X_batch[i].reshape(150, 150), cmap=plt.
     →get_cmap('gray'))
             # show the plot
             plt.show()
             break
```



```
[]: from keras.layers import Conv2D, BatchNormalization, MaxPooling2D, Dropout,
     →Flatten, Dense
     from keras.models import Sequential
     from keras import backend
     backend.clear_session()
     model = Sequential()
     model.add(Conv2D(64, (3, 3), activation='relu', input_shape=(150, 150, 1)))
     model.add(BatchNormalization())
     model.add(MaxPooling2D((2, 2)))
     model.add(Conv2D(64, (3, 3), activation='relu'))
     model.add(BatchNormalization())
     model.add(MaxPooling2D((2, 2)))
     model.add(Conv2D(128, (3, 3), activation='relu'))
     model.add(BatchNormalization())
     model.add(MaxPooling2D((2, 2)))
     model.add(Conv2D(128, (3, 3), activation='relu'))
     model.add(BatchNormalization())
     model.add(MaxPooling2D((2, 2)))
     model.add(Flatten())
     model.add(Dropout(0.5))
     model.add(Dense(512, activation='relu'))
     model.add(Dense(64, activation='relu'))
     model.add(Dense(3, activation='softmax'))
```

# model.summary()

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 64)	640
batch_normalization (BatchNo	(None, 148, 148, 64)	256
max_pooling2d (MaxPooling2D)	(None, 74, 74, 64)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	36928
batch_normalization_1 (Batch	(None, 72, 72, 64)	256
max_pooling2d_1 (MaxPooling2	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73856
batch_normalization_2 (Batch	(None, 34, 34, 128)	512
max_pooling2d_2 (MaxPooling2	(None, 17, 17, 128)	0
conv2d_3 (Conv2D)	(None, 15, 15, 128)	147584
batch_normalization_3 (Batch	(None, 15, 15, 128)	512
max_pooling2d_3 (MaxPooling2	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 6272)	0
dropout (Dropout)	(None, 6272)	0
dense (Dense)	(None, 512)	3211776
dense_1 (Dense)	(None, 64)	32832
dense_2 (Dense)	(None, 3)	195 

Total params: 3,505,347 Trainable params: 3,504,579 Non-trainable params: 768

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# []: from keras import optimizers

```
# opt = RMSprop(lr=0.0001, decay=1e-6)
opt = optimizers.Adam(learning_rate=1e-5, decay=1e-7)
model.compile(loss='categorical_crossentropy', optimizer=opt, use metrics=['accuracy'])
```

```
[]: import numpy as np
     from sklearn.utils import class_weight
     from keras.callbacks import EarlyStopping
     from keras.callbacks import ModelCheckpoint
     classes = train_generator.classes
     class_weights = class_weight.compute_class_weight(None,
                                                      np.unique(classes),
                                                      classes)
     best_model_path = os.path.join(BASE_PATH, 'best_model.h5')
     es = EarlyStopping(monitor='val loss', mode='min', verbose=1, patience=8)
     mc = ModelCheckpoint(best_model_path, monitor='val_accuracy', mode='max',_
     →verbose=1, save_best_only=True)
     history = model.fit(
         train_generator,
         steps_per_epoch=train_generator.n // 32,
         epochs=150,
         validation_data=validation_generator,
         class_weight=dict(zip(np.unique(classes), class_weights)),
         callbacks=[es, mc]
     )
```

```
331/331 [============= ] - 32s 97ms/step - loss: 0.4964 -
accuracy: 0.7868 - val_loss: 0.3578 - val_accuracy: 0.8460
Epoch 00004: val_accuracy improved from 0.82138 to 0.84602, saving model to
/home/hivini/learn/research/new-covid/best model.h5
Epoch 5/150
331/331 [============= ] - 33s 98ms/step - loss: 0.4639 -
accuracy: 0.8095 - val_loss: 0.3470 - val_accuracy: 0.8482
Epoch 00005: val_accuracy improved from 0.84602 to 0.84822, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 6/150
331/331 [============ ] - 32s 97ms/step - loss: 0.4297 -
accuracy: 0.8165 - val_loss: 0.3197 - val_accuracy: 0.8614
Epoch 00006: val_accuracy improved from 0.84822 to 0.86142, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 7/150
accuracy: 0.8239 - val_loss: 0.3027 - val_accuracy: 0.8667
Epoch 00007: val accuracy improved from 0.86142 to 0.86670, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 8/150
331/331 [============= ] - 32s 98ms/step - loss: 0.3966 -
accuracy: 0.8354 - val_loss: 0.2895 - val_accuracy: 0.8759
Epoch 00008: val_accuracy improved from 0.86670 to 0.87593, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 9/150
331/331 [============ ] - 32s 97ms/step - loss: 0.3773 -
accuracy: 0.8380 - val_loss: 0.2666 - val_accuracy: 0.8852
Epoch 00009: val_accuracy improved from 0.87593 to 0.88517, saving model to
/home/hivini/learn/research/new-covid/best model.h5
Epoch 10/150
accuracy: 0.8536 - val_loss: 0.2635 - val_accuracy: 0.8861
Epoch 00010: val_accuracy improved from 0.88517 to 0.88605, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 11/150
331/331 [============ ] - 32s 98ms/step - loss: 0.3531 -
accuracy: 0.8498 - val_loss: 0.2518 - val_accuracy: 0.8962
Epoch 00011: val_accuracy improved from 0.88605 to 0.89617, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 12/150
```

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accuracy: 0.8685 - val_loss: 0.2681 - val_accuracy: 0.8755
Epoch 00012: val_accuracy did not improve from 0.89617
Epoch 13/150
331/331 [============ ] - 33s 99ms/step - loss: 0.3219 -
accuracy: 0.8657 - val_loss: 0.2387 - val_accuracy: 0.9001
Epoch 00013: val accuracy improved from 0.89617 to 0.90013, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 14/150
331/331 [============ ] - 32s 98ms/step - loss: 0.3104 -
accuracy: 0.8723 - val_loss: 0.2520 - val_accuracy: 0.8869
Epoch 00014: val_accuracy did not improve from 0.90013
Epoch 15/150
331/331 [============ ] - 32s 98ms/step - loss: 0.2965 -
accuracy: 0.8830 - val_loss: 0.2434 - val_accuracy: 0.8971
Epoch 00015: val_accuracy did not improve from 0.90013
Epoch 16/150
accuracy: 0.8806 - val_loss: 0.2118 - val_accuracy: 0.9147
Epoch 00016: val_accuracy improved from 0.90013 to 0.91465, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 17/150
331/331 [============ ] - 32s 97ms/step - loss: 0.2868 -
accuracy: 0.8831 - val_loss: 0.2367 - val_accuracy: 0.9028
Epoch 00017: val_accuracy did not improve from 0.91465
Epoch 18/150
331/331 [============ ] - 32s 97ms/step - loss: 0.2923 -
accuracy: 0.8842 - val_loss: 0.2188 - val_accuracy: 0.9138
Epoch 00018: val_accuracy did not improve from 0.91465
Epoch 19/150
331/331 [============= ] - 32s 97ms/step - loss: 0.2632 -
accuracy: 0.8945 - val_loss: 0.2025 - val_accuracy: 0.9243
Epoch 00019: val_accuracy improved from 0.91465 to 0.92433, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 20/150
accuracy: 0.8963 - val_loss: 0.2460 - val_accuracy: 0.9001
Epoch 00020: val_accuracy did not improve from 0.92433
Epoch 21/150
```

```
accuracy: 0.9013 - val_loss: 0.2119 - val_accuracy: 0.9173
Epoch 00021: val_accuracy did not improve from 0.92433
Epoch 22/150
accuracy: 0.9100 - val_loss: 0.2993 - val_accuracy: 0.8869
Epoch 00022: val_accuracy did not improve from 0.92433
Epoch 23/150
331/331 [============== ] - 33s 101ms/step - loss: 0.2528 -
accuracy: 0.9013 - val_loss: 0.2243 - val_accuracy: 0.9081
Epoch 00023: val_accuracy did not improve from 0.92433
Epoch 24/150
331/331 [============== ] - 32s 97ms/step - loss: 0.2335 -
accuracy: 0.9075 - val_loss: 0.1725 - val_accuracy: 0.9344
Epoch 00024: val_accuracy improved from 0.92433 to 0.93445, saving model to
/home/hivini/learn/research/new-covid/best model.h5
Epoch 25/150
331/331 [============= ] - 32s 97ms/step - loss: 0.2201 -
accuracy: 0.9155 - val_loss: 0.2458 - val_accuracy: 0.9045
Epoch 00025: val_accuracy did not improve from 0.93445
Epoch 26/150
331/331 [============ ] - 32s 97ms/step - loss: 0.2123 -
accuracy: 0.9144 - val_loss: 0.1720 - val_accuracy: 0.9340
Epoch 00026: val_accuracy did not improve from 0.93445
Epoch 27/150
331/331 [=========== ] - 32s 97ms/step - loss: 0.2226 -
accuracy: 0.9140 - val_loss: 0.2461 - val_accuracy: 0.9028
Epoch 00027: val_accuracy did not improve from 0.93445
Epoch 28/150
accuracy: 0.9187 - val_loss: 0.1939 - val_accuracy: 0.9278
Epoch 00028: val_accuracy did not improve from 0.93445
Epoch 29/150
331/331 [============ ] - 32s 97ms/step - loss: 0.2133 -
accuracy: 0.9168 - val_loss: 0.1702 - val_accuracy: 0.9362
Epoch 00029: val_accuracy improved from 0.93445 to 0.93621, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 30/150
331/331 [============ ] - 32s 97ms/step - loss: 0.2060 -
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accuracy: 0.9200 - val_loss: 0.2272 - val_accuracy: 0.9168
Epoch 00030: val_accuracy did not improve from 0.93621
Epoch 31/150
331/331 [============== ] - 33s 100ms/step - loss: 0.1989 -
accuracy: 0.9221 - val_loss: 0.1639 - val_accuracy: 0.9419
Epoch 00031: val_accuracy improved from 0.93621 to 0.94193, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 32/150
331/331 [============ ] - 32s 98ms/step - loss: 0.2006 -
accuracy: 0.9201 - val_loss: 0.1861 - val_accuracy: 0.9296
Epoch 00032: val_accuracy did not improve from 0.94193
Epoch 33/150
accuracy: 0.9280 - val_loss: 0.1598 - val_accuracy: 0.9393
Epoch 00033: val_accuracy did not improve from 0.94193
Epoch 34/150
331/331 [============ ] - 32s 98ms/step - loss: 0.1854 -
accuracy: 0.9290 - val_loss: 0.1560 - val_accuracy: 0.9415
Epoch 00034: val_accuracy did not improve from 0.94193
Epoch 35/150
accuracy: 0.9256 - val_loss: 0.1750 - val_accuracy: 0.9362
Epoch 00035: val_accuracy did not improve from 0.94193
Epoch 36/150
accuracy: 0.9320 - val_loss: 0.1888 - val_accuracy: 0.9300
Epoch 00036: val_accuracy did not improve from 0.94193
Epoch 37/150
accuracy: 0.9343 - val_loss: 0.1431 - val_accuracy: 0.9485
Epoch 00037: val_accuracy improved from 0.94193 to 0.94853, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 38/150
331/331 [============ ] - 32s 97ms/step - loss: 0.1706 -
accuracy: 0.9365 - val_loss: 0.2093 - val_accuracy: 0.9182
Epoch 00038: val_accuracy did not improve from 0.94853
Epoch 39/150
331/331 [============= ] - 33s 99ms/step - loss: 0.1698 -
accuracy: 0.9343 - val_loss: 0.1483 - val_accuracy: 0.9459
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Epoch 00039: val_accuracy did not improve from 0.94853
Epoch 40/150
accuracy: 0.9300 - val_loss: 0.3303 - val_accuracy: 0.8808
Epoch 00040: val accuracy did not improve from 0.94853
Epoch 41/150
accuracy: 0.9342 - val_loss: 0.1278 - val_accuracy: 0.9538
Epoch 00041: val_accuracy improved from 0.94853 to 0.95381, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 42/150
accuracy: 0.9406 - val_loss: 0.1282 - val_accuracy: 0.9529
Epoch 00042: val_accuracy did not improve from 0.95381
Epoch 43/150
accuracy: 0.9362 - val_loss: 0.1600 - val_accuracy: 0.9459
Epoch 00043: val_accuracy did not improve from 0.95381
Epoch 44/150
331/331 [============= ] - 32s 98ms/step - loss: 0.1678 -
accuracy: 0.9350 - val_loss: 0.1712 - val_accuracy: 0.9388
Epoch 00044: val_accuracy did not improve from 0.95381
Epoch 45/150
331/331 [============ ] - 32s 98ms/step - loss: 0.1472 -
accuracy: 0.9466 - val_loss: 0.2125 - val_accuracy: 0.9221
Epoch 00045: val_accuracy did not improve from 0.95381
Epoch 46/150
accuracy: 0.9405 - val_loss: 0.1405 - val_accuracy: 0.9463
Epoch 00046: val_accuracy did not improve from 0.95381
Epoch 47/150
accuracy: 0.9422 - val_loss: 0.1406 - val_accuracy: 0.9454
Epoch 00047: val_accuracy did not improve from 0.95381
Epoch 48/150
accuracy: 0.9406 - val_loss: 0.1440 - val_accuracy: 0.9415
Epoch 00048: val_accuracy did not improve from 0.95381
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Epoch 49/150
331/331 [============ ] - 33s 98ms/step - loss: 0.1411 -
accuracy: 0.9506 - val_loss: 0.1244 - val_accuracy: 0.9520
Epoch 00049: val accuracy did not improve from 0.95381
Epoch 50/150
331/331 [============ ] - 32s 98ms/step - loss: 0.1466 -
accuracy: 0.9471 - val_loss: 0.1227 - val_accuracy: 0.9542
Epoch 00050: val_accuracy improved from 0.95381 to 0.95425, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 51/150
331/331 [============ ] - 32s 98ms/step - loss: 0.1399 -
accuracy: 0.9502 - val_loss: 0.1145 - val_accuracy: 0.9604
Epoch 00051: val_accuracy improved from 0.95425 to 0.96040, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 52/150
accuracy: 0.9454 - val_loss: 0.1282 - val_accuracy: 0.9534
Epoch 00052: val_accuracy did not improve from 0.96040
Epoch 53/150
accuracy: 0.9471 - val_loss: 0.1304 - val_accuracy: 0.9525
Epoch 00053: val_accuracy did not improve from 0.96040
Epoch 54/150
accuracy: 0.9455 - val_loss: 0.1264 - val_accuracy: 0.9534
Epoch 00054: val_accuracy did not improve from 0.96040
Epoch 55/150
331/331 [============ ] - 33s 99ms/step - loss: 0.1311 -
accuracy: 0.9511 - val loss: 0.1231 - val accuracy: 0.9556
Epoch 00055: val_accuracy did not improve from 0.96040
Epoch 56/150
accuracy: 0.9511 - val_loss: 0.1078 - val_accuracy: 0.9630
Epoch 00056: val_accuracy improved from 0.96040 to 0.96304, saving model to
/home/hivini/learn/research/new-covid/best_model.h5
Epoch 57/150
accuracy: 0.9520 - val_loss: 0.1473 - val_accuracy: 0.9424
```

Epoch 00057: val\_accuracy did not improve from 0.96304

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Epoch 58/150
accuracy: 0.9513 - val_loss: 0.3040 - val_accuracy: 0.8883
Epoch 00058: val_accuracy did not improve from 0.96304
Epoch 59/150
accuracy: 0.9511 - val_loss: 0.1260 - val_accuracy: 0.9551
Epoch 00059: val_accuracy did not improve from 0.96304
Epoch 60/150
accuracy: 0.9503 - val_loss: 0.2046 - val_accuracy: 0.9212
Epoch 00060: val_accuracy did not improve from 0.96304
Epoch 61/150
accuracy: 0.9499 - val_loss: 0.1233 - val_accuracy: 0.9534
Epoch 00061: val_accuracy did not improve from 0.96304
Epoch 62/150
331/331 [============ ] - 33s 98ms/step - loss: 0.1302 -
accuracy: 0.9519 - val_loss: 0.1722 - val_accuracy: 0.9305
Epoch 00062: val_accuracy did not improve from 0.96304
Epoch 63/150
331/331 [============ ] - 32s 98ms/step - loss: 0.1256 -
accuracy: 0.9552 - val_loss: 0.1041 - val_accuracy: 0.9626
Epoch 00063: val_accuracy did not improve from 0.96304
Epoch 64/150
331/331 [============ ] - 33s 98ms/step - loss: 0.1235 -
accuracy: 0.9542 - val_loss: 0.1200 - val_accuracy: 0.9573
Epoch 00064: val_accuracy did not improve from 0.96304
Epoch 65/150
accuracy: 0.9580 - val_loss: 0.1047 - val_accuracy: 0.9604
Epoch 00065: val_accuracy did not improve from 0.96304
Epoch 66/150
331/331 [============ ] - 32s 97ms/step - loss: 0.1067 -
accuracy: 0.9613 - val_loss: 0.1170 - val_accuracy: 0.9564
Epoch 00066: val_accuracy did not improve from 0.96304
Epoch 67/150
331/331 [============= ] - 32s 97ms/step - loss: 0.1211 -
accuracy: 0.9561 - val_loss: 0.1134 - val_accuracy: 0.9613
```

```
Epoch 00067: val_accuracy did not improve from 0.96304
   Epoch 68/150
   331/331 [============ ] - 32s 97ms/step - loss: 0.1259 -
   accuracy: 0.9533 - val_loss: 0.1126 - val_accuracy: 0.9591
   Epoch 00068: val accuracy did not improve from 0.96304
   Epoch 69/150
   331/331 [============== ] - 33s 100ms/step - loss: 0.1228 -
   accuracy: 0.9567 - val_loss: 0.1229 - val_accuracy: 0.9542
   Epoch 00069: val_accuracy did not improve from 0.96304
   Epoch 70/150
   accuracy: 0.9597 - val_loss: 0.1443 - val_accuracy: 0.9450
   Epoch 00070: val_accuracy did not improve from 0.96304
   Epoch 71/150
   accuracy: 0.9566 - val_loss: 0.1493 - val_accuracy: 0.9468
   Epoch 00071: val_accuracy did not improve from 0.96304
   Epoch 00071: early stopping
[]: model.save(os.path.join(BASE_PATH, 'covid_classifier_result.h5'))
[]: test_loss, test_acc = model.evaluate(test_generator)
    print("Loss on test set: ", test_loss)
    print("Accuracy on test set: ", test_acc)
   0.9529
   Loss on test set: 0.1348775327205658
   Accuracy on test set: 0.9529463648796082
[]: import matplotlib.pyplot as plt
    acc = history.history['accuracy']
    val_acc = history.history['val_accuracy']
    loss = history.history['loss']
    val_loss = history.history['val_loss']
    epochs = range(1, len(acc) + 1)
    # bo is for blue dot.
    plt.plot(epochs, loss, 'g', label='Training loss')
    # b is for solid blue line
    plt.plot(epochs, val_loss, 'b', label='Validation loss')
```

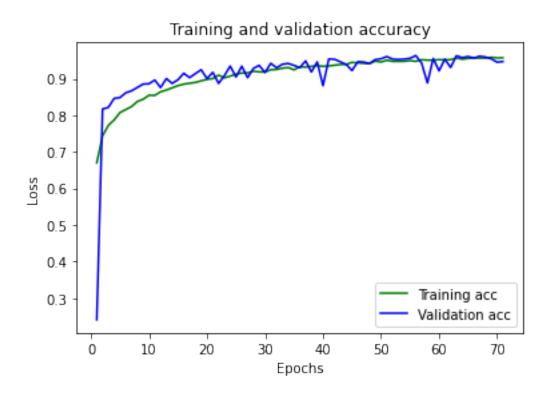
```
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

# Training and validation loss Training loss 1.6 Validation loss 1.4 1.2 1.0 0.8 0.6 0.4 0.2 50 0 10 20 30 40 60 70 Epochs

```
plt.clf()

plt.plot(epochs, acc, 'g', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



```
X_{test} = []
     Y_{test} = []
     # Extract the data
     for X, Y in test_generator:
         X_test.append(X)
         Y_test.append(Y)
     X_test = np.array(X_test)
     Y_test = np.array(Y_test)
     predictions = model.predict_classes(X_test)
     predictions = predictions.reshape(1, -1)[0]
     print(classification_report(Y_test, predictions, target_names=[
           'Covid (Class 0)', 'Normal (Class 1)', 'Viral Pneumonia (Class 2)']))
[]: import pandas as pd
     import seaborn as sns
     labels = ['covid', 'normal', 'viral_pneumonia']
     cm = confusion_matrix(Y_test,predictions)
```

[]: from sklearn.metrics import classification\_report, confusion\_matrix

```
cm = pd.DataFrame(cm , index = ['0','1'] , columns = ['0','1'])
plt.figure(figsize = (10,10))
sns.heatmap(cm,cmap= "Reds", linecolor = 'black' , linewidth = 1 , annot = True, fmt='',xticklabels = labels,yticklabels = labels)
```