Importing Packages:

```
In [1]:
         import numpy as np
         from keras.preprocessing.image import img to array
         import matplotlib.pyplot as plt
         import pandas as pd
         import shutil
         import os
         from tqdm import tqdm
         from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
         from sklearn.linear model import LogisticRegression
         from sklearn.naive bayes import GaussianNB
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.svm import SVC
         from sklearn.metrics import accuracy score
         from PIL import Image
```

```
In [2]:
         import numpy as np
         import pickle
         import cv2
         from os import listdir
         import tensorflow as tf
         from sklearn.preprocessing import LabelBinarizer
         import keras
         from keras.models import Sequential
         from keras.layers import BatchNormalization
         from tensorflow.keras.layers import GlobalAveragePooling2D
         from keras.preprocessing.image import ImageDataGenerator
         from keras.layers.convolutional import Conv2D
         from keras.layers.convolutional import MaxPooling2D
         from keras.layers.core import Activation, Flatten, Dropout, Dense
         from keras import optimizers
         from keras import backend as K
         from keras.preprocessing.image import ImageDataGenerator
         from keras.preprocessing import image
         from keras.preprocessing.image import img to array
         from sklearn.preprocessing import MultiLabelBinarizer
         from sklearn.model_selection import train_test_split
         from keras.callbacks import ModelCheckpoint
         import matplotlib.pyplot as plt
```

```
In [3]:
    from google.colab import drive
    drive.mount('/content/gdrive')
```

Mounted at /content/gdrive

For training and test dataset I have clicked pictures of various plant leaves from nearby villages and using these images I will be training a model which will later predict whether a plant is healthy or not by using an image of a leaf as input.

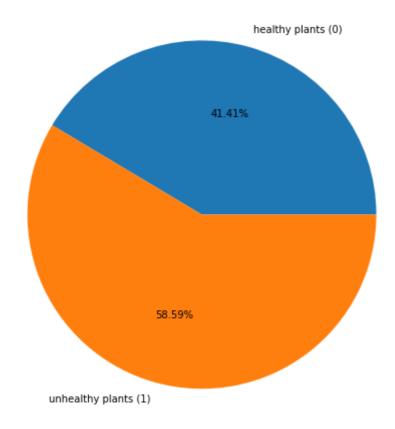
Exploratory Data Ananlysis:

```
In []:
    train_wd= os.listdir('/content/gdrive/MyDrive/plant_disease/self_collected_datain_woutd= os.listdir('/content/gdrive/MyDrive/plant_disease/self_collected_val_wd= os.listdir('/content/gdrive/MyDrive/plant_disease/self_collected_data
```

```
val_woutd= os.listdir('/content/gdrive/MyDrive/plant_disease/self_collected_c
train_wd_percent= len(train_wd)/len(train_wd+train_woutd)
train_woutd_percent= len(train_woutd)/len(train_wd+train_woutd)
val_wd_percent= len(val_wd)/len(val_wd+val_woutd)
val_woutd_percent= len(val_woutd)/len(val_wd+ val_woutd)
print("Ratio of healthy and unhealthy plants in training dataset is {}:{}".fc
print("Ratio of healthy and unhealthy plants in validation dataset is {}:{}".
```

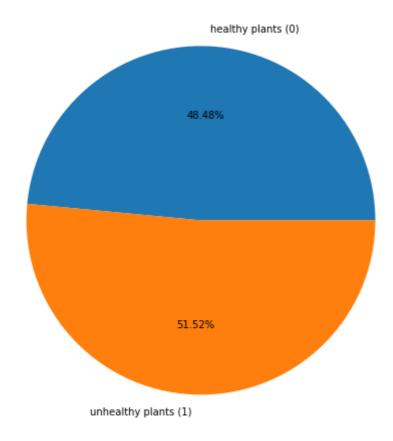
Ratio of healthy and unhealthy plants in training dataset is 41:58 Ratio of healthy and unhealthy plants in validation dataset is 48:51

Pie Chart denoting ratio of healthy and unhleahty images from training dataset:



Ratio of healthy and unhealthy plants in training dataset is 41:58 Pie Chart denoting ratio of healthy and unhleahty images from validation dataset:

```
autopct='%1.2f%%')
plt.show()
print("Ratio of healthy and unhealthy plants in validation dataset is {}:{}"
```



Ratio of healthy and unhealthy plants in validation dataset is 48:51 Dataset is almost balanced with slight unbalancing in train dataset. Validation dataset seems to be almost balanced with a very slight difference.

Preview of dataset

Lets take a quick look at some of the images from our dataset (healthy and unhealthy plants):

Plants with diseases

```
In []: # create figure
fig = plt.figure(figsize=(11, 9))

# reading images
Img_1 = Image.open('/content/gdrive/MyDrive/plant_disease/self_collected_data
Img_2 = Image.open('/content/gdrive/MyDrive/plant_disease/self_collected_data
Img_3 = Image.open('/content/gdrive/MyDrive/plant_disease/self_collected_data
Img_4 = Image.open('/content/gdrive/MyDrive/plant_disease/self_collected_data
# Add subplot at the 1st position
fig.add_subplot(2, 2, 1)

# show image
plt.imshow(Img_1)
plt.axis('off')
plt.title("Leaf 1")
```

```
# Add subplot at the 2nd position
fig.add_subplot(2, 2, 2)
# show image
plt.imshow(Img 2)
plt.axis('off')
plt.title("Leaf 2")
# Add subplot at the 3rd position
fig.add subplot(2, 2, 3)
# show image
plt.imshow(Img 3)
plt.axis('off')
plt.title("Leaf 3")
# Add subplot at the 4th position
fig.add subplot(2, 2, 4)
# show image
plt.imshow(Img 4)
plt.axis('off')
plt.title("Leaf 4")
```

Out[]: Text(0.5, 1.0, 'Leaf 4')





Leaf 2



Leaf 3



Leaf 4



As we can see from the above images that plants with disease seems to look a lot different from healthy plants' leaves. Plants suffering from disease tend to have discolored leaves like yellow color and also dry in nature. Apart from that leaves often tend to be disfigures, shrink or have cuts at different places.

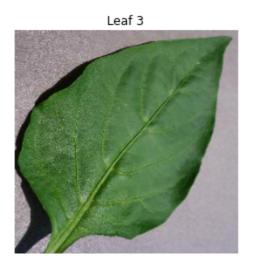
Plants without diseases

```
In [ ]:
         # create figure
         fig = plt.figure(figsize=(11, 9))
         # reading images
         Img 1 = Image.open('/content/gdrive/MyDrive/plant disease/self collected data
         Img_2 = Image.open('/content/gdrive/MyDrive/plant_disease/self_collected_data
         Img_3 = Image.open('/content/gdrive/MyDrive/plant_disease/self_collected_data
         Img 4 = Image.open('/content/gdrive/MyDrive/plant disease/self collected data
         # Add subplot at the 1st position
         fig.add subplot(2, 2, 1)
         # show image
         plt.imshow(Img 1)
         plt.axis('off')
         plt.title("Leaf 1")
         # Add subplot at the 2nd position
         fig.add subplot(2, 2, 2)
         # show image
         plt.imshow(Img 2)
         plt.axis('off')
         plt.title("Leaf 2")
         # Add subplot at the 3rd position
         fig.add subplot(2, 2, 3)
         # show image
         plt.imshow(Img 3)
         plt.axis('off')
         plt.title("Leaf 3")
         # Add subplot at the 4th position
         fig.add subplot(2, 2, 4)
         # show image
         plt.imshow(Img 4)
         plt.axis('off')
         plt.title("Leaf 4")
```

```
Out[]: Text(0.5, 1.0, 'Leaf 4')
```









Healthy plants look all green in color without any disfigured leaf, without any cuts anywhere in leaf part discoloration or dryness.

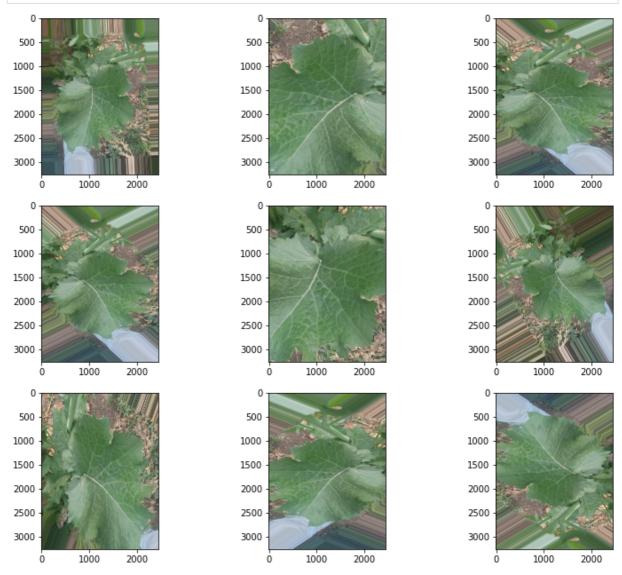
Preprocessing:

For preprocessing, I will be using ImageDataGenerator to transform images as per following:

- rotation
- zoom
- · vertical_flip
- · horizontal_flip
- shear_range

Now, lets check how our ImageDataGenerator will give output image when a single image is input to it:

```
horizontal_flip=True,
                                     vertical_flip=True,
                                     validation split=0.2)
# make iterator
it = datagen.flow(samples, batch size=1)
fig = plt.figure(figsize=(13, 11))
# generate samples and plot
for i in range(9):
    # define subplot
    fig.add_subplot(330 + 1 + i)
    # generate batch of images
    batch = it.next()
    # convert to unsigned integers for viewing
    image = batch[0].astype('uint8')
    # plot raw pixel data
    plt.imshow(image)
# show the figure
plt.show()
```



Reading images from directory in ImageDataGenerator:

```
directory=r"/content/gdrive/MyDrive/self_collected/data",
    subset='training',
    target_size=(254, 254),
    color_mode="rgb",
    batch size= 32,
    class mode="categorical",
    shuffle=True,
    seed=42
valid generator = data generator.flow from directory(
    directory=r"/content/gdrive/MyDrive/self collected/data",
    subset='validation',
    target size=(254, 254),
    color mode="rgb",
    batch size= 32,
    class mode="categorical",
    shuffle=True,
    seed=42
```

Found 1697 images belonging to 2 classes. Found 726 images belonging to 2 classes.

Since our data is small and we also have little computation power, so to get better performing model we will be using transfer learning using a pre trained weights like 'imagenet'.

Training on 'Plant Village' dataset to get weights for transfer learning:

Converting 'Plant Village' dataset into Binary class Dataset:

'Plant Village' dataset originally contains folders with various plants and particular diseases they are suffering from and healthy plants. So originally 'Plant Village' dataset is multiclass dataset. So I will be changing this dataset into binary class dataset by seperating images of 'healthy' and 'unhealthy' leaves into seperate folders:

```
In [ ]:
         import shutil
         import os
         from tqdm import tqdm
         src path= '/content/PlantVillage/'
         src root = os.listdir('/content/PlantVillage/')
         wd=[] #with disease
         wtd=[] #without disease
         #seperating healthy and unhealthy plants folder names:
         for folder in tqdm(src_root):
           full_folder_name= src_path + folder
           for file name in os.listdir(full folder name):
             if full_folder_name[-7:]!='healthy':
               wd.append(full_folder_name)
             else:
               wtd.append(full_folder_name)
```

Jut[]: "import shutil\nimport os\nfrom tqdm import tqdm\n\nsrc_path= '/content/Plant
 Village/'\nsrc_root = os.listdir('/content/PlantVillage/')\nwd=[]\nwtd=[]\n\n
 for folder in tqdm(src_root):\n full_folder_name= src_path + folder\n for f
 ile_name in os.listdir(full_folder_name):\n if full_folder_name[-7:]!='hea

```
wd.append(full_folder_name)\n
                                                        else:\n
                                                                     wtd.append(full f
        lthy':\n
        older_name)"
In [ ]:
         # copy all images of unhealthy leavse into 'wd' i.e with disease folder
         for full folder name in list(set(wd)):
           for file name in tqdm(os.listdir(full folder name)):
             full_file_name = full_folder_name + '/' + file_name
             dest= '/content/drive/MyDrive/plant disease/plant village/data/wd'
             shutil.copy(full file name, dest)
             cnt.append(1)
                         952/952 [00:11<00:00, 82.68it/s]
        100%
        100%|
                         1771/1771 [00:20<00:00, 87.17it/s]
                         2127/2127 [00:24<00:00, 86.49it/s]
        100%
        100%|
                         1000/1000 [00:11<00:00, 85.52it/s]
        100%|
                         997/997 [00:11<00:00, 86.16it/s]
        100%|
                         1404/1404 [00:16<00:00, 85.84it/s]
        100%|
                         1909/1909 [00:21<00:00, 88.20it/s]
                         1676/1676 [00:19<00:00, 87.70it/s]
        100%
                         1000/1000 [00:11<00:00, 85.82it/s]
        100%
                         1000/1000 [00:11<00:00, 87.60it/s]
        100%
                         3209/3209 [00:36<00:00, 87.04it/s]
        100%
                         373/373 [00:04<00:00, 86.56it/s]
        100%
In [ ]:
         len(cnt) #count of images of unhealthy leaves
Out[]: 17418
In []:
         # copy all images of healthy leavse into 'wtd' i.e without disease folder
         for full folder name in list(set(wtd)):
           for file name in tqdm(os.listdir(full folder name)):
             full file name = full folder name + '/' + file name
             dest= '/content/drive/MyDrive/plant disease/plant village/data/wtd'
             shutil.copy(full file name, dest)
             cnt.append(1)
        100%
                         1478/1478 [00:17<00:00, 85.25it/s]
        100%
                         152/152 [00:01<00:00, 92.09it/s]
        100%
                         1591/1591 [00:18<00:00, 87.76it/s]
In [ ]:
         len(cnt) #count of images of healthy leaves
Out[]: 3221
```

Reading Plant Village Data:

Now that we have plant village dataset as Binary Class i.e 'healthy' and 'unhealthy' class we can begin reading this dataset.

g)

```
tf.Tensor(b'/content/gdrive/MyDrive/plant_disease/plant_village/data/wd/0982d
        864-182e-4d36-959a-dcc67d85d9e6___RS_Erly.B 9481.JPG', shape=(), dtype=strin
        tf.Tensor(b'/content/gdrive/MyDrive/plant_disease/plant_village/data/wd/23857
        b36-24f3-4745-a877-dedde5c5931c YLCV NREC 2520.JPG', shape=(), dtype=strin
        tf.Tensor(b'/content/gdrive/MyDrive/plant disease/plant village/data/wd/a87b8
        e0c-2279-4cf7-85a4-0fba63130902 RS Late.B 5323.JPG', shape=(), dtype=strin
        tf.Tensor(b'/content/gdrive/MyDrive/plant disease/plant village/data/wd/56920
        6bf-423e-4508-b1b4-2ca6821aceac RS Early.B 7554.JPG', shape=(), dtype=strin
        tf.Tensor(b'/content/qdrive/MyDrive/plant disease/plant village/data/wd/58d5c
        tf.Tensor(b'/content/gdrive/MyDrive/plant_disease/plant_village/data/wd/de583
        596-e89f-4a21-be43-a6629318bd6e NREC B.Spot 1840.JPG', shape=(), dtype=stri
        tf.Tensor(b'/content/gdrive/MyDrive/plant disease/plant village/data/wd/edlal
        e55-f2b9-46d3-ab88-8742f569e831 GHLB2 Leaf 8758.JPG', shape=(), dtype=strin
        tf.Tensor(b'/content/gdrive/MyDrive/plant disease/plant village/data/wd/1b589
        f92-a658-4e58-96de-db4lacc411ce JR B.Spot 3239.JPG', shape=(), dtype=strin
        tf.Tensor(b'/content/gdrive/MyDrive/plant disease/plant village/data/wtd/c5f1
        eec0-35c2-43ce-8a14-575d86258f73___RS_HL 0337.JPG', shape=(), dtype=string)
        tf.Tensor(b'/content/gdrive/MyDrive/plant disease/plant village/data/wtd/dad1
        27e0-8761-47bd-8ea1-21727847a1f4 RS HL 0416.JPG', shape=(), dtype=string)
        tf.Tensor(b'/content/gdrive/MyDrive/plant disease/plant village/data/wtd/1317
        fd49-1819-4065-b3a4-d74f9763c7c4 RS HL 0252.JPG', shape=(), dtype=string)
        tf.Tensor(b'/content/gdrive/MyDrive/plant disease/plant village/data/wd/2741b
        105-dacf-4ed8-bedf-4fc395f8947c Keller.St CG 1943.JPG', shape=(), dtype=str
        tf.Tensor(b'/content/gdrive/MyDrive/plant disease/plant village/data/wd/152c3
        594-234d-4385-b487-83ea574cd860___Com.G_TgS_FL 1132.JPG', shape=(), dtype=str
In [ ]:
        image count= 3000 # number of images(data size)
       Due to memory constraints maximum RAM can hold without crashing is 3000 images
In [ ]:
        data size= int(image count) # set size
        data= images ds.take(data_size) # get data
In [ ]:
         # function to get label
        def get_label(file_path):
          import os
           return tf.strings.split(file path, os.path.sep)[-2]
In [ ]:
        #function to get image and label
        def process_image(file_path):
          label= get label(file_path)
          img= tf.io.read file(file path)
          img= tf.image.decode jpeg(img)
          img= tf.image.resize(img, [254,254])
          img = img/255
          return img, label
In [ ]:
```

```
x=[]
y=[]

for image, label in tqdm(data.map(process_image)):
    x.append(image)
    y.append(label)
```

100%| 3000/3000 [09:23<00:00, 5.33it/s]

```
Dump and load pickle file:
In [ ]:
         import pickle
         '''with open('/content/gdrive/MyDrive/plant disease/plant village nondata/pic
           pickle.dump(x, p)
         with open('/content/gdrive/MyDrive/plant disease/plant village nondata/pickle
           pickle.dump(y, p)'''
In [ ]:
         with open('/content/gdrive/MyDrive/plant disease/plant village nondata/pickle
           x= pickle.load(p)
         with open('/content/gdrive/MyDrive/plant disease/plant village nondata/pickle
           y= pickle.load(p)
In [ ]:
         # converting images to numpy array
         x= np.array(x)
         y arr= np.array(y)
         y= []
         for i in y arr:
           i= ((str(i).split(',')[0][12:])[:-1])
           y.append(i)
         del y arr
         y= np.asarray(y)
In [ ]:
         #converting strings of y into label (1s and 0s) using LabelBinarizer:
         label binarizer = LabelBinarizer()
         y label = label binarizer.fit transform(y)
         n classes = len(label binarizer.classes )
        Train test split
In [ ]:
         x_train, x_test, y_train, y_test = train_test_split(x, y_label, test_size=0.3
         x test, x val, y test, y val = train test split(x test, y test, test size=0.3
In [ ]:
         epochs_{-} = 50
         learning rate = 1e-2
         batch_size = 32
         width=254
         height=254
```

Image Augmentation

depth=3

```
In [ ]:
```

```
aug = ImageDataGenerator(
    width_shift_range=0.1,
    height_shift_range=0.1,
    rotation_range=30,
    zoom_range=0.25,
    shear_range=0.25,
    horizontal_flip=True,
    fill_mode="nearest")
```

Making Model

```
In [ ]:
         #defining input shape
         input shape = (height, width, depth)
         chanDim = -1
         if K.image data format() == "channels first":
             input shape = (depth, height, width)
             chanDim = 1
         #model activation="tanh"
         model activation="relu"
In [ ]:
         #note for self: set initial dropouts to 0.25
         model = Sequential()
         inputShape = (height, width, depth)
         chanDim = -1
         if K.image data format() == "channels first":
             inputShape = (depth, height, width)
             chanDim = 1
         model.add(Conv2D(16, (3, 3), padding="same",input_shape=inputShape, name='Cor
         model.add(Activation("relu", name='relu 1'))
         model.add(BatchNormalization(axis=chanDim, name='BatchNormalization 1'))
         model.add(MaxPooling2D(pool_size=(3, 3), name='MaxPool 1'))
         model.add(Dropout(0.25))
         model.add(Conv2D(32, (3, 3), padding="same", name='Conv2D_2'))
         model.add(Activation("relu", name='relu 2'))
         model.add(BatchNormalization(axis=chanDim, name='BatchNormalization 2'))
         model.add(Conv2D(64, (3, 3), padding="same", name='Conv2D_3'))
         model.add(Activation("relu", name='relu_3'))
         model.add(BatchNormalization(axis=chanDim, name='BatchNormalization 3'))
         model.add(MaxPooling2D(pool size=(2, 2), name='MaxPool 2'))
         model.add(Dropout(0.25))
         model.add(Conv2D(128, (3, 3), padding="same", name='Conv2D_4'))
         model.add(Activation("relu", name='relu 4'))
         model.add(BatchNormalization(axis=chanDim, name='BatchNormalization 4'))
         model.add(Conv2D(256, (3, 3), padding="same", name='Conv2D 5'))
         model.add(Activation("relu", name='relu_5'))
         model.add(BatchNormalization(axis=chanDim, name='BatchNormalization 5'))
         model.add(MaxPooling2D(pool size=(2, 2), name='MaxPool 3'))
         model.add(Dropout(0.25))
         model.add(Flatten())
         model.add(Dense(512))
         model.add(Activation("relu", name='relu 6'))
         model.add(BatchNormalization(name='BatchNormalization_6'))
```

```
model.add(Dropout(0.5))

model.add(Dense(1024))
model.add(Activation("relu", name='relu_7'))
model.add(BatchNormalization(name='BatchNormalization_7'))
model.add(Dropout(0.5))

model.add(Dense(1, activation='sigmoid'))
```

In []: model.summary()

Model: "sequential_3"

Hodet: Sequentiat_5		
Layer (type)	Output Shape	Param #
Conv2D_1 (Conv2D)	(None, 254, 254, 16)	448
relu_1 (Activation)	(None, 254, 254, 16)	0
BatchNormalization_1 (BatchN	(None, 254, 254, 16)	64
MaxPool_1 (MaxPooling2D)	(None, 84, 84, 16)	0
dropout_5 (Dropout)	(None, 84, 84, 16)	0
Conv2D_2 (Conv2D)	(None, 84, 84, 32)	4640
relu_2 (Activation)	(None, 84, 84, 32)	0
BatchNormalization_2 (BatchN	(None, 84, 84, 32)	128
Conv2D_3 (Conv2D)	(None, 84, 84, 64)	18496
relu_3 (Activation)	(None, 84, 84, 64)	0
BatchNormalization_3 (BatchN	(None, 84, 84, 64)	256
MaxPool_2 (MaxPooling2D)	(None, 42, 42, 64)	0
dropout_6 (Dropout)	(None, 42, 42, 64)	0
Conv2D_4 (Conv2D)	(None, 42, 42, 128)	73856
relu_4 (Activation)	(None, 42, 42, 128)	0
BatchNormalization_4 (BatchN	(None, 42, 42, 128)	512
Conv2D_5 (Conv2D)	(None, 42, 42, 256)	295168
relu_5 (Activation)	(None, 42, 42, 256)	0
BatchNormalization_5 (BatchN	(None, 42, 42, 256)	1024
MaxPool_3 (MaxPooling2D)	(None, 21, 21, 256)	0
dropout_7 (Dropout)	(None, 21, 21, 256)	0
flatten_1 (Flatten)	(None, 112896)	0
dense_3 (Dense)	(None, 512)	57803264
relu_6 (Activation)	(None, 512)	0
BatchNormalization_6 (BatchN	(None, 512)	2048
dropout_8 (Dropout)	(None, 512)	0

dense_4 (Dense)

```
relu 7 (Activation)
                                (None, 1024)
       BatchNormalization_7 (BatchN (None, 1024)
                                                      4096
       dropout 9 (Dropout)
                                (None, 1024)
                                                      0
       dense 5 (Dense)
                                                      1025
                                (None, 1)
       _____
       Total params: 58,730,337
       Trainable params: 58,726,273
       Non-trainable params: 4,064
In [ ]:
       from keras.callbacks import ModelCheckpoint
       filepath = "/content/gdrive/MyDrive/plant disease/plant village nondata/plant
       checkpoint = ModelCheckpoint(filepath, monitor='val accuracy', verbose=1, sal
       callbacks list = [checkpoint]
In [ ]:
       #defining optimizer with learning rate decay with every epochs
       opt = tf.keras.optimizers.Adam(learning rate=learning rate, decay=learning rate
       model.compile(loss="binary crossentropy", optimizer=opt,metrics=["accuracy"])
In [ ]:
       history = model.fit(
           aug.flow(x_train, y_train, batch_size=batch_size),
           validation_data=(x_test, y_test),
           steps per epoch=len(x train) // batch size,
           epochs=epochs ,
           callbacks=callbacks list,
           verbose=1
       Epoch 1/50
       racy: 0.9584 - val loss: 0.7685 - val accuracy: 0.8016
       Epoch 00001: val accuracy improved from -inf to 0.80159, saving model to /con
       tent/gdrive/MyDrive/plant_disease/plant_village_nondata/plant_village_weights
       aug 18 3.hdf5
       Epoch 2/50
       racy: 0.9565 - val loss: 0.6672 - val accuracy: 0.8238
       Epoch 00002: val accuracy improved from 0.80159 to 0.82381, saving model to /
       content/gdrive/MyDrive/plant disease/plant village nondata/plant village weig
       hts aug 18 3.hdf5
       Epoch 3/50
       racy: 0.9613 - val loss: 0.6055 - val accuracy: 0.8698
       Epoch 00003: val accuracy improved from 0.82381 to 0.86984, saving model to /
       content/gdrive/MyDrive/plant disease/plant village nondata/plant village weig
       hts aug 18 3.hdf5
       Epoch 4/50
                       65/65 [=======
       racy: 0.9734 - val_loss: 0.2140 - val_accuracy: 0.9587
       Epoch 00004: val accuracy improved from 0.86984 to 0.95873, saving model to /
       content/gdrive/MyDrive/plant disease/plant village nondata/plant village weig
       hts aug 18 3.hdf5
       Epoch 5/50
       65/65 [=========================] - 35s 536ms/step - loss: 0.1079 - accu
```

(None, 1024)

525312

```
racy: 0.9632 - val_loss: 0.7646 - val_accuracy: 0.7905
Epoch 00005: val accuracy did not improve from 0.95873
Epoch 6/50
racy: 0.8738 - val loss: 1.0060 - val accuracy: 0.7730
Epoch 00006: val accuracy did not improve from 0.95873
Epoch 7/50
racy: 0.8617 - val loss: 0.3595 - val accuracy: 0.8746
Epoch 00007: val accuracy did not improve from 0.95873
Epoch 8/50
racy: 0.8994 - val loss: 0.4858 - val accuracy: 0.8556
Epoch 00008: val accuracy did not improve from 0.95873
Epoch 9/50
racy: 0.9144 - val loss: 0.2654 - val accuracy: 0.9111
Epoch 00009: val accuracy did not improve from 0.95873
Epoch 10/50
racy: 0.9221 - val loss: 0.1482 - val accuracy: 0.9349
Epoch 00010: val accuracy did not improve from 0.95873
Epoch 11/50
racy: 0.9289 - val loss: 0.1046 - val accuracy: 0.9587
Epoch 00011: val accuracy did not improve from 0.95873
Epoch 12/50
racy: 0.9400 - val loss: 0.1805 - val accuracy: 0.9238
Epoch 00012: val accuracy did not improve from 0.95873
Epoch 13/50
racy: 0.9473 - val loss: 0.3911 - val accuracy: 0.8444
Epoch 00013: val accuracy did not improve from 0.95873
Epoch 14/50
65/65 [=========================] - 33s 507ms/step - loss: 0.1359 - accu
racy: 0.9386 - val loss: 0.3580 - val accuracy: 0.8571
Epoch 00014: val accuracy did not improve from 0.95873
racy: 0.9492 - val loss: 0.1334 - val_accuracy: 0.9397
Epoch 00015: val accuracy did not improve from 0.95873
Epoch 16/50
racy: 0.9507 - val loss: 0.0982 - val accuracy: 0.9619
Epoch 00016: val accuracy improved from 0.95873 to 0.96190, saving model to /
content/gdrive/MyDrive/plant disease/plant village nondata/plant village weig
hts aug 18 3.hdf5
Epoch 17/50
65/65 [=========================] - 35s 539ms/step - loss: 0.1008 - accu
racy: 0.9560 - val loss: 0.1106 - val accuracy: 0.9651
Epoch 00017: val accuracy improved from 0.96190 to 0.96508, saving model to /
content/gdrive/MyDrive/plant disease/plant village nondata/plant village weig
hts aug 18 3.hdf5
Epoch 18/50
```

```
racy: 0.9531 - val_loss: 0.0915 - val_accuracy: 0.9714
Epoch 00018: val_accuracy improved from 0.96508 to 0.97143, saving model to /
content/gdrive/MyDrive/plant_disease/plant_village_nondata/plant_village_weig
hts_aug_18_3.hdf5
Epoch 19/50
racy: 0.9599 - val loss: 0.1530 - val accuracy: 0.9413
Epoch 00019: val accuracy did not improve from 0.97143
Epoch 20/50
racy: 0.9565 - val loss: 0.0905 - val accuracy: 0.9698
Epoch 00020: val accuracy did not improve from 0.97143
Epoch 21/50
racy: 0.9657 - val loss: 0.0946 - val accuracy: 0.9651
Epoch 00021: val accuracy did not improve from 0.97143
Epoch 22/50
racy: 0.9695 - val loss: 0.1197 - val accuracy: 0.9746
Epoch 00022: val accuracy improved from 0.97143 to 0.97460, saving model to /
content/gdrive/MyDrive/plant disease/plant village nondata/plant village weig
hts_aug_18_3.hdf5
Epoch \overline{23}/5\overline{0}
65/65 [=========================] - 35s 533ms/step - loss: 0.0949 - accu
racy: 0.9628 - val loss: 0.1498 - val_accuracy: 0.9651
Epoch 00023: val accuracy did not improve from 0.97460
Epoch 24/50
racy: 0.9613 - val loss: 0.2126 - val accuracy: 0.9175
Epoch 00024: val accuracy did not improve from 0.97460
Epoch 25/50
racy: 0.9666 - val loss: 0.0895 - val accuracy: 0.9714
Epoch 00025: val accuracy did not improve from 0.97460
Epoch 26/50
racy: 0.9647 - val loss: 0.1972 - val accuracy: 0.9206
Epoch 00026: val accuracy did not improve from 0.97460
Epoch 27/50
racy: 0.9652 - val loss: 0.3819 - val_accuracy: 0.8667
Epoch 00027: val accuracy did not improve from 0.97460
racy: 0.9724 - val loss: 0.4951 - val_accuracy: 0.9444
Epoch 00028: val accuracy did not improve from 0.97460
Epoch 29/50
racy: 0.9681 - val loss: 0.6628 - val accuracy: 0.9524
Epoch 00029: val accuracy did not improve from 0.97460
Epoch 30/50
65/65 [=========================] - 33s 502ms/step - loss: 0.0749 - accu
racy: 0.9739 - val loss: 1.1722 - val accuracy: 0.8524
Epoch 00030: val_accuracy did not improve from 0.97460
Epoch 31/50
```

```
racy: 0.9729 - val_loss: 0.8733 - val_accuracy: 0.8857
Epoch 00031: val accuracy did not improve from 0.97460
racy: 0.9763 - val loss: 0.7038 - val accuracy: 0.9270
Epoch 00032: val accuracy did not improve from 0.97460
Epoch 33/50
racy: 0.9773 - val loss: 0.8078 - val accuracy: 0.9794
Epoch 00033: val_accuracy improved from 0.97460 to 0.97937, saving model to /
content/gdrive/MyDrive/plant disease/plant village nondata/plant village weig
hts aug 18 3.hdf5
Epoch 34/50
racy: 0.9468 - val loss: 2.1306 - val accuracy: 0.6651
Epoch 00034: val accuracy did not improve from 0.97937
Epoch 35/50
racy: 0.9260 - val loss: 0.2308 - val accuracy: 0.9238
Epoch 00035: val accuracy did not improve from 0.97937
Epoch 36/50
racy: 0.9420 - val loss: 0.1276 - val accuracy: 0.9492
Epoch 00036: val accuracy did not improve from 0.97937
Epoch 37/50
racy: 0.9497 - val loss: 0.1018 - val accuracy: 0.9635
Epoch 00037: val accuracy did not improve from 0.97937
Epoch 38/50
65/65 [=========================] - 33s 507ms/step - loss: 0.1155 - accu
racy: 0.9531 - val loss: 0.1714 - val accuracy: 0.9302
Epoch 00038: val accuracy did not improve from 0.97937
Epoch 39/50
65/65 [=========================] - 33s 508ms/step - loss: 0.0778 - accu
racy: 0.9739 - val loss: 0.0954 - val accuracy: 0.9667
Epoch 00039: val_accuracy did not improve from 0.97937
Epoch 40/50
65/65 [=========================] - 33s 509ms/step - loss: 0.0787 - accu
racy: 0.9715 - val loss: 0.0703 - val accuracy: 0.9841
Epoch 00040: val accuracy improved from 0.97937 to 0.98413, saving model to /
content/qdrive/MyDrive/plant disease/plant village_nondata/plant_village_weig
hts aug 18 3.hdf5
Epoch 41/50
racy: 0.9671 - val loss: 0.0554 - val_accuracy: 0.9857
Epoch 00041: val accuracy improved from 0.98413 to 0.98571, saving model to /
content/gdrive/MyDrive/plant disease/plant village nondata/plant village weig
hts aug 18 3.hdf5
Epoch 42/50
racy: 0.9657 - val loss: 0.0719 - val_accuracy: 0.9778
Epoch 00042: val accuracy did not improve from 0.98571
Epoch 43/50
65/65 [=========================] - 33s 507ms/step - loss: 0.0736 - accu
racy: 0.9729 - val loss: 0.0709 - val accuracy: 0.9810
Epoch 00043: val accuracy did not improve from 0.98571
```

Epoch 44/50

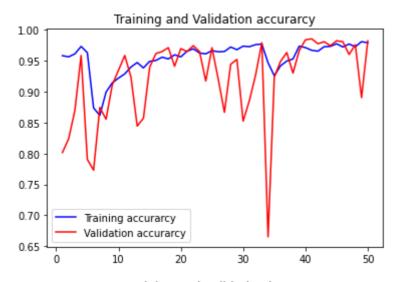
```
65/65 [=========================] - 34s 515ms/step - loss: 0.0610 - accu
racy: 0.9734 - val_loss: 1.3283 - val_accuracy: 0.9746
Epoch 00044: val_accuracy did not improve from 0.98571
Epoch 45/50
racy: 0.9778 - val loss: 0.0521 - val accuracy: 0.9825
Epoch 00045: val accuracy did not improve from 0.98571
Epoch 46/50
racy: 0.9724 - val loss: 0.0595 - val accuracy: 0.9810
Epoch 00046: val accuracy did not improve from 0.98571
Epoch 47/50
racy: 0.9773 - val loss: 0.1113 - val accuracy: 0.9603
Epoch 00047: val accuracy did not improve from 0.98571
Epoch 48/50
racy: 0.9729 - val loss: 0.0583 - val accuracy: 0.9762
Epoch 00048: val_accuracy did not improve from 0.98571
Epoch 49/50
racy: 0.9811 - val loss: 0.3098 - val_accuracy: 0.8905
Epoch 00049: val accuracy did not improve from 0.98571
Epoch 50/50
racy: 0.9792 - val loss: 0.0602 - val accuracy: 0.9825
Epoch 00050: val accuracy did not improve from 0.98571
Now that the model has been trained with 94+ percent accuracy I will save these weights and
```

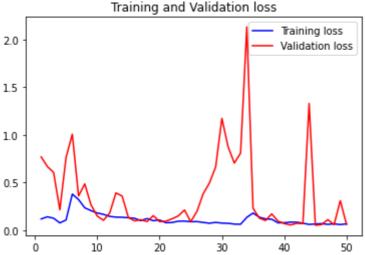
```
In [ ]: model.save_weights('/content/gdrive/MyDrive/Plant_disease/aug_20_4.h5')
```

Evaluating the performance of model:

use later for Transfer Learning on my self collected dataset.

```
In [ ]:
         validation accuracy = history.history['val accuracy']
         train_accuracy = history.history['accuracy']
         train loss = history.history['loss']
         validation loss = history.history['val loss']
         epochs = range(1, len(train_accuracy) + 1)
         #Train and validation accuracy
         plt.plot(epochs, train_accuracy, 'b', label='Training accurarcy')
         plt.plot(epochs, validation_accuracy, 'r', label='Validation accurarcy')
         plt.title('Training and Validation accurarcy')
         plt.legend()
         plt.figure()
         #Train and validation loss
         plt.plot(epochs, train_loss, 'b', label='Training loss')
         plt.plot(epochs, validation_loss, 'r', label='Validation loss')
         plt.title('Training and Validation loss')
         plt.legend()
         plt.show()
```





```
In [ ]:
         x, y = x_{test}, y_{test}
         x.shape, y.shape
         from sklearn.metrics import confusion matrix, fl score, precision score, rece
         from keras.utils.np_utils import to_categorical
         import tensorflow as tf
         scores = model.evaluate(x_test, y_test)
         y_pred=[]
         for pred in ((model.predict(x_test))): #custom loop with threshold as 0.5
           if pred >= 0.5:
             y_pred.append(1)
           else:
             y_pred.append(0)
         y_test_new= []
         for y in y_test:
           y= np.array_str(y)
           y = int(y[1])
           y_test_new.append(y)
         print("CONFUSION MATRIX:")
         print( confusion_matrix(y_test_new , y_pred))
         print("=======
         print(f"ACCURACY for test dataset is:
                                                      {scores[1]}")
         print("F1_SCORE for test datset is
                                                     {}".format(f1_score(y_test_new , )
```

```
print("PRECISION_SCORE for test datset is {}".format(precision_score(y_test_print("RECALL_SCORE for test datset is {}".format(recall_score(y_test_new)) {}".format(recall_score(y_test_new)) {}".format(recall_score(y_test_new)) {}".format(recall_score(y_test_new)) {}".format(recall_score(y_test_new)) {}".format(recall_score(y_test_new)) {}".format(recall_score(y_test_new)) {}".format(recall_score(y_test_new)) {}".format(precision_score(y_test_new)) {}".format(precision_score(y_t
```

Trainig Model on self collected data:

```
In [ ]:
         images ds= tf.data.Dataset.list files("/content/gdrive/MyDrive/Plant disease/
In [ ]:
         for images in images ds.take(3):
           print(images)
        tf.Tensor(b'/content/gdrive/MyDrive/Plant disease/self collected/data/without
         _disease/IMG_20200112_180808.jpg', shape=(), dtype=string)
        tf.Tensor(b'/content/gdrive/MyDrive/Plant disease/self collected/data/with di
        sease/withd035 copy.jpg', shape=(), dtype=string)
        tf.Tensor(b'/content/gdrive/MyDrive/Plant disease/self collected/data/without
        _disease/wd251 copy.jpg', shape=(), dtype=string)
In [ ]:
         image count=len(images ds) #get number of images(data size)
         image count
Out[]: 2423
In [ ]:
         train size= int(image count) # set train size
         data= images ds.take(train size) # get train data
In [ ]:
         # function to get label
         def get label(file path):
           import os
           return tf.strings.split(file path, os.path.sep)[-2]
In [ ]:
         #function to get image and label
         def process image(file path):
           label= get label(file path)
           img= tf.io.read file(file path)
           img= tf.image.decode jpeg(img)
           img= tf.image.resize(img, [254,254])
           img = img/255
           return img, label
In [ ]:
         x=[]
         y=[]
```

```
for image, label in tqdm(data.map(process_image)):
           x.append(image)
           y.append(label)
               | 2423/2423 [09:10<00:00,
                                                     4.40it/s]
In [ ]:
         x = np.array(x)
         y arr= np.array(y)
In [ ]:
         y= []
         for i in y arr:
           i= ((str(i).split(',')[0][12:])[:-1])
           y.append(i)
         del y arr
In [ ]:
         y= np.asarray(y)
In [ ]:
         #converting strings of y into label (1s and 0s):
         label binarizer = LabelBinarizer()
         y_label = label_binarizer.fit transform(y)
         n classes = len(label binarizer.classes )
        Saving data to pickle:
In [ ]:
         import pickle
         with open('/content/gdrive/MyDrive/Plant disease/pickle/x.pkl','wb') as p:
           pickle.dump(x, p)
         with open('/content/gdrive/MyDrive/Plant disease/pickle/y label.pkl','wb') as
           pickle.dump(y label, p)
In [ ]:
         with open('/content/gdrive/MyDrive/Plant_disease/pickle/x.pkl','rb') as p:
           x= pickle.load(p)
         with open('/content/gdrive/MyDrive/Plant disease/pickle/y label.pkl','rb') as
           y label= pickle.load(p)
        Train_test_split
In [ ]:
         x_train, x_test, y_train, y_test = train_test_split(x, y_label, test_size=0.3
         x test, x val, y test, y val = train test split(x test, y test, test size=0.3
In [ ]:
         print(x_train.shape)
         print(x_val.shape)
         print(x_test.shape)
         print(y_train.shape)
         print(y_val.shape)
         print(y_test.shape)
         (1696, 254, 254, 3)
         (219, 254, 254, 3)
(508, 254, 254, 3)
        (1696, 1)
(219, 1)
(508, 1)
In [4]:
```

```
learning_rate = 1e-2
batch_size = 32
epochs_ = 300
width=254
height=254
depth=3
```

ImageAugmentation using ImageDataGenerator

```
In [6]: aug = ImageDataGenerator(
    width_shift_range=0.1,
    height_shift_range=0.1,
    rotation_range=30,
    zoom_range=0.25,
    shear_range=0.25,
    horizontal_flip=True,
    fill_mode="nearest")
```

Defining model:

```
In [7]: #defining input_shape
  input_shape = (height, width, depth)
  chanDim = -1

if K.image_data_format() == "channels_first":
    input_shape = (depth, height, width)
    chanDim = 1

model_activation="relu"
```

```
In [8]:
         #note for self: set initial dropouts to 0.25
         model = Sequential()
         inputShape = (height, width, depth)
         chanDim = -1
         if K.image_data_format() == "channels_first":
             inputShape = (depth, height, width)
             chanDim = 1
         model.add(Conv2D(16, (3, 3), padding="same",input_shape=inputShape, name='Cor
         model.add(Activation("relu", name='relu_1'))
         model.add(BatchNormalization(axis=chanDim, name='BatchNormalization 1'))
         model.add(MaxPooling2D(pool_size=(3, 3), name='MaxPool_1'))
         model.add(Dropout(0.25))
         model.add(Conv2D(32, (3, 3), padding="same", name='Conv2D_2'))
         model.add(Activation("relu", name='relu_2'))
         model.add(BatchNormalization(axis=chanDim, name='BatchNormalization_2'))
         model.add(Conv2D(64, (3, 3), padding="same", name='Conv2D_3'))
         model.add(Activation("relu", name='relu 3'))
         model.add(BatchNormalization(axis=chanDim, name='BatchNormalization 3'))
         model.add(MaxPooling2D(pool size=(2, 2), name='MaxPool 2'))
         model.add(Dropout(0.25))
         model.add(Conv2D(128, (3, 3), padding="same", name='Conv2D_4'))
         model.add(Activation("relu", name='relu_4'))
         model.add(BatchNormalization(axis=chanDim, name='BatchNormalization_4'))
```

```
model.add(Conv2D(256, (3, 3), padding="same", name='Conv2D_5'))
model.add(Activation("relu", name='relu_5'))
model.add(BatchNormalization(axis=chanDim, name='BatchNormalization_5'))
model.add(MaxPooling2D(pool_size=(2, 2), name='MaxPool_3'))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512))
model.add(Activation("relu", name='relu_6'))
model.add(BatchNormalization(name='BatchNormalization_6'))
model.add(Dense(1024))
model.add(Activation("relu", name='relu_7'))
model.add(BatchNormalization(name='BatchNormalization_7'))
model.add(Dropout(0.5))

model.add(Dense(1, activation='sigmoid'))
```

Load weights from model previously trained on plant village dataset:

As we have trained a model previously on 'Plant Village' dataset, the weights obtained after that training will be helpfull for classifiying our dataset well.

```
In [ ]: model.load_weights("/content/gdrive/MyDrive/Plant_disease/aug_20_4.h5")
```

Now that the weights have been loaded, I will be freezing all the layers except last 5 layers of the model on which our collected data will train on:

```
In [9]: # unfreezing only last 5 layers
for layer in model.layers[:-5]:
    layer.trainable = False

In [10]: for l in model.layers:
    print(l.name, l.trainable)

Conv2D_1 False
    relu_1 False
    BatchNormalization_1 False
    MaxPool 1 False
```

MaxPool_1 False dropout False Conv2D 2 False relu 2 False BatchNormalization 2 False Conv2D 3 False relu 3 False BatchNormalization 3 False MaxPool 2 False dropout 1 False Conv2D $\overline{4}$ False relu 4 False BatchNormalization 4 False Conv2D 5 False relu 5 False BatchNormalization 5 False MaxPool_3 False dropout_2 False flatten False dense False relu_6 False BatchNormalization 6 False

dropout_3 False
dense_1 True
relu_7 True
BatchNormalization_7 True
dropout_4 True
dense_2 True

As we can see above that only last 5 layers are trainable now. Rest all layers have ben freezed.

from keras.callbacks import ModelCheckpoint

filepath = "/content/gdrive/MyDrive/Plant_disease/aug_20_1.hdf5"
 checkpoint = ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1, sav callbacks_list = [checkpoint]

In [11]:

model.summary()

Model: "sequential"

•		
Layer (type)	Output Shape	Param #
Conv2D_1 (Conv2D)	(None, 254, 254, 16)	448
relu_1 (Activation)	(None, 254, 254, 16)	0
BatchNormalization_1 (BatchN	(None, 254, 254, 16)	64
MaxPool_1 (MaxPooling2D)	(None, 84, 84, 16)	0
dropout (Dropout)	(None, 84, 84, 16)	0
Conv2D_2 (Conv2D)	(None, 84, 84, 32)	4640
relu_2 (Activation)	(None, 84, 84, 32)	0
BatchNormalization_2 (BatchN	(None, 84, 84, 32)	128
Conv2D_3 (Conv2D)	(None, 84, 84, 64)	18496
relu_3 (Activation)	(None, 84, 84, 64)	0
BatchNormalization_3 (BatchN	(None, 84, 84, 64)	256
MaxPool_2 (MaxPooling2D)	(None, 42, 42, 64)	0
dropout_1 (Dropout)	(None, 42, 42, 64)	0
Conv2D_4 (Conv2D)	(None, 42, 42, 128)	73856
relu_4 (Activation)	(None, 42, 42, 128)	0
BatchNormalization_4 (BatchN	(None, 42, 42, 128)	512
Conv2D_5 (Conv2D)	(None, 42, 42, 256)	295168
relu_5 (Activation)	(None, 42, 42, 256)	0
BatchNormalization_5 (BatchN	(None, 42, 42, 256)	1024
MaxPool_3 (MaxPooling2D)	(None, 21, 21, 256)	0
dropout_2 (Dropout)	(None, 21, 21, 256)	0
flatten (Flatten)	(None, 112896)	0
dense (Dense)	(None, 512)	57803264

```
relu_6 (Activation)
      BatchNormalization 6 (BatchN (None, 512)
                                                2048
      dropout_3 (Dropout)
                            (None, 512)
                                                525312
      dense 1 (Dense)
                            (None, 1024)
      relu 7 (Activation)
                            (None, 1024)
      BatchNormalization 7 (BatchN (None, 1024)
                                                4096
      dropout 4 (Dropout)
                            (None, 1024)
      dense 2 (Dense)
                                                1025
                            (None, 1)
      _____
      Total params: 58,730,337
      Trainable params: 528,385
      Non-trainable params: 58,201,952
In [ ]:
      # defining optimizer
       opt = tf.keras.optimizers.Adam(learning rate=learning rate, decay=learning rate
       model.compile(loss="binary crossentropy", optimizer=opt,metrics=["accuracy"])
In [ ]:
      history = model.fit(
          aug.flow(x_train, y_train, batch_size= batch_size),
          validation data=(x val, y val),
          steps per epoch=len(x train) // batch size,
          callbacks = callbacks list,
          epochs= epochs ,
          verbose=1
      Epoch 1/300
      racy: 0.7358 - val loss: 0.6558 - val accuracy: 0.7854
      Epoch 00001: val accuracy improved from -inf to 0.78539, saving model to /con
      tent/gdrive/MyDrive/Plant disease/aug 20 2.hdf5
      Epoch 2/300
      racy: 0.7871 - val loss: 0.8256 - val accuracy: 0.7808
      Epoch 00002: val accuracy did not improve from 0.78539
      Epoch 3/300
      racy: 0.7759 - val loss: 0.6078 - val accuracy: 0.7854
      Epoch 00003: val accuracy did not improve from 0.78539
      Epoch 4/300
      racy: 0.8078 - val loss: 0.4754 - val accuracy: 0.8493
      Epoch 00004: val_accuracy improved from 0.78539 to 0.84932, saving model to /
      content/gdrive/MyDrive/Plant_disease/aug_20_2.hdf5
      Epoch 5/300
      racy: 0.7983 - val loss: 0.3797 - val accuracy: 0.8128
      Epoch 00005: val accuracy did not improve from 0.84932
      Epoch 6/300
      racy: 0.8019 - val_loss: 0.3856 - val_accuracy: 0.8584
```

Epoch 00006: val_accuracy improved from 0.84932 to 0.85845, saving model to /

(None, 512)

0

```
content/gdrive/MyDrive/Plant_disease/aug_20_2.hdf5
Epoch 7/300
racy: 0.8066 - val_loss: 0.6857 - val_accuracy: 0.7169
Epoch 00007: val accuracy did not improve from 0.85845
Epoch 8/300
racy: 0.8213 - val loss: 0.5013 - val accuracy: 0.7808
Epoch 00008: val accuracy did not improve from 0.85845
Epoch 9/300
racy: 0.8231 - val loss: 0.5935 - val accuracy: 0.7443
Epoch 00009: val accuracy did not improve from 0.85845
Epoch 10/300
racy: 0.8066 - val loss: 0.5691 - val accuracy: 0.7306
Epoch 00010: val accuracy did not improve from 0.85845
Epoch 11/300
racy: 0.8202 - val loss: 0.4930 - val accuracy: 0.7900
Epoch 00011: val accuracy did not improve from 0.85845
Epoch 12/300
racy: 0.8196 - val loss: 0.4387 - val accuracy: 0.8128
Epoch 00012: val accuracy did not improve from 0.85845
Epoch 13/300
racy: 0.8154 - val loss: 0.4043 - val accuracy: 0.8356
Epoch 00013: val accuracy did not improve from 0.85845
Epoch 14/300
racy: 0.8172 - val loss: 0.4072 - val accuracy: 0.8630
Epoch 00014: val accuracy improved from 0.85845 to 0.86301, saving model to /
content/gdrive/MyDrive/Plant disease/aug 20 2.hdf5
Epoch 15/300
racy: 0.8284 - val loss: 0.3272 - val accuracy: 0.8630
Epoch 00015: val accuracy did not improve from 0.86301
Epoch 16/300
racy: 0.8272 - val loss: 0.3473 - val accuracy: 0.8402
Epoch 00016: val accuracy did not improve from 0.86301
Epoch 17/300
racy: 0.8225 - val loss: 0.4213 - val accuracy: 0.7945
Epoch 00017: val accuracy did not improve from 0.86301
Epoch 18/300
racy: 0.8267 - val loss: 0.3546 - val accuracy: 0.8676
Epoch 00018: val accuracy improved from 0.86301 to 0.86758, saving model to /
content/gdrive/MyDrive/Plant disease/aug 20 2.hdf5
Epoch 19/300
racy: 0.8355 - val_loss: 0.3774 - val_accuracy: 0.8174
Epoch 00019: val accuracy did not improve from 0.86758
Epoch 20/300
```

```
racy: 0.8461 - val_loss: 0.3150 - val_accuracy: 0.8676
Epoch 00020: val_accuracy did not improve from 0.86758
Epoch 21/300
53/53 [========================= ] - 26s 484ms/step - loss: 0.3670 - accu
racy: 0.8502 - val loss: 0.4015 - val accuracy: 0.8128
Epoch 00021: val accuracy did not improve from 0.86758
Epoch 22/300
racy: 0.8550 - val loss: 0.3752 - val accuracy: 0.8128
Epoch 00022: val accuracy did not improve from 0.86758
Epoch 23/300
racy: 0.8432 - val loss: 0.3668 - val accuracy: 0.8082
Epoch 00023: val accuracy did not improve from 0.86758
Epoch 24/300
racy: 0.8467 - val loss: 0.3646 - val_accuracy: 0.8356
Epoch 00024: val accuracy did not improve from 0.86758
Epoch 25/300
racy: 0.8697 - val loss: 0.3944 - val accuracy: 0.8265
Epoch 00025: val accuracy did not improve from 0.86758
Epoch 26/300
racy: 0.8603 - val loss: 0.4033 - val accuracy: 0.8265
Epoch 00026: val accuracy did not improve from 0.86758
Epoch 27/300
racy: 0.8485 - val loss: 0.4195 - val accuracy: 0.7808
Epoch 00027: val accuracy did not improve from 0.86758
Epoch 28/300
racy: 0.8538 - val loss: 0.4790 - val accuracy: 0.7808
Epoch 00028: val accuracy did not improve from 0.86758
Epoch 29/300
racy: 0.8520 - val loss: 0.4143 - val_accuracy: 0.8402
Epoch 00029: val accuracy did not improve from 0.86758
Epoch 30/300
racy: 0.8508 - val loss: 0.3698 - val_accuracy: 0.8584
Epoch 00030: val accuracy did not improve from 0.86758
Epoch 31/300
racy: 0.8591 - val loss: 0.3629 - val accuracy: 0.8447
Epoch 00031: val accuracy did not improve from 0.86758
Epoch 32/300
racy: 0.8591 - val loss: 0.4151 - val accuracy: 0.8082
Epoch 00032: val accuracy did not improve from 0.86758
Epoch 33/300
racy: 0.8667 - val_loss: 0.3093 - val_accuracy: 0.8767
```

Epoch 00033: val_accuracy improved from 0.86758 to 0.87671, saving model to /

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content/gdrive/MyDrive/Plant_disease/aug_20_2.hdf5
Epoch 34/300
racy: 0.8491 - val_loss: 0.3271 - val_accuracy: 0.8721
Epoch 00034: val accuracy did not improve from 0.87671
Epoch 35/300
53/53 [========================= ] - 25s 466ms/step - loss: 0.3371 - accu
racy: 0.8550 - val loss: 0.4928 - val accuracy: 0.7808
Epoch 00035: val accuracy did not improve from 0.87671
Epoch 36/300
racy: 0.8691 - val loss: 0.4055 - val accuracy: 0.7945
Epoch 00036: val accuracy did not improve from 0.87671
Epoch 37/300
racy: 0.8608 - val loss: 0.3902 - val accuracy: 0.8128
Epoch 00037: val accuracy did not improve from 0.87671
Epoch 38/300
racy: 0.8620 - val loss: 0.3068 - val_accuracy: 0.8630
Epoch 00038: val accuracy did not improve from 0.87671
Epoch 39/300
racy: 0.8650 - val loss: 0.3941 - val accuracy: 0.8265
Epoch 00039: val accuracy did not improve from 0.87671
Epoch 40/300
racy: 0.8608 - val loss: 0.4861 - val accuracy: 0.7489
Epoch 00040: val accuracy did not improve from 0.87671
Epoch 41/300
racy: 0.8449 - val loss: 0.2998 - val accuracy: 0.8676
Epoch 00041: val accuracy did not improve from 0.87671
Epoch 42/300
racy: 0.8644 - val loss: 0.3392 - val accuracy: 0.8311
Epoch 00042: val accuracy did not improve from 0.87671
Epoch 43/300
racy: 0.8726 - val loss: 0.4536 - val_accuracy: 0.7854
Epoch 00043: val accuracy did not improve from 0.87671
Epoch 44/300
racy: 0.8756 - val loss: 0.3335 - val accuracy: 0.8539
Epoch 00044: val accuracy did not improve from 0.87671
Epoch 45/300
racy: 0.8768 - val loss: 0.4528 - val accuracy: 0.7854
Epoch 00045: val accuracy did not improve from 0.87671
Epoch 46/300
racy: 0.8715 - val loss: 0.4942 - val accuracy: 0.7352
Epoch 00046: val accuracy did not improve from 0.87671
Epoch 47/300
53/53 [=========================] - 26s 480ms/step - loss: 0.3264 - accu
racy: 0.8608 - val_loss: 0.3154 - val_accuracy: 0.8402
```

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Epoch 00047: val accuracy did not improve from 0.87671
Epoch 48/300
racy: 0.8662 - val_loss: 0.2171 - val_accuracy: 0.9178
Epoch 00048: val_accuracy improved from 0.87671 to 0.91781, saving model to /
content/gdrive/MyDrive/Plant disease/aug 20 2.hdf5
Epoch 49/300
53/53 [========================= ] - 27s 514ms/step - loss: 0.3250 - accu
racy: 0.8644 - val loss: 0.3127 - val accuracy: 0.8767
Epoch 00049: val accuracy did not improve from 0.91781
Epoch 50/300
racy: 0.8620 - val loss: 0.3074 - val accuracy: 0.8630
Epoch 00050: val accuracy did not improve from 0.91781
Epoch 51/300
racy: 0.8662 - val loss: 0.2487 - val accuracy: 0.8995
Epoch 00051: val accuracy did not improve from 0.91781
Epoch 52/300
racy: 0.8703 - val loss: 0.3249 - val accuracy: 0.8447
Epoch 00052: val accuracy did not improve from 0.91781
Epoch 53/300
53/53 [========================= ] - 25s 466ms/step - loss: 0.3036 - accu
racy: 0.8809 - val loss: 0.3550 - val accuracy: 0.8219
Epoch 00053: val accuracy did not improve from 0.91781
Epoch 54/300
53/53 [========================== ] - 25s 473ms/step - loss: 0.3019 - accu
racy: 0.8697 - val loss: 0.3378 - val accuracy: 0.8447
Epoch 00054: val accuracy did not improve from 0.91781
Epoch 55/300
racy: 0.8632 - val loss: 0.4078 - val accuracy: 0.7900
Epoch 00055: val accuracy did not improve from 0.91781
Epoch 56/300
racy: 0.8779 - val loss: 0.4717 - val accuracy: 0.7397
Epoch 00056: val accuracy did not improve from 0.91781
Epoch 57/300
racy: 0.8579 - val loss: 0.3125 - val_accuracy: 0.8539
Epoch 00057: val accuracy did not improve from 0.91781
Epoch 58/300
racy: 0.8815 - val loss: 0.3962 - val accuracy: 0.7991
Epoch 00058: val accuracy did not improve from 0.91781
Epoch 59/300
53/53 [=========================] - 24s 460ms/step - loss: 0.2795 - accu
racy: 0.8821 - val loss: 0.3754 - val accuracy: 0.8402
Epoch 00059: val accuracy did not improve from 0.91781
Epoch 60/300
racy: 0.8715 - val_loss: 0.3455 - val_accuracy: 0.8082
Epoch 00060: val accuracy did not improve from 0.91781
Epoch 61/300
```

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racy: 0.8797 - val_loss: 0.5841 - val_accuracy: 0.6484
Epoch 00061: val_accuracy did not improve from 0.91781
Epoch 62/300
53/53 [========================== ] - 25s 466ms/step - loss: 0.3034 - accu
racy: 0.8768 - val loss: 0.5230 - val accuracy: 0.7032
Epoch 00062: val accuracy did not improve from 0.91781
Epoch 63/300
racy: 0.8756 - val loss: 0.3592 - val accuracy: 0.8265
Epoch 00063: val accuracy did not improve from 0.91781
Epoch 64/300
racy: 0.8697 - val loss: 0.6846 - val accuracy: 0.6986
Epoch 00064: val accuracy did not improve from 0.91781
Epoch 65/300
racy: 0.8721 - val loss: 0.3183 - val accuracy: 0.8721
Epoch 00065: val accuracy did not improve from 0.91781
Epoch 66/300
racy: 0.8862 - val loss: 0.7295 - val accuracy: 0.6347
Epoch 00066: val accuracy did not improve from 0.91781
Epoch 67/300
racy: 0.8750 - val loss: 0.3662 - val accuracy: 0.8311
Epoch 00067: val accuracy did not improve from 0.91781
Epoch 68/300
racy: 0.8638 - val loss: 0.3245 - val accuracy: 0.8630
Epoch 00068: val accuracy did not improve from 0.91781
Epoch 69/300
racy: 0.8721 - val loss: 0.3662 - val accuracy: 0.8174
Epoch 00069: val accuracy did not improve from 0.91781
Epoch 70/300
racy: 0.8756 - val loss: 0.5506 - val_accuracy: 0.6895
Epoch 00070: val accuracy did not improve from 0.91781
Epoch 71/300
racy: 0.8862 - val loss: 0.5050 - val_accuracy: 0.7352
Epoch 00071: val accuracy did not improve from 0.91781
Epoch 72/300
racy: 0.8756 - val loss: 0.2905 - val accuracy: 0.8630
Epoch 00072: val accuracy did not improve from 0.91781
Epoch 73/300
racy: 0.8950 - val loss: 0.3810 - val accuracy: 0.8174
Epoch 00073: val accuracy did not improve from 0.91781
Epoch 74/300
53/53 [=========================] - 25s 468ms/step - loss: 0.3021 - accu
racy: 0.8815 - val_loss: 0.3218 - val_accuracy: 0.8447
Epoch 00074: val_accuracy did not improve from 0.91781
```

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Epoch 75/300
racy: 0.8815 - val_loss: 0.6737 - val_accuracy: 0.6530
Epoch 00075: val_accuracy did not improve from 0.91781
Epoch 76/300
racy: 0.8856 - val loss: 0.6239 - val accuracy: 0.6530
Epoch 00076: val accuracy did not improve from 0.91781
Epoch 77/300
racy: 0.8809 - val loss: 0.5301 - val accuracy: 0.6849
Epoch 00077: val accuracy did not improve from 0.91781
Epoch 78/300
racy: 0.8809 - val loss: 0.3621 - val accuracy: 0.8219
Epoch 00078: val accuracy did not improve from 0.91781
Epoch 79/300
racy: 0.8785 - val loss: 0.3261 - val accuracy: 0.8311
Epoch 00079: val_accuracy did not improve from 0.91781
Epoch 80/300
racy: 0.8862 - val loss: 0.2814 - val accuracy: 0.9224
Epoch 00080: val accuracy improved from 0.91781 to 0.92237, saving model to /
content/gdrive/MyDrive/Plant disease/aug 20 2.hdf5
Epoch 81/300
53/53 [========================= ] - 27s 505ms/step - loss: 0.2807 - accu
racy: 0.8791 - val loss: 0.4087 - val accuracy: 0.7854
Epoch 00081: val accuracy did not improve from 0.92237
Epoch 82/300
racy: 0.8892 - val loss: 0.4820 - val accuracy: 0.8037
Epoch 00082: val accuracy did not improve from 0.92237
Epoch 83/300
53/53 [========================= ] - 25s 464ms/step - loss: 0.2771 - accu
racy: 0.8833 - val loss: 0.3238 - val accuracy: 0.8356
Epoch 00083: val accuracy did not improve from 0.92237
Epoch 84/300
racy: 0.8915 - val loss: 0.4974 - val_accuracy: 0.7397
Epoch 00084: val accuracy did not improve from 0.92237
Epoch 85/300
racy: 0.8803 - val loss: 0.4737 - val_accuracy: 0.7352
Epoch 00085: val accuracy did not improve from 0.92237
Epoch 86/300
racy: 0.8821 - val loss: 0.3620 - val accuracy: 0.8493
Epoch 00086: val accuracy did not improve from 0.92237
Epoch 87/300
53/53 [=========================] - 25s 474ms/step - loss: 0.2820 - accu
racy: 0.8815 - val loss: 0.4064 - val accuracy: 0.7900
Epoch 00087: val accuracy did not improve from 0.92237
Epoch 88/300
53/53 [=========================] - 25s 465ms/step - loss: 0.3084 - accu
racy: 0.8685 - val_loss: 0.4226 - val_accuracy: 0.7900
```

```
Epoch 00088: val_accuracy did not improve from 0.92237
Epoch 89/300
racy: 0.8779 - val_loss: 0.3675 - val_accuracy: 0.8402
Epoch 00089: val accuracy did not improve from 0.92237
Epoch 90/300
racy: 0.8909 - val loss: 0.5678 - val accuracy: 0.7215
Epoch 00090: val accuracy did not improve from 0.92237
Epoch 91/300
racy: 0.8974 - val loss: 0.5760 - val accuracy: 0.7078
Epoch 00091: val accuracy did not improve from 0.92237
Epoch 92/300
racy: 0.8897 - val loss: 0.3721 - val accuracy: 0.8082
Epoch 00092: val accuracy did not improve from 0.92237
Epoch 93/300
racy: 0.8897 - val loss: 0.2800 - val accuracy: 0.8858
Epoch 00093: val accuracy did not improve from 0.92237
Epoch 94/300
racy: 0.8779 - val loss: 0.3243 - val accuracy: 0.8493
Epoch 00094: val accuracy did not improve from 0.92237
Epoch 95/300
racy: 0.8903 - val loss: 0.2947 - val accuracy: 0.8630
Epoch 00095: val accuracy did not improve from 0.92237
Epoch 96/300
53/53 [========================= ] - 25s 469ms/step - loss: 0.2815 - accu
racy: 0.8850 - val loss: 0.4364 - val accuracy: 0.7671
Epoch 00096: val accuracy did not improve from 0.92237
Epoch 97/300
racy: 0.8874 - val loss: 0.3101 - val accuracy: 0.8813
Epoch 00097: val accuracy did not improve from 0.92237
Epoch 98/300
racy: 0.8886 - val loss: 0.5564 - val_accuracy: 0.6986
Epoch 00098: val accuracy did not improve from 0.92237
Epoch 99/300
racy: 0.8974 - val loss: 0.4565 - val accuracy: 0.7671
Epoch 00099: val accuracy did not improve from 0.92237
Epoch 100/300
racy: 0.8886 - val loss: 0.3669 - val accuracy: 0.8311
Epoch 00100: val accuracy did not improve from 0.92237
Epoch 101/300
53/53 [=========================] - 25s 474ms/step - loss: 0.2581 - accu
racy: 0.8868 - val loss: 0.6498 - val accuracy: 0.6941
Epoch 00101: val_accuracy did not improve from 0.92237
Epoch 102/300
```

```
racy: 0.8862 - val_loss: 0.5386 - val_accuracy: 0.7078
Epoch 00102: val_accuracy did not improve from 0.92237
.
Epoch 103/300
racy: 0.8850 - val loss: 0.8173 - val accuracy: 0.6256
Epoch 00103: val accuracy did not improve from 0.92237
Epoch 104/300
53/53 [========================= ] - 25s 463ms/step - loss: 0.2723 - accu
racy: 0.8980 - val loss: 0.4681 - val accuracy: 0.7626
Epoch 00104: val accuracy did not improve from 0.92237
Epoch 105/300
racy: 0.8903 - val loss: 0.2430 - val accuracy: 0.9087
Epoch 00105: val accuracy did not improve from 0.92237
Epoch 106/300
racy: 0.8927 - val loss: 0.3895 - val accuracy: 0.8082
Epoch 00106: val accuracy did not improve from 0.92237
Epoch 107/300
racy: 0.8856 - val loss: 0.4670 - val accuracy: 0.7352
Epoch 00107: val accuracy did not improve from 0.92237
Epoch 108/300
racy: 0.8921 - val loss: 0.6170 - val accuracy: 0.6941
Epoch 00108: val accuracy did not improve from 0.92237
Epoch 109/300
racy: 0.8844 - val loss: 0.2706 - val accuracy: 0.8858
Epoch 00109: val accuracy did not improve from 0.92237
Epoch 110/300
racy: 0.8939 - val loss: 0.3283 - val accuracy: 0.8493
Epoch 00110: val accuracy did not improve from 0.92237
Epoch 111/300
racy: 0.9068 - val loss: 0.4599 - val_accuracy: 0.7854
Epoch 00111: val accuracy did not improve from 0.92237
Epoch 112/300
racy: 0.8921 - val loss: 0.4782 - val_accuracy: 0.7489
Epoch 00112: val accuracy did not improve from 0.92237
Epoch 113/300
racy: 0.8892 - val loss: 0.4700 - val accuracy: 0.7397
Epoch 00113: val accuracy did not improve from 0.92237
Epoch 114/300
racy: 0.8909 - val loss: 0.4744 - val accuracy: 0.7763
Epoch 00114: val accuracy did not improve from 0.92237
Epoch 115/300
racy: 0.8921 - val_loss: 0.3975 - val_accuracy: 0.8128
Epoch 00115: val accuracy did not improve from 0.92237
Epoch 116/300
```

```
racy: 0.8892 - val_loss: 0.4046 - val_accuracy: 0.8082
Epoch 00116: val_accuracy did not improve from 0.92237
Epoch 117/300
racy: 0.8998 - val loss: 0.4979 - val accuracy: 0.7443
Epoch 00117: val accuracy did not improve from 0.92237
Epoch 118/300
racy: 0.8962 - val loss: 0.5922 - val accuracy: 0.7078
Epoch 00118: val accuracy did not improve from 0.92237
Epoch 119/300
racy: 0.8927 - val loss: 0.5498 - val accuracy: 0.7123
Epoch 00119: val accuracy did not improve from 0.92237
Epoch 120/300
racy: 0.8950 - val loss: 0.4502 - val accuracy: 0.7580
Epoch 00120: val accuracy did not improve from 0.92237
Epoch 121/300
racy: 0.8945 - val loss: 0.3786 - val accuracy: 0.8174
Epoch 00121: val accuracy did not improve from 0.92237
Epoch 122/300
racy: 0.8856 - val loss: 0.4813 - val accuracy: 0.7626
Epoch 00122: val accuracy did not improve from 0.92237
Epoch 123/300
racy: 0.9098 - val loss: 0.4764 - val accuracy: 0.7534
Epoch 00123: val accuracy did not improve from 0.92237
Epoch 124/300
racy: 0.8921 - val loss: 0.4779 - val accuracy: 0.7626
Epoch 00124: val accuracy did not improve from 0.92237
Epoch 125/300
racy: 0.8986 - val loss: 0.4090 - val accuracy: 0.7945
Epoch 00125: val accuracy did not improve from 0.92237
Epoch 126/300
racy: 0.8974 - val loss: 0.4025 - val accuracy: 0.8174
Epoch 00126: val accuracy did not improve from 0.92237
Epoch 127/300
racy: 0.8986 - val loss: 0.4407 - val accuracy: 0.7854
Epoch 00127: val accuracy did not improve from 0.92237
Epoch 128/300
53/53 [=========================] - 25s 476ms/step - loss: 0.2279 - accu
racy: 0.9057 - val loss: 0.3586 - val accuracy: 0.8447
Epoch 00128: val accuracy did not improve from 0.92237
Epoch 129/300
53/53 [=========================] - 26s 484ms/step - loss: 0.2862 - accu
racy: 0.8797 - val_loss: 0.3778 - val_accuracy: 0.8311
Epoch 00129: val_accuracy did not improve from 0.92237
```

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Epoch 130/300
racy: 0.9004 - val_loss: 0.5412 - val_accuracy: 0.7352
Epoch 00130: val_accuracy did not improve from 0.92237
Epoch 131/300
racy: 0.8844 - val loss: 0.3450 - val accuracy: 0.8402
Epoch 00131: val accuracy did not improve from 0.92237
Epoch 132/300
racy: 0.8903 - val loss: 0.4415 - val accuracy: 0.7580
Epoch 00132: val accuracy did not improve from 0.92237
Epoch 133/300
racy: 0.9004 - val loss: 0.4513 - val_accuracy: 0.7671
Epoch 00133: val accuracy did not improve from 0.92237
Epoch 134/300
racy: 0.8950 - val loss: 0.4457 - val accuracy: 0.7808
Epoch 00134: val accuracy did not improve from 0.92237
Epoch 135/300
racy: 0.8956 - val loss: 0.3682 - val accuracy: 0.8311
Epoch 00135: val accuracy did not improve from 0.92237
Epoch 136/300
racy: 0.9086 - val loss: 0.3657 - val accuracy: 0.8356
Epoch 00136: val accuracy did not improve from 0.92237
Epoch 137/300
racy: 0.8998 - val loss: 0.5002 - val accuracy: 0.7580
Epoch 00137: val accuracy did not improve from 0.92237
Epoch 138/300
racy: 0.8992 - val loss: 0.4681 - val accuracy: 0.7534
Epoch 00138: val_accuracy did not improve from 0.92237
Epoch 139/300
53/53 [=========================] - 25s 468ms/step - loss: 0.2280 - accu
racy: 0.9027 - val_loss: 0.4271 - val_accuracy: 0.7808
Epoch 00139: val accuracy did not improve from 0.92237
Epoch 140/300
racy: 0.8956 - val loss: 0.4221 - val accuracy: 0.7900
Epoch 00140: val accuracy did not improve from 0.92237
Epoch 141/300
racy: 0.9004 - val loss: 0.3653 - val accuracy: 0.8219
Epoch 00141: val accuracy did not improve from 0.92237
Epoch 142/300
53/53 [=========================] - 26s 480ms/step - loss: 0.2373 - accu
racy: 0.9021 - val loss: 0.5245 - val accuracy: 0.7215
Epoch 00142: val_accuracy did not improve from 0.92237
Epoch 143/300
53/53 [=========================] - 25s 477ms/step - loss: 0.2439 - accu
racy: 0.8945 - val_loss: 0.5764 - val_accuracy: 0.6986
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Epoch 00143: val_accuracy did not improve from 0.92237
Epoch 144/300
racy: 0.8956 - val_loss: 0.5093 - val_accuracy: 0.7306
Epoch 00144: val accuracy did not improve from 0.92237
Epoch 145/300
racy: 0.8927 - val loss: 0.5888 - val accuracy: 0.6804
Epoch 00145: val accuracy did not improve from 0.92237
Epoch 146/300
racy: 0.9092 - val loss: 0.5242 - val accuracy: 0.7306
Epoch 00146: val accuracy did not improve from 0.92237
Epoch 147/300
racy: 0.8844 - val loss: 0.5094 - val accuracy: 0.7306
Epoch 00147: val accuracy did not improve from 0.92237
Epoch 148/300
racy: 0.8915 - val loss: 0.3015 - val_accuracy: 0.8904
Epoch 00148: val accuracy did not improve from 0.92237
Epoch 149/300
racy: 0.9133 - val loss: 0.5347 - val accuracy: 0.7260
Epoch 00149: val accuracy did not improve from 0.92237
Epoch 150/300
racy: 0.8921 - val loss: 0.5017 - val accuracy: 0.7306
Epoch 00150: val accuracy did not improve from 0.92237
Epoch 151/300
racy: 0.9039 - val loss: 0.4402 - val accuracy: 0.7671
Epoch 00151: val accuracy did not improve from 0.92237
Epoch 152/300
racy: 0.9057 - val loss: 0.6179 - val accuracy: 0.6849
Epoch 00152: val accuracy did not improve from 0.92237
Epoch 153/300
racy: 0.9133 - val loss: 0.5036 - val_accuracy: 0.7626
Epoch 00153: val accuracy did not improve from 0.92237
Epoch 154/300
racy: 0.9033 - val loss: 0.3935 - val accuracy: 0.8082
Epoch 00154: val accuracy did not improve from 0.92237
Epoch 155/300
racy: 0.8921 - val loss: 0.4217 - val accuracy: 0.7808
Epoch 00155: val accuracy did not improve from 0.92237
Epoch 156/300
53/53 [=========================] - 25s 471ms/step - loss: 0.2500 - accu
racy: 0.9057 - val_loss: 0.3737 - val_accuracy: 0.8082
Epoch 00156: val accuracy did not improve from 0.92237
Epoch 157/300
53/53 [=========================] - 25s 474ms/step - loss: 0.2199 - accu
racy: 0.9116 - val_loss: 0.3191 - val_accuracy: 0.8767
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Epoch 00157: val accuracy did not improve from 0.92237
Epoch 158/300
racy: 0.8968 - val_loss: 0.6796 - val_accuracy: 0.6895
Epoch 00158: val accuracy did not improve from 0.92237
Epoch 159/300
racy: 0.8915 - val loss: 0.4266 - val accuracy: 0.7808
Epoch 00159: val accuracy did not improve from 0.92237
Epoch 160/300
racy: 0.9062 - val loss: 0.5537 - val accuracy: 0.7078
Epoch 00160: val accuracy did not improve from 0.92237
Epoch 161/300
racy: 0.9116 - val loss: 0.5952 - val accuracy: 0.7123
Epoch 00161: val accuracy did not improve from 0.92237
Epoch 162/300
racy: 0.8968 - val loss: 0.4751 - val accuracy: 0.7991
Epoch 00162: val accuracy did not improve from 0.92237
Epoch 163/300
racy: 0.8921 - val loss: 0.3594 - val accuracy: 0.8037
Epoch 00163: val accuracy did not improve from 0.92237
Epoch 164/300
racy: 0.8992 - val loss: 0.3309 - val accuracy: 0.8356
Epoch 00164: val accuracy did not improve from 0.92237
Epoch 165/300
racy: 0.9104 - val loss: 0.3674 - val accuracy: 0.8037
Epoch 00165: val accuracy did not improve from 0.92237
Epoch 166/300
racy: 0.9057 - val loss: 0.4728 - val accuracy: 0.7717
Epoch 00166: val accuracy did not improve from 0.92237
Epoch 167/300
racy: 0.9015 - val loss: 0.4969 - val_accuracy: 0.7489
Epoch 00167: val accuracy did not improve from 0.92237
Epoch 168/300
racy: 0.8986 - val loss: 0.4222 - val accuracy: 0.7945
Epoch 00168: val accuracy did not improve from 0.92237
Epoch 169/300
racy: 0.9051 - val loss: 0.5893 - val accuracy: 0.7078
Epoch 00169: val accuracy did not improve from 0.92237
Epoch 170/300
53/53 [=========================] - 25s 478ms/step - loss: 0.2357 - accu
racy: 0.9039 - val_loss: 0.5814 - val_accuracy: 0.7078
Epoch 00170: val_accuracy did not improve from 0.92237
Epoch 171/300
```

```
racy: 0.9098 - val_loss: 0.6641 - val_accuracy: 0.6758
Epoch 00171: val_accuracy did not improve from 0.92237
.
Epoch 172/300
racy: 0.8998 - val loss: 0.4717 - val accuracy: 0.7671
Epoch 00172: val accuracy did not improve from 0.92237
Epoch 173/300
53/53 [========================= ] - 25s 465ms/step - loss: 0.2301 - accu
racy: 0.9110 - val loss: 0.5439 - val accuracy: 0.7397
Epoch 00173: val accuracy did not improve from 0.92237
Epoch 174/300
racy: 0.9151 - val loss: 0.3917 - val accuracy: 0.8082
Epoch 00174: val accuracy did not improve from 0.92237
Epoch 175/300
racy: 0.9051 - val loss: 0.6435 - val accuracy: 0.7169
Epoch 00175: val accuracy did not improve from 0.92237
Epoch 176/300
racy: 0.9021 - val loss: 0.6182 - val accuracy: 0.6941
Epoch 00176: val accuracy did not improve from 0.92237
Epoch 177/300
racy: 0.9092 - val loss: 0.5875 - val accuracy: 0.7215
Epoch 00177: val accuracy did not improve from 0.92237
Epoch 178/300
racy: 0.9033 - val loss: 0.6015 - val accuracy: 0.6895
Epoch 00178: val accuracy did not improve from 0.92237
Epoch 179/300
racy: 0.8986 - val loss: 0.6155 - val accuracy: 0.6941
Epoch 00179: val accuracy did not improve from 0.92237
Epoch 180/300
racy: 0.8980 - val loss: 0.4473 - val accuracy: 0.7763
Epoch 00180: val accuracy did not improve from 0.92237
Epoch 181/300
racy: 0.9051 - val loss: 0.6871 - val_accuracy: 0.6712
Epoch 00181: val accuracy did not improve from 0.92237
Epoch 182/300
racy: 0.9057 - val loss: 0.7686 - val accuracy: 0.6758
Epoch 00182: val accuracy did not improve from 0.92237
Epoch 183/300
racy: 0.9145 - val loss: 0.3813 - val accuracy: 0.8082
Epoch 00183: val accuracy did not improve from 0.92237
Epoch 184/300
racy: 0.9021 - val_loss: 0.5587 - val_accuracy: 0.7306
Epoch 00184: val accuracy did not improve from 0.92237
Epoch 185/300
```

```
racy: 0.9139 - val_loss: 0.7363 - val_accuracy: 0.6849
Epoch 00185: val_accuracy did not improve from 0.92237
Epoch 186/300
racy: 0.9092 - val loss: 0.7220 - val accuracy: 0.6849
Epoch 00186: val accuracy did not improve from 0.92237
Epoch 187/300
racy: 0.9051 - val loss: 0.8684 - val accuracy: 0.6530
Epoch 00187: val accuracy did not improve from 0.92237
Epoch 188/300
racy: 0.9027 - val loss: 0.4480 - val accuracy: 0.7991
Epoch 00188: val accuracy did not improve from 0.92237
Epoch 189/300
racy: 0.9015 - val loss: 0.7262 - val accuracy: 0.6575
Epoch 00189: val accuracy did not improve from 0.92237
Epoch 190/300
racy: 0.9127 - val loss: 0.5803 - val accuracy: 0.7078
Epoch 00190: val accuracy did not improve from 0.92237
Epoch 191/300
53/53 [========================= ] - 25s 465ms/step - loss: 0.2374 - accu
racy: 0.9009 - val loss: 0.6379 - val accuracy: 0.7032
Epoch 00191: val accuracy did not improve from 0.92237
Epoch 192/300
racy: 0.9104 - val loss: 0.5414 - val accuracy: 0.7489
Epoch 00192: val accuracy did not improve from 0.92237
Epoch 193/300
racy: 0.9004 - val loss: 0.4490 - val accuracy: 0.7763
Epoch 00193: val accuracy did not improve from 0.92237
Epoch 194/300
racy: 0.9145 - val loss: 0.5603 - val_accuracy: 0.7489
Epoch 00194: val accuracy did not improve from 0.92237
Epoch 195/300
racy: 0.8980 - val loss: 0.5546 - val accuracy: 0.7260
Epoch 00195: val accuracy did not improve from 0.92237
Epoch 196/300
racy: 0.9098 - val loss: 0.6443 - val accuracy: 0.6895
Epoch 00196: val accuracy did not improve from 0.92237
Epoch 197/300
53/53 [=========================] - 25s 465ms/step - loss: 0.2176 - accu
racy: 0.9157 - val loss: 0.5552 - val accuracy: 0.7123
Epoch 00197: val accuracy did not improve from 0.92237
Epoch 198/300
53/53 [=========================] - 25s 465ms/step - loss: 0.2206 - accu
racy: 0.9045 - val_loss: 0.4158 - val_accuracy: 0.7900
```

Epoch 00198: val_accuracy did not improve from 0.92237

```
Epoch 199/300
racy: 0.8980 - val_loss: 0.5791 - val_accuracy: 0.7260
Epoch 00199: val_accuracy did not improve from 0.92237
Epoch 200/300
racy: 0.9169 - val loss: 0.6413 - val accuracy: 0.7078
Epoch 00200: val accuracy did not improve from 0.92237
Epoch 201/300
racy: 0.9169 - val loss: 0.3564 - val accuracy: 0.8356
Epoch 00201: val accuracy did not improve from 0.92237
Epoch 202/300
racy: 0.9027 - val loss: 0.4240 - val accuracy: 0.7854
Epoch 00202: val accuracy did not improve from 0.92237
Epoch 203/300
racy: 0.9051 - val loss: 0.5750 - val accuracy: 0.7260
Epoch 00203: val accuracy did not improve from 0.92237
Epoch 204/300
racy: 0.9004 - val loss: 0.4742 - val accuracy: 0.7443
Epoch 00204: val accuracy did not improve from 0.92237
Epoch 205/300
racy: 0.9127 - val loss: 0.5510 - val accuracy: 0.7169
Epoch 00205: val accuracy did not improve from 0.92237
Epoch 206/300
racy: 0.9139 - val loss: 0.3699 - val accuracy: 0.8128
Epoch 00206: val accuracy did not improve from 0.92237
Epoch 207/300
racy: 0.9057 - val loss: 0.5690 - val accuracy: 0.7260
Epoch 00207: val_accuracy did not improve from 0.92237
Epoch 208/300
racy: 0.9169 - val_loss: 0.8073 - val_accuracy: 0.6804
Epoch 00208: val accuracy did not improve from 0.92237
Epoch 209/300
racy: 0.9127 - val loss: 0.5418 - val accuracy: 0.7215
Epoch 00209: val accuracy did not improve from 0.92237
Epoch 210/300
racy: 0.9169 - val loss: 0.6880 - val accuracy: 0.6895
Epoch 00210: val accuracy did not improve from 0.92237
Epoch 211/300
racy: 0.9186 - val loss: 0.4083 - val accuracy: 0.7854
Epoch 00211: val_accuracy did not improve from 0.92237
Epoch 212/300
53/53 [=========================] - 26s 483ms/step - loss: 0.2242 - accu
racy: 0.9151 - val_loss: 0.4774 - val_accuracy: 0.7534
```

```
Epoch 00212: val_accuracy did not improve from 0.92237
Epoch 213/300
racy: 0.9086 - val_loss: 0.5610 - val_accuracy: 0.7443
Epoch 00213: val accuracy did not improve from 0.92237
Epoch 214/300
racy: 0.9133 - val loss: 0.6050 - val accuracy: 0.7169
Epoch 00214: val accuracy did not improve from 0.92237
Epoch 215/300
racy: 0.9127 - val loss: 0.5495 - val accuracy: 0.7260
Epoch 00215: val accuracy did not improve from 0.92237
Epoch 216/300
racy: 0.9139 - val loss: 0.8301 - val accuracy: 0.6621
Epoch 00216: val accuracy did not improve from 0.92237
Epoch 217/300
racy: 0.9021 - val loss: 0.6228 - val_accuracy: 0.7078
Epoch 00217: val accuracy did not improve from 0.92237
Epoch 218/300
racy: 0.8968 - val loss: 0.5883 - val accuracy: 0.7352
Epoch 00218: val accuracy did not improve from 0.92237
Epoch 219/300
racy: 0.9133 - val loss: 0.7788 - val accuracy: 0.6941
Epoch 00219: val accuracy did not improve from 0.92237
Epoch 220/300
racy: 0.9186 - val loss: 0.4147 - val accuracy: 0.7808
Epoch 00220: val accuracy did not improve from 0.92237
Epoch 221/300
53/53 [========================= ] - 25s 463ms/step - loss: 0.2002 - accu
racy: 0.9192 - val loss: 0.6821 - val accuracy: 0.6941
Epoch 00221: val accuracy did not improve from 0.92237
Epoch 222/300
racy: 0.9127 - val loss: 0.3907 - val_accuracy: 0.7945
Epoch 00222: val accuracy did not improve from 0.92237
Epoch 223/300
racy: 0.9169 - val loss: 0.5154 - val accuracy: 0.7397
Epoch 00223: val accuracy did not improve from 0.92237
Epoch 224/300
racy: 0.9009 - val loss: 0.3973 - val accuracy: 0.8037
Epoch 00224: val accuracy did not improve from 0.92237
Epoch 225/300
53/53 [=========================] - 24s 458ms/step - loss: 0.2257 - accu
racy: 0.9116 - val loss: 0.5063 - val accuracy: 0.7306
Epoch 00225: val accuracy did not improve from 0.92237
Epoch 226/300
53/53 [=========================] - 25s 471ms/step - loss: 0.2231 - accu
racy: 0.9092 - val_loss: 0.6196 - val_accuracy: 0.7123
```

```
Epoch 00226: val_accuracy did not improve from 0.92237
Epoch 227/300
racy: 0.9021 - val_loss: 0.5623 - val_accuracy: 0.7169
Epoch 00227: val accuracy did not improve from 0.92237
Epoch 228/300
53/53 [========================= ] - 25s 480ms/step - loss: 0.2141 - accu
racy: 0.9157 - val loss: 0.6996 - val accuracy: 0.7123
Epoch 00228: val accuracy did not improve from 0.92237
Epoch 229/300
racy: 0.9127 - val loss: 0.6633 - val accuracy: 0.6941
Epoch 00229: val accuracy did not improve from 0.92237
Epoch 230/300
racy: 0.9104 - val loss: 0.5336 - val_accuracy: 0.7352
Epoch 00230: val accuracy did not improve from 0.92237
Epoch 231/300
racy: 0.9080 - val loss: 0.5651 - val accuracy: 0.7123
Epoch 00231: val accuracy did not improve from 0.92237
Epoch 232/300
racy: 0.9104 - val loss: 0.5875 - val accuracy: 0.7215
Epoch 00232: val accuracy did not improve from 0.92237
Epoch 233/300
racy: 0.9281 - val loss: 0.4416 - val accuracy: 0.7854
Epoch 00233: val accuracy did not improve from 0.92237
Epoch 234/300
racy: 0.9045 - val loss: 0.7359 - val accuracy: 0.6849
Epoch 00234: val accuracy did not improve from 0.92237
Epoch 235/300
racy: 0.9062 - val loss: 0.6037 - val accuracy: 0.7123
Epoch 00235: val accuracy did not improve from 0.92237
Epoch 236/300
racy: 0.9133 - val loss: 0.4638 - val_accuracy: 0.7626
Epoch 00236: val accuracy did not improve from 0.92237
Epoch 237/300
racy: 0.9086 - val loss: 0.4477 - val accuracy: 0.7671
Epoch 00237: val accuracy did not improve from 0.92237
Epoch 238/300
racy: 0.9192 - val loss: 0.6358 - val accuracy: 0.7123
Epoch 00238: val accuracy did not improve from 0.92237
Epoch 239/300
53/53 [=========================] - 25s 473ms/step - loss: 0.2369 - accu
racy: 0.9086 - val_loss: 0.4881 - val_accuracy: 0.7443
Epoch 00239: val_accuracy did not improve from 0.92237
Epoch 240/300
```

```
racy: 0.9186 - val_loss: 0.7100 - val_accuracy: 0.6849
Epoch 00240: val_accuracy did not improve from 0.92237
.
Epoch 241/300
racy: 0.9110 - val_loss: 0.6042 - val_accuracy: 0.7169
Epoch 00241: val accuracy did not improve from 0.92237
Epoch 242/300
racy: 0.9233 - val loss: 0.6149 - val accuracy: 0.7215
Epoch 00242: val accuracy did not improve from 0.92237
Epoch 243/300
racy: 0.9198 - val loss: 0.5166 - val accuracy: 0.7443
Epoch 00243: val accuracy did not improve from 0.92237
Epoch 244/300
racy: 0.9057 - val loss: 0.6480 - val accuracy: 0.7215
Epoch 00244: val accuracy did not improve from 0.92237
Epoch 245/300
racy: 0.9027 - val loss: 0.5385 - val_accuracy: 0.7123
Epoch 00245: val accuracy did not improve from 0.92237
Epoch 246/300
racy: 0.9098 - val loss: 0.4511 - val accuracy: 0.7489
Epoch 00246: val accuracy did not improve from 0.92237
Epoch 247/300
racy: 0.9086 - val loss: 0.7711 - val accuracy: 0.6849
Epoch 00247: val accuracy did not improve from 0.92237
Epoch 248/300
racy: 0.9180 - val loss: 0.4295 - val accuracy: 0.7854
Epoch 00248: val accuracy did not improve from 0.92237
Epoch 249/300
racy: 0.9157 - val loss: 0.5760 - val accuracy: 0.7352
Epoch 00249: val accuracy did not improve from 0.92237
Epoch 250/300
racy: 0.9133 - val loss: 0.3181 - val_accuracy: 0.8447
Epoch 00250: val accuracy did not improve from 0.92237
Epoch 251/300
racy: 0.9180 - val loss: 0.5794 - val accuracy: 0.7123
Epoch 00251: val accuracy did not improve from 0.92237
Epoch 252/300
racy: 0.9057 - val loss: 0.7081 - val accuracy: 0.6895
Epoch 00252: val accuracy did not improve from 0.92237
Epoch 253/300
53/53 [=========================] - 25s 464ms/step - loss: 0.2102 - accu
racy: 0.9151 - val_loss: 0.5093 - val_accuracy: 0.7443
Epoch 00253: val accuracy did not improve from 0.92237
Epoch 254/300
```

```
racy: 0.9086 - val_loss: 0.5608 - val_accuracy: 0.7215
Epoch 00254: val_accuracy did not improve from 0.92237
Epoch 255/300
racy: 0.9163 - val loss: 0.5502 - val accuracy: 0.7306
Epoch 00255: val accuracy did not improve from 0.92237
Epoch 256/300
racy: 0.9175 - val loss: 0.5205 - val accuracy: 0.7397
Epoch 00256: val accuracy did not improve from 0.92237
Epoch 257/300
racy: 0.9216 - val loss: 0.5861 - val accuracy: 0.7260
Epoch 00257: val accuracy did not improve from 0.92237
Epoch 258/300
racy: 0.9251 - val loss: 0.5898 - val accuracy: 0.7306
Epoch 00258: val accuracy did not improve from 0.92237
Epoch 259/300
racy: 0.9281 - val loss: 0.6250 - val accuracy: 0.7306
Epoch 00259: val accuracy did not improve from 0.92237
Epoch 260/300
racy: 0.9204 - val loss: 0.6476 - val accuracy: 0.7215
Epoch 00260: val accuracy did not improve from 0.92237
Epoch 261/300
racy: 0.9163 - val loss: 0.4858 - val accuracy: 0.7717
Epoch 00261: val accuracy did not improve from 0.92237
Epoch 262/300
53/53 [========================= ] - 24s 462ms/step - loss: 0.2056 - accu
racy: 0.9139 - val loss: 0.5184 - val accuracy: 0.7352
Epoch 00262: val accuracy did not improve from 0.92237
Epoch 263/300
racy: 0.9180 - val loss: 0.4989 - val_accuracy: 0.7671
Epoch 00263: val accuracy did not improve from 0.92237
Epoch 264/300
racy: 0.9222 - val loss: 0.9079 - val_accuracy: 0.6712
Epoch 00264: val accuracy did not improve from 0.92237
Epoch 265/300
racy: 0.9116 - val loss: 0.6674 - val accuracy: 0.7032
Epoch 00265: val accuracy did not improve from 0.92237
Epoch 266/300
racy: 0.9133 - val loss: 0.5885 - val accuracy: 0.7397
Epoch 00266: val accuracy did not improve from 0.92237
Epoch 267/300
53/53 [=========================] - 25s 466ms/step - loss: 0.1967 - accu
racy: 0.9233 - val_loss: 0.6510 - val_accuracy: 0.7215
Epoch 00267: val_accuracy did not improve from 0.92237
```

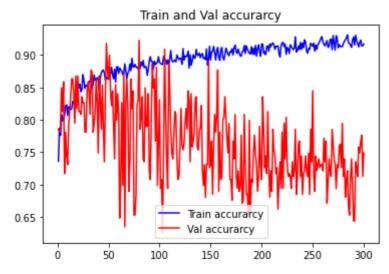
```
Epoch 268/300
racy: 0.9245 - val_loss: 0.6759 - val_accuracy: 0.7123
Epoch 00268: val_accuracy did not improve from 0.92237
Epoch 269/300
racy: 0.9080 - val loss: 0.4322 - val accuracy: 0.7854
Epoch 00269: val accuracy did not improve from 0.92237
Epoch 270/300
racy: 0.9298 - val loss: 0.5048 - val accuracy: 0.7626
Epoch 00270: val accuracy did not improve from 0.92237
Epoch 271/300
racy: 0.9192 - val loss: 0.5478 - val accuracy: 0.7397
Epoch 00271: val accuracy did not improve from 0.92237
Epoch 272/300
racy: 0.9074 - val loss: 0.5589 - val accuracy: 0.7306
Epoch 00272: val accuracy did not improve from 0.92237
Epoch 273/300
racy: 0.9298 - val loss: 0.6570 - val accuracy: 0.6941
Epoch 00273: val accuracy did not improve from 0.92237
Epoch 274/300
racy: 0.9239 - val loss: 0.5865 - val accuracy: 0.7306
Epoch 00274: val accuracy did not improve from 0.92237
Epoch 275/300
racy: 0.9110 - val loss: 0.5397 - val accuracy: 0.7260
Epoch 00275: val accuracy did not improve from 0.92237
Epoch 276/300
racy: 0.9157 - val loss: 0.5232 - val accuracy: 0.7580
Epoch 00276: val_accuracy did not improve from 0.92237
Epoch 277/300
53/53 [=========================] - 24s 457ms/step - loss: 0.2118 - accu
racy: 0.9133 - val_loss: 0.4881 - val_accuracy: 0.7626
Epoch 00277: val accuracy did not improve from 0.92237
Epoch 278/300
racy: 0.9127 - val loss: 0.6472 - val accuracy: 0.7260
Epoch 00278: val accuracy did not improve from 0.92237
Epoch 279/300
racy: 0.9127 - val loss: 0.4108 - val accuracy: 0.7945
Epoch 00279: val accuracy did not improve from 0.92237
Epoch 280/300
racy: 0.9175 - val loss: 0.6603 - val accuracy: 0.7123
Epoch 00280: val_accuracy did not improve from 0.92237
Epoch 281/300
53/53 [=========================] - 24s 458ms/step - loss: 0.1901 - accu
racy: 0.9210 - val_loss: 0.5114 - val_accuracy: 0.7397
```

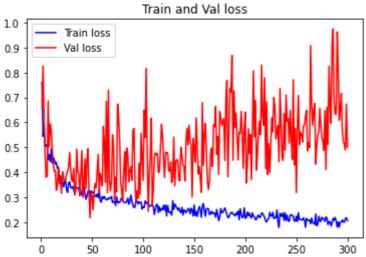
```
Epoch 00281: val_accuracy did not improve from 0.92237
Epoch 282/300
racy: 0.9233 - val_loss: 0.8246 - val_accuracy: 0.6804
Epoch 00282: val_accuracy did not improve from 0.92237
Epoch 283/300
53/53 [========================== ] - 24s 460ms/step - loss: 0.2029 - accu
racy: 0.9263 - val loss: 0.6691 - val accuracy: 0.7078
Epoch 00283: val accuracy did not improve from 0.92237
Epoch 284/300
racy: 0.9310 - val loss: 0.5958 - val accuracy: 0.7215
Epoch 00284: val accuracy did not improve from 0.92237
Epoch 285/300
racy: 0.9186 - val loss: 0.9141 - val accuracy: 0.6667
Epoch 00285: val_accuracy did not improve from 0.92237
Epoch 286/300
racy: 0.9175 - val loss: 0.9750 - val_accuracy: 0.6530
Epoch 00286: val accuracy did not improve from 0.92237
Epoch 287/300
racy: 0.9151 - val loss: 0.6825 - val accuracy: 0.7078
Epoch 00287: val accuracy did not improve from 0.92237
Epoch 288/300
racy: 0.9116 - val loss: 0.6359 - val accuracy: 0.7397
Epoch 00288: val accuracy did not improve from 0.92237
Epoch 289/300
racy: 0.9233 - val loss: 0.6315 - val accuracy: 0.6986
Epoch 00289: val accuracy did not improve from 0.92237
Epoch 290/300
racy: 0.9275 - val loss: 0.9631 - val accuracy: 0.6438
Epoch 00290: val accuracy did not improve from 0.92237
Epoch 291/300
racy: 0.9151 - val loss: 0.8148 - val_accuracy: 0.6438
Epoch 00291: val accuracy did not improve from 0.92237
Epoch 292/300
racy: 0.9304 - val loss: 0.6086 - val accuracy: 0.7352
Epoch 00292: val accuracy did not improve from 0.92237
Epoch 293/300
racy: 0.9222 - val loss: 0.6510 - val accuracy: 0.7260
Epoch 00293: val accuracy did not improve from 0.92237
Epoch 294/300
53/53 [=========================] - 25s 475ms/step - loss: 0.2005 - accu
racy: 0.9169 - val loss: 0.7162 - val accuracy: 0.7123
Epoch 00294: val accuracy did not improve from 0.92237
Epoch 295/300
53/53 [=========================] - 25s 473ms/step - loss: 0.2088 - accu
racy: 0.9121 - val_loss: 0.5723 - val_accuracy: 0.7580
```

```
Epoch 00295: val accuracy did not improve from 0.92237
Epoch 296/300
racy: 0.9192 - val_loss: 0.5249 - val_accuracy: 0.7489
Epoch 00296: val accuracy did not improve from 0.92237
Epoch 297/300
racy: 0.9228 - val loss: 0.5112 - val accuracy: 0.7671
Epoch 00297: val accuracy did not improve from 0.92237
Epoch 298/300
racy: 0.9139 - val loss: 0.4895 - val accuracy: 0.7763
Epoch 00298: val accuracy did not improve from 0.92237
Epoch 299/300
racy: 0.9139 - val loss: 0.6733 - val accuracy: 0.7123
Epoch 00299: val accuracy did not improve from 0.92237
Epoch 300/300
racy: 0.9169 - val loss: 0.5006 - val accuracy: 0.7489
Epoch 00300: val accuracy did not improve from 0.92237
```

Evaluating final trained model:

```
In [ ]:
         train accuracy = history.history['accuracy']
         validation accuracy = history.history['val accuracy']
          train loss = history.history['loss']
          validation loss = history.history['val loss']
          epochs = range(1, len(train accuracy) + 1)
          #Train and validation accuracy
         plt.plot(epochs, train_accuracy, 'b', label='Training accuracy')
plt.plot(epochs, validation_accuracy, 'r', label='Validation accuracy')
          plt.title('Training and Validation accurarcy')
          plt.legend()
          plt.figure()
          #Train and validation loss
          plt.plot(epochs, train_loss, 'b', label='Training loss')
          plt.plot(epochs, validation_loss, 'r', label='Validation loss')
          plt.title('Training and Validation loss')
          plt.legend()
          plt.show()
```





```
In [ ]: #load model:
    path_to_model= "/content/gdrive/MyDrive/Plant_disease/aug_20_2.hdf5"
    model = keras.models.load_model(path_to_model)
```

```
In [ ]:
         x, y = x_{test}, y_{test}
         x.shape, y.shape
         from sklearn.metrics import confusion_matrix, f1_score, precision_score, reca
         from keras.utils.np_utils import to_categorical
         import tensorflow as tf
         scores = model.evaluate(x_test, y_test)
         y_pred=[]
         for pred in ((model.predict(x_test))): #custom loop with threshold as 0.1
           if pred >= 0.5:
             y_pred.append(1)
             y_pred.append(0)
         y_test_new= []
         for y in y_test:
           y= np.array_str(y)
           y = int(y[1])
           y_test_new.append(y)
         print("CONFUSION MATRIX:")
         print( confusion_matrix(y_test_new , y_pred))
```

```
print("======"")
print(f"ACCURACY for test dataset is:
                                          {scores[1]}")
print("F1 SCORE for test datset is
                                         {}".format(f1_score(y_test_new , y
print("PRECISION SCORE for test datset is {}".format(precision score(y test
print("RECALL SCORE for test datset is
                                         {}".format(recall score(y test new
                       ========] - 1s 64ms/step - loss: 0.3158 - accura
16/16 [=========
cy: 0.8642
CONFUSION MATRIX:
[[174 26]
 [ 43 265]]
ACCURACY for test dataset is:
                                  0.8641732335090637
F1 SCORE for test datset is
                                  0.8848080133555927
PRECISION_SCORE for test datset is 0.9106529209621993
RECALL_SCORE for test datset is 0.8603896103896104
```

Conclusion:

As we can see that it didn't take much training and results are very great on our data. This is possible because we incorporated 'Transfer Learning' for training on our dataset. The model trained from 'Plant Village' dataset learned greatly to classify healthy and unhealthy plants. Saved Weights from that model helped our second model to train well on self collected data and yields good results.