Plant Disease Detection!

In [0]:

```
from IPython.display import Image
Image('image.jpg',height=500,width=1000)
```

Out[0]:

Data Description-

The dataset contains 54,305 images. The images span 14 crop species: Apple, Blueberry,Corn, Cherry, Grape, Orange, Peach, Bell Pepper, Potato, Raspberry, Soybean, Squash, Strawberry, and Tomato.

It contains images of 17 fungal diseases, 4 bacterial diseases, 2 molds (oomycete) diseases, 2 viral diseases, and 1 disease caused by a mite.

12 crop species also have images of healthy leaves that are not visibly affected by a disease.

It has 14 crop species and 26 diseases belonging to 38 classes.

The goal of this challenge is to develop algorithms than can accurately diagnose a disease based on an image.

Dataset link-(used only colored image)

https://github.com/spMohanty/PlantVillage-Dataset

Metric

- F1_score,Precision,Recall
- Confusion matrix
- Precision matrix-It tells What proportion of positive identifications was actually correct.

- Recall matrix-It tells What proportion of actual positives was identified correctly.

Loss

As it is multiclass classification problem,i have used multi log loss (cross entropy) to minimize.

References:-

1- https://arxiv.org/ftp/arxiv/papers/1604/1604.03169.pdf

2-https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html

3-https://github.com/bkleyn/plant_diseases

Loading data And understanding the data

In [0]:

```
#importing necessary libraries

"""

these are some important libraries which needed to be installed for easy working

"""

%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from mpl_toolkits.axes_grid1 import ImageGrid

import re
import os
import numpy as np
import pandas as pd
import seaborn as sns
from shutil import copyfile
from tqdm import tqdm

import keras
from keras.models import Sequential, load_model,Model
from keras.layers import Dense, Dropout, Activation,ReLU,Flatten, Conv2D,
MaxPooling2D,BatchNormalization
from keras.optimizers import Adam
from keras.callbacks import Callback, EarlyStopping, ModelCheckpoint
from keras.preprocessing import image
from keras import regularizers

import tensorflow as tf
from keras.layers import GlobalAveragePooling2D
from keras.callbacks import ReduceLROnPlateau, CSVLogger
from keras.preprocessing.image import ImageDataGenerator

from PIL import Image
import numpy as np
from skimage import transform
```

```
Using TensorFlow backend.
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.
We recommend you upgrade now or ensure your notebook will continue to use TensorFlow 1.x via the `%tensorflow_version 1.x` magic: more info.

In [0]:

```
# Path variables
```

```
"""
in data dir,we mention the path which contains the data folder
"""

data_dir = "color/"

# Get list of all classes

""" this will get all name of all the subfolders present in data dir"""

classes = os.listdir(data_dir)
classes
```

Out[0]:

```
['Pepper,_bell___Bacterial_spot',
 'Corn_(maize)___Northern_Leaf_Blight',
 'Orange___Haunglongbing_(Citrus_greening)',
 'Cherry_(including_sour)___healthy',
 'Grape___Black_rot',
 'Tomato___Early_blight',
 'Grape___healthy',
 'Grape___Esca_(Black_Measles)',
 'Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot',
 'Apple___Black_rot',
 'Apple___Apple_scab',
 'Peach___healthy',
 'Tomato___healthy',
 'Soybean___healthy',
 'Apple___healthy',
 'Apple___Cedar_apple_rust',
 'Corn_(maize)___healthy',
 'Tomato___Leaf_Mold',
 'Peach___Bacterial_spot',
 'Potato___healthy',
 'Corn_(maize)___Common_rust_',
 'Blueberry___healthy',
 'Tomato___Target_Spot',
 'Tomato___Septoria_leaf_spot',
 'Grape___Leaf_blight_(Isariopsis_Leaf_Spot)',
 'Strawberry___healthy',
 'Raspberry___healthy',
 'Strawberry___Leaf_scorch',
 'Pepper,_bell___healthy',
 'Potato___Late_blight',
 'Squash___Powdery_mildew',
 'Cherry_(including_sour)___Powdery_mildew',
 'Tomato___Spider_mites Two-spotted_spider_mite',
 'Tomato___Tomato_Yellow_Leaf_Curl_Virus',
 'Tomato___Late_blight',
 'Tomato___Bacterial_spot',
 'Tomato___Tomato_mosaic_virus',
 'Potato___Early_blight']
```

In [0]:

```
# Number of images in each class

"""in this code snippet,we count the number of images in each class and represent this as a datafr
ame.

working of the code- using a for loop we count the # of images in each subfolder (contained in mai
n folder)
and append it to a dictionary and from that dict we make a dataframe."""

image_counts = {}
for c in classes:
    try:
        path = data_dir + c
        count = len(os.listdir(path))
        image_counts[c] = count
    except:
        pass

df=pd.DataFrame.from_dict(image_counts, orient='index')
df
```

Out[0]:

	0
Pepper,_bell___Bacterial_spot	997
Corn_(maize)___Northern_Leaf_Blight	985
Orange___Haunglongbing_(Citrus_greening)	5507
Cherry_(including_sour)___healthy	854
Grape___Black_rot	1180
Tomato___Early_blight	1000
Grape___healthy	423
Grape___Esca_(Black_Measles)	1383
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	513
Apple___Black_rot	621
Apple___Apple_scab	630
Peach___healthy	360
Tomato___healthy	1591
Soybean___healthy	5090
Apple___healthy	1645
Apple___Cedar_apple_rust	275
Corn_(maize)___healthy	1162
Tomato___Leaf_Mold	952
Peach___Bacterial_spot	2297
Potato___healthy	152
Corn_(maize)___Common_rust_	1192
Blueberry___healthy	1502
Tomato___Target_Spot	1404
Tomato___Septoria_leaf_spot	1771
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1076
Strawberry___healthy	456
Raspberry___healthy	371
Strawberry___Leaf_scorch	1109
Pepper,_bell___healthy	1478
Potato___Late_blight	1000
Squash___Powdery_mildew	1835
Cherry_(including_sour)___Powdery_mildew	1052
Tomato___Spider_mites Two-spotted_spider_mite	1676
Tomato___Tomato_Yellow_Leaf_Curl_Virus	5357
Tomato___Late_blight	1909
Tomato___Bacterial_spot	2127
Tomato___Tomato_mosaic_virus	373
Potato___Early_blight	1000

In [0]:

```
#total number of images
print("Total number of images:", sum(image_counts.values()))
```

```
Total number of images: 54305
```

In [0]:

```
# Get path and label for each image

"""enumerate function allows us to loop over something and have an automatic counter.

we make a dataframe here which contains the file,label and its class name.

working of the code- we go to each subfolder available in the main folder and since the name of ea
ch subfolder
is the class_name, we append the files in each subfolder while naming it in the format of class_na
me/file_name
to a list df along with label(with help of enumerate) and class name

"""

df=[]
for label, class_name in enumerate(classes):
    path = data_dir + class_name
    for file in os.listdir(path):
        df.append(['{}/{}'.format(class_name, file), label, class_name])

df = pd.DataFrame(df, columns=['file', 'label', 'class_name'])
```

In [0]:

```
#showing few datapoints
df.head()
```

Out[0]:

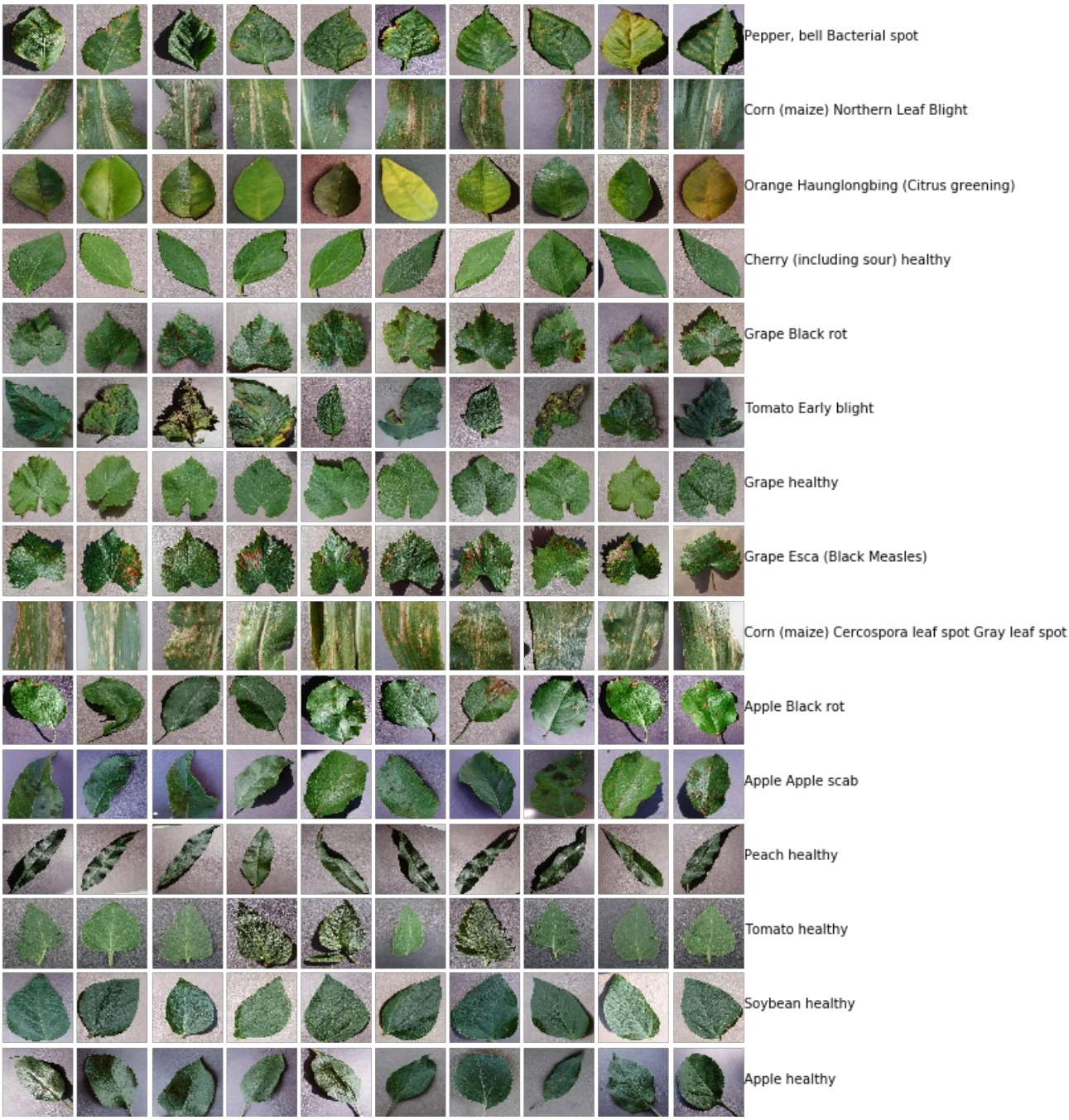
	file	label	class_name
0	Pepper,_bell___Bacterial_spot/113d374f-8b12-45...	0	Pepper,_bell___Bacterial_spot
1	Pepper,_bell___Bacterial_spot/197fdd19-46d1-46...	0	Pepper,_bell___Bacterial_spot
2	Pepper,_bell___Bacterial_spot/162f0add-8d7d-47...	0	Pepper,_bell___Bacterial_spot
3	Pepper,_bell___Bacterial_spot/b8b69a41-e188-4c...	0	Pepper,_bell___Bacterial_spot
4	Pepper,_bell___Bacterial_spot/70985466-254f-47...	0	Pepper,_bell___Bacterial_spot

In [0]:

```
#function used in plotting
import re

"""read_img function is used to take a image and convert it to array
and format_name is used to replace _ with space
"""

def read_img(filepath, size):

    """Read and resize image.
    # Arguments
        filepath: path of image
        size: resize the original image.
    # Returns
        Image as numpy array.
    """

    img = image.load_img(data_dir + filepath, target_size=size)
    img = image.img_to_array(img)
    return img

def format_name(s):
    return re.sub('_+', ' ', s)
```

In [0]:

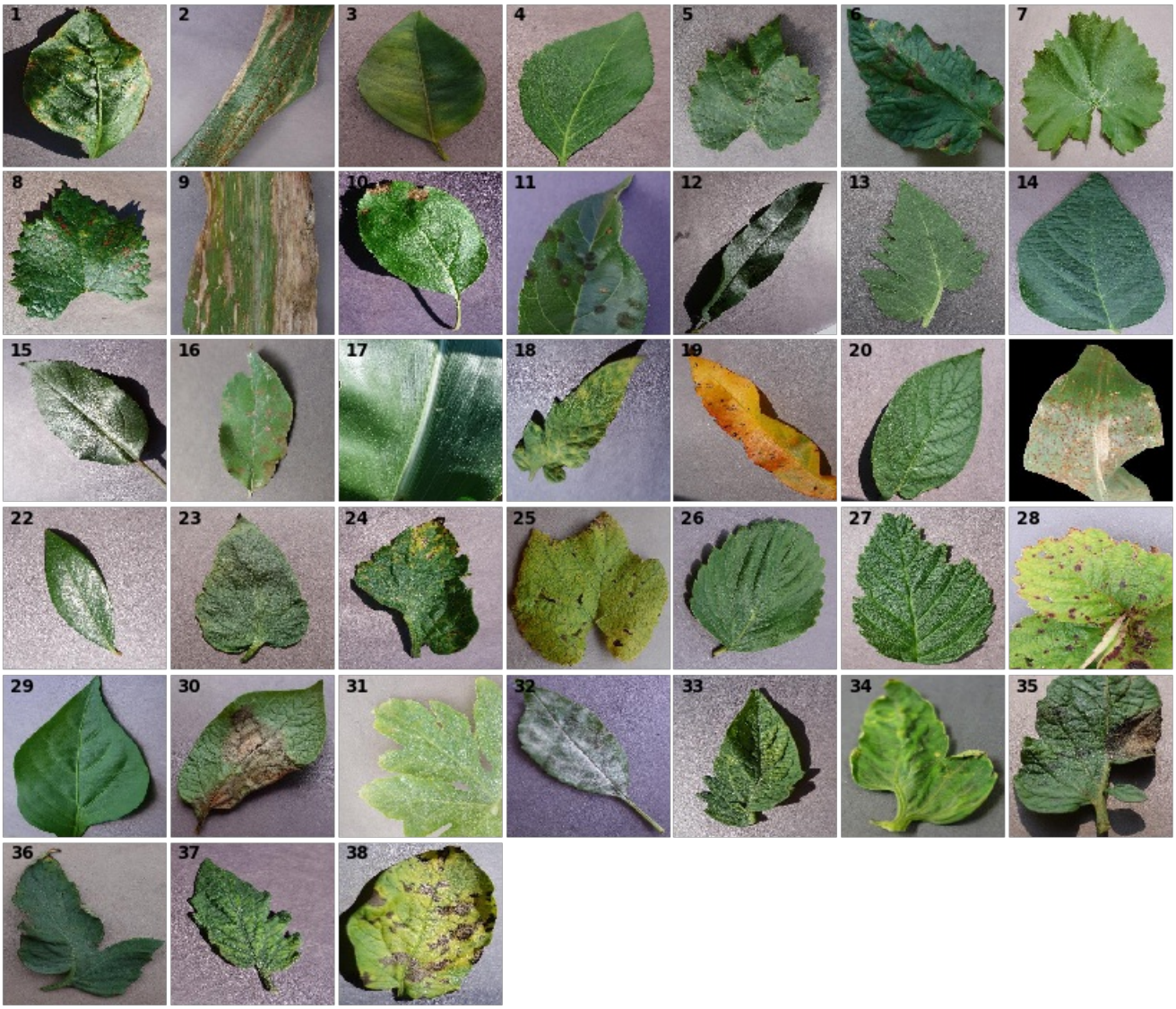
```
from matplotlib import pyplot as plt

""" this code is plotting 10 images from each class"""


# Plot some images
num_classes = len(classes)
fig = plt.figure(1, figsize=(10, 40))
grid = ImageGrid(fig, 111, nrows_ncols=(num_classes, 10), axes_pad=0.05)

i = 0
for label, class_name in enumerate(classes):
    for filepath in df['file'][df['class_name'] == class_name].values[:10]:
        ax = grid[i]
        img = read_img(filepath, (256, 256))
        ax.imshow(img / 255.)
        ax.axis('off')
        if i % 10 == 10 - 1:
            name = format_name(filepath.split('/')[0])
            ax.text(260, 112, name , verticalalignment='center')
        i += 1

plt.show()
#plt.savefig("fig1.png")
```




Apple Cedar apple rust
Corn (maize) healthy
Tomato Leaf Mold
Peach Bacterial spot
Potato healthy
Corn (maize) Common rust
Blueberry healthy
Tomato Target Spot
Tomato Septoria leaf spot
Grape Leaf blight (Isariopsis Leaf Spot)
Strawberry healthy
Raspberry healthy
Strawberry Leaf scorch
Pepper, bell healthy
Potato Late blight
Squash Powdery mildew
Cherry (including sour) Powdery mildew
Tomato Spider mites Two-spotted spider mite
Tomato Tomato Yellow Leaf Curl Virus
Tomato Late blight
Tomato Bacterial spot
Tomato Tomato mosaic virus
Potato Early blight

In [0]:

```
# Plot image from each class

"""showing and labelling one image from each class"""

fig = plt.figure(1, figsize=(15, 10))
grid = ImageGrid(fig, 111, nrows_ncols=(6, 7), axes_pad=0.05)

for i in range(42):
    ax = grid[i]
    ax.axis('off')
    if i < len(classes):
        class_name = classes[i]
        for filepath in df[df['class_name'] == class_name]['file'].values[:1]:
            img = read_img(filepath, (256, 256))
            ax.imshow(img / 255.)
            ax.annotate(i+1, xy=(10,25), color="black", fontsize=12, fontweight='bold')
plt.tight_layout()
#plt.savefig("fig2.png")
```



Train -Test split

Process of splitting into train & test-

- make two folder within the data folder and name them train and test.
- In the train and test folder make c subfolder where c is number of classes present in the data folder with the name same as class

class.

- Now make a dataframe which contains the path of the image(eg Apple__Apple_scab/00075aa8..) as file_name,label and class name.
- Using the numpy bionomial number generator,generate 54305(equal to num of images) number with n=1(#trails), p=0.8(train_size).
- Start a loop over filename in df,If the number generated is 1,then append that image(filename) to train else it will go to the test.

In [0]:

```
# Set input directory

"""
in data dir,we mention the path which contains the data folder
"""

data_dir = "color/"

# Get classes

"""this will get name of all the subfolders present in main folder"""

classes = os.listdir(data_dir)
num_classes = len(classes)
print("Number of classes:",num_classes)


# Create train test directories

"""with help of mkdir ,we will create two folder named as train and test in main folder"""

os.mkdir(data_dir+'train')
os.mkdir(data_dir+'test')


# Create new class directories for train and test images

"""within train and test folder,make c subfolder where c is number of subfolder present in the mai
n
   folder with the same name as subfolder's name. """

for c in classes:
    os.mkdir(data_dir+'train/' + c)
    os.mkdir(data_dir+'test/' + c)


# Get path and label for each image

"""
we make a dataframe here which contains the file,label and its class name.
we go to each subfolder available in the main folder and since the name of each subfolder
is the class name, we append the files in each subfolder while naming it in the format of class_na
me/file_name
to df along with label(with help of enumerate) and class name.
"""

df = []
for label, class_name in enumerate(classes):
    path = data_dir + class_name

    for file in os.listdir(path):
        df.append(['{}/{}'.format(class_name, file), label, class_name])


df = pd.DataFrame(df, columns=['file', 'label', 'class_name'])

#gives total no. of classes which is same as total no. of subfolder with the main folder.
num_images = len(df)

print("Number of images:", num_images)
```

```
Number of classes: 38
Number of images: 54305
```

In [0]:

```
#showing some datapoints
df.head()
```

Out[0]:

	file	label	class_name
0	Pepper,_bell___Bacterial_spot/113d374f-8b12-45...	0	Pepper,_bell___Bacterial_spot
1	Pepper,_bell___Bacterial_spot/197fdd19-46d1-46...	0	Pepper,_bell___Bacterial_spot
2	Pepper,_bell___Bacterial_spot/162f0add-8d7d-47...	0	Pepper,_bell___Bacterial_spot
3	Pepper,_bell___Bacterial_spot/b8b69a41-e188-4c...	0	Pepper,_bell___Bacterial_spot
4	Pepper,_bell___Bacterial_spot/70985466-254f-47...	0	Pepper,_bell___Bacterial_spot

In [0]:

```
# Sample train/test observations

"""
Using the numpy bionomial number generator,generate 54305(equal to num of images)
number with n=1(#trails), p=0.8(train_size).
Start a loop over filename in df,If the number generated is 1,then append that image(filename)
to train else it will go to the test.
"""

tr_size=0.8
np.random.seed(50)
num = np.random.binomial(1,tr_size, num_images)

# Import images
i = 0
for file in tqdm(df['file'].values):

    from_path = data_dir + file
    if num[i] == 1:
        to_path = data_dir+'train/' + file
    else:
        to_path = data_dir+'test/' + file

    copyfile(from_path, to_path)
    i += 1
```

```
100%|██████████| 54305/54305 [00:05<00:00, 9354.79it/s]
```

In [0]:

```
#mentioning the train and test dir
TRAIN_DIR = "color/train/"
TEST_DIR = "color/test/"
```

In [0]:

```
# Get path and label for each image in test and train dir and calculating no. of samples in train
and test

"""we make a dataframe here which contains the file,label,class name & train_ind.
we go to each subfolder available in the train & test folder and since the name of each subfolder
is the class name, we append the files in each subfolder while naming it in the format of class_na
me/file_name
to df along with label(with help of enumerate),class name and train_ind.
if the train_ind=1,then it is showing that the file is in train folder while 0 shows the file lies
withing test folder
"""

df=[]
for label, class_name in enumerate(classes):
```

```
    # Train
    path = TRAIN_DIR + class_name
    for file in os.listdir(path):
        df.append(['{}/{}'.format(class_name, file), label, class_name, 1])

    # test
    path = TEST_DIR + class_name
    for file in os.listdir(path):
        df.append(['{}/{}'.format(class_name, file), label, class_name, 0])

df = pd.DataFrame(df, columns=['file', 'label', 'class_name', 'train_ind'])

num_train_samples = df.train_ind.sum()
num_test_samples = len(df) - num_train_samples

print("Number of train images:", num_train_samples)
print("Number of test images:", num_test_samples)
```

```
Number of train images: 43616
Number of test images: 10689
```

In [0]:

```
#showing some datapoints
df.head()
```

Out[0]:

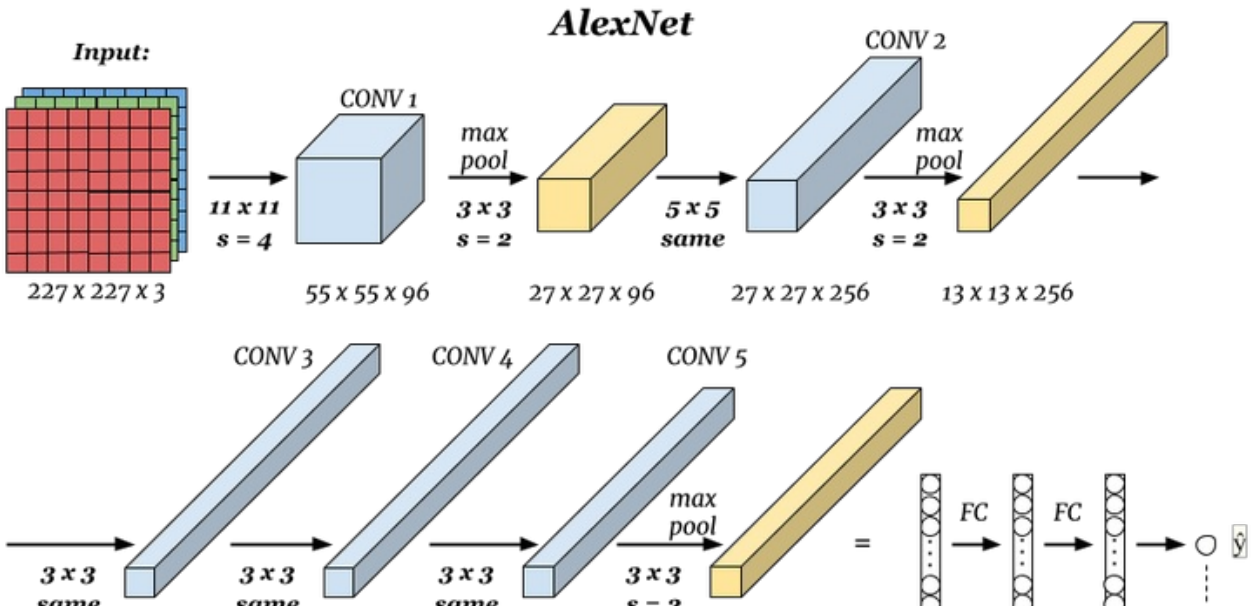
	file	label	class_name	train_ind
0	Pepper,_bell___Bacterial_spot/113d374f-8b12-45...	0	Pepper,_bell___Bacterial_spot	1
1	Pepper,_bell___Bacterial_spot/197fdd19-46d1-46...	0	Pepper,_bell___Bacterial_spot	1
2	Pepper,_bell___Bacterial_spot/162f0add-8d7d-47...	0	Pepper,_bell___Bacterial_spot	1
3	Pepper,_bell___Bacterial_spot/b8b69a41-e188-4c...	0	Pepper,_bell___Bacterial_spot	1
4	Pepper,_bell___Bacterial_spot/70985466-254f-47...	0	Pepper,_bell___Bacterial_spot	1

AlexNet Model from scratch

In [0]:

```
from IPython.display import Image
Image('alexnet.png',height=500,width=800)
```

Out[0]:



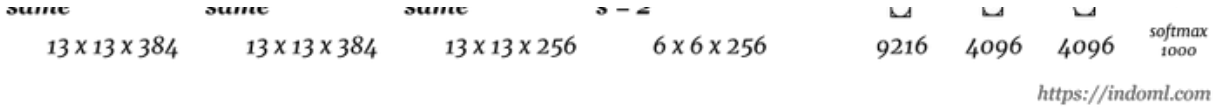


Image Augmentations techniques are methods of artificially increasing the variations of images in our data-set by using horizontal/vertical flips, rotations, variations in brightness of images, horizontal/vertical shifts etc and this image augmentation is performed by ImageDataGenerator.

In [0]:

```
# Specify data generator inputs
train_datagen = ImageDataGenerator(rescale=1./255,
    rotation_range=30,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True)

test_datagen = ImageDataGenerator(rescale=1./255)
```

here we are using keras flow from directory to get the train and test data.

Remember to set shuffle=False in test_generator otherwise there will randomness while predicting.

In [0]:

```
width,height,depth= 256, 256 ,3
batch =100

train_generator = train_datagen.flow_from_directory(
    TRAIN_DIR,
    target_size=(height,width),
    batch_size=batch)


test_generator = test_datagen.flow_from_directory(
    TEST_DIR,
    target_size=(height,width),
    batch_size=batch,
    shuffle=False)
```

```
Found 43616 images belonging to 38 classes.
Found 10689 images belonging to 38 classes.
```

Alexnet architecture--

It contains 5 convolutional layers and 3 fully connected layers.

Relu is applied after every convolutional and fully connected layer.

Dropout is applied before the first and the second fully connected year. The image size in the architecture is 256*256

In [0]:

```
#define the architecture of the model

model = Sequential()

# 1st Convolutional Layer
model.add(Conv2D(filters=96, input_shape=(256,256,3), kernel_size=(11,11), strides=(4,4), padding='
valid'))
model.add(Activation('relu'))
    #normalization
model.add(BatchNormalization())
    # Max Pooling
model.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='valid'))

# 2nd Convolutional Layer
```

```
model.add(Conv2D(filters=256, kernel_size=(11,11), strides=(1,1), padding='valid'))
model.add(Activation('relu'))
    #normalization
model.add(BatchNormalization())
   # Max Pooling
model.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='valid'))

# 3rd Convolutional Layer
model.add(Conv2D(filters=384, kernel_size=(3,3), strides=(1,1), padding='valid'))
model.add(Activation('relu'))

# 4th Convolutional Layer
model.add(Conv2D(filters=384, kernel_size=(3,3), strides=(1,1), padding='valid'))
model.add(Activation('relu'))

# 5th Convolutional Layer
model.add(Conv2D(filters=256, kernel_size=(3,3), strides=(1,1), padding='valid'))
model.add(Activation('relu'))
   # Max Pooling
model.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='valid'))

# Passing it to a Fully Connected layer
model.add(Flatten())
# 1st Fully Connected Layer
model.add(Dense(512, input_shape=(256*256*3,)))
model.add(Activation('relu'))
# Add Dropout to prevent overfitting
model.add(Dropout(0.5))

# 2nd Fully Connected Layer
model.add(Dense(128))
model.add(Activation('relu'))
# Add Dropout
model.add(Dropout(0.5))
model.add(BatchNormalization())

# 3rd Fully Connected Layer
model.add(Dense(64))
model.add(Activation('relu'))


# Output Layer
model.add(Dense(38))
model.add(Activation('softmax'))
```

In [0]:

```
#it will show the layers used and no. of parameters after each layer
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 62, 62, 96)        34944
_________________________________________________________________
activation_1 (Activation)    (None, 62, 62, 96)        0
_________________________________________________________________
batch_normalization_1 (Batch (None, 62, 62, 96)        384
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 31, 31, 96)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 21, 21, 256)       2973952
_________________________________________________________________
activation_2 (Activation)    (None, 21, 21, 256)       0
_________________________________________________________________
batch_normalization_2 (Batch (None, 21, 21, 256)       1024
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 10, 10, 256)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 8, 8, 384)         885120
_________________________________________________________________
activation_3 (Activation)    (None, 8, 8, 384)         0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 6, 6, 384)         1327488
```

```
_________________________________________________________________
activation_4 (Activation)    (None, 6, 6, 384)         0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 4, 4, 256)         884992
_________________________________________________________________
activation_5 (Activation)    (None, 4, 4, 256)         0
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 2, 2, 256)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               524800
_________________________________________________________________
activation_6 (Activation)    (None, 512)               0
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               65664
_________________________________________________________________
activation_7 (Activation)    (None, 128)               0
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
batch_normalization_3 (Batch (None, 128)               512
_________________________________________________________________
dense_3 (Dense)              (None, 64)                8256
_________________________________________________________________
activation_8 (Activation)    (None, 64)                0
_________________________________________________________________
dense_4 (Dense)              (None, 38)                2470
_________________________________________________________________
activation_9 (Activation)    (None, 38)                0
=================================================================
Total params: 6,709,606
Trainable params: 6,708,646
Non-trainable params: 960
_________________________________________________________________
```

As F1_score,precision and recall are not readily available in Keras to be used as metric so we introduce it via keras callback.

we create class Metrics and define attributes train_data,val_data and batch size using **init** method and to get the attributes of parent class (callback) we will use super() keyword.

now we define on_train_begin method in which we will have f1,precision and recall for train and val data whose entry will be written by later method.

and then we have on_epoch_end method in which we will calculate weighted f1 score,precision and recall (using sklearn function) for train and val data after end of each epoch and print it.

In [0]:

```
#custom metric

#https://github.com/keras-team/keras/issues/10472

import itertools

class Metrics(Callback):
        def __init__(self,tr_data, val_data, batch_size):
            super().__init__()
            self.train_data=tr_data
            self.validation_data = val_data
            self.batch_size = batch_size

        def on_train_begin(self, logs={}):
            self.tr_f1s=[]
            self.tr_recalls=[]
            self.tr_precisions=[]
```

```
            self.val_f1s = []
            self.val_recalls = []
            self.val_precisions = []

        def on_epoch_end(self, epoch, logs={}):

            batch_tr=len(self.train_data)
            total_tr=batch_tr*self.batch_size

            tr_pred= []
            tr_true= []

            for batch in range(batch_tr):
                xtr,ytr=next(self.train_data)

                tr_pred_batch=np.zeros((len(xtr)))
                tr_true_batch=np.zeros((len(ytr)))

                tr_pred_batch=np.argmax(np.asarray(self.model.predict(xtr)),axis=-1)
                tr_true_batch=np.argmax(ytr,axis=-1)

                tr_pred.append(tr_pred_batch)
                tr_true.append(tr_true_batch)

            tr_pred = np.asarray(list(itertools.chain.from_iterable(tr_pred)))
            tr_true = np.asarray(list(itertools.chain.from_iterable(tr_true)))


            _tr_f1 = f1_score(tr_true, tr_pred,average="weighted")
            _tr_precision = precision_score(tr_true, tr_pred,average="weighted")
            _tr_recall = recall_score(tr_true, tr_pred,average="weighted")

            self.tr_f1s.append(_tr_f1)
            self.tr_recalls.append(_tr_recall)
            self.tr_precisions.append(_tr_precision)

            logs['tr_f1s']= _tr_f1
            logs["tr_recall"]= _tr_recall
            logs["tr_precision"]= _tr_precision

            print("— tr_f1: {} — tr_recall: {} — tr_precision {}".format(_tr_f1, _tr_recall, _tr_pr
ecision))


            #for valid data
            batches = len(self.validation_data)
            total = batches * self.batch_size

            val_pred = []
            val_true = []

            for batch in range(batches):

                xVal, yVal = next(self.validation_data)

                val_pred_batch = np.zeros((len(xVal)))
                val_true_batch = np.zeros((len(xVal)))

                val_pred_batch = np.argmax(np.asarray(self.model.predict(xVal)), axis=-1)
                val_true_batch = np.argmax(yVal,axis=-1)


                val_pred.append(val_pred_batch)
                val_true.append(val_true_batch)


            val_pred = np.asarray(list(itertools.chain.from_iterable(val_pred)))
            val_true = np.asarray(list(itertools.chain.from_iterable(val_true)))


            _val_f1 = f1_score(val_true, val_pred,average="weighted")
            _val_precision = precision_score(val_true, val_pred,average="weighted")
            _val_recall = recall_score(val_true, val_pred,average="weighted")

            self.val_f1s.append(_val_f1)
            self.val_recalls.append(_val_recall)
            self.val_precisions.append(_val_precision)
```

```
            logs['val_f1s']= _val_f1
            logs["val_recall"]= _val_recall
            logs["val_precision"]= _val_precision

            print("— val_f1: {} — val_recall: {} — val_precision {}".format(
                 _val_f1, _val_recall, _val_precision))

            return

metric=Metrics(train_generator,test_generator,batch_size=100)
```

In [0]:

```
# Compile model

"""Compile defines the loss function, the optimizer and the metrics."""

model.compile(optimizer="adam",loss='categorical_crossentropy')
```

In [0]:

```
# Load the TensorBoard notebook extension

import tensorflow as tf
from keras.callbacks import TensorBoard
import datetime

"""Tensorboard is the interface used to visualize the graph and
 other tools to understand, debug, and optimize the model. """

#https://www.tensorflow.org/tensorboard/r1/summaries
log_dir="log/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensor = TensorBoard(log_dir=log_dir)

'''The ModelCheckpoint callback class allows to define where to checkpoint the model weights,
   how the file should named and under what circumstances to make a checkpoint of the model'''

path="alex"+'.hdf5'
checkpoint = ModelCheckpoint(path,
                             monitor='val_loss',
                             mode='min',
                             verbose=1,
                             save_best_only=True)

'''ReduceLROnPlateau callback monitors a quantity and if no improvement is seen for
   a 'patience' number of epochs, the learning rate is reduced. '''

reduce_lr = ReduceLROnPlateau(monitor='val_loss',
                              factor=0.2,
                               patience=5,
                               cooldown=5)

'''CSVLogger Callback store epoch results to a csv file.'''

filepath = "alex" + ".csv"
csv_log = CSVLogger(filepath)
```

In [0]:

```
# Fit transfer learning model
history = model.fit_generator(train_generator,
    epochs=12,
    steps_per_epoch=num_train_samples//batch,
    validation_data=test_generator,
    validation_steps=num_test_samples//batch,
    callbacks=[metric,checkpoint,reduce_lr,csv_log,tensor])
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow_core/python/ops/math_grad.py:1424: where (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please us
e tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is deprecated. Please use tf
.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1122: The name t
f.summary.merge_all is deprecated. Please use tf.compat.v1.summary.merge_all instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1125: The name t
f.summary.FileWriter is deprecated. Please use tf.compat.v1.summary.FileWriter instead.

Epoch 1/12
436/436 [==============================] - 733s 2s/step - loss: 3.0144 - val_loss: 4.2128
— tr_f1: 0.05614632785853618 — tr_recall: 0.1316030814380044 — tr_precision 0.1202936570094709
— val_f1: 0.06228297416598425 — val_recall: 0.13443727196182992 — val_precision 0.1541262684950112

Epoch 00001: val_loss improved from inf to 4.21279, saving model to alex.hdf5
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1265: The name t
f.Summary is deprecated. Please use tf.compat.v1.Summary instead.

Epoch 2/12
436/436 [==============================] - 719s 2s/step - loss: 2.3010 - val_loss: 2.5720
— tr_f1: 0.2296768797492647 — tr_recall: 0.2838866471019809 — tr_precision 0.315948789538517
— val_f1: 0.27988843936466706 — val_recall: 0.3335204415754514 — val_precision 0.3259304073251775

Epoch 00002: val_loss improved from 4.21279 to 2.57199, saving model to alex.hdf5
Epoch 3/12
436/436 [==============================] - 704s 2s/step - loss: 1.7846 - val_loss: 2.3006
— tr_f1: 0.39687806507408785 — tr_recall: 0.4382795304475422 — tr_precision 0.4264987205257996
— val_f1: 0.38495742285585427 — val_recall: 0.42735522499766115 — val_precision
0.41776184504351804

Epoch 00003: val_loss improved from 2.57199 to 2.30064, saving model to alex.hdf5
Epoch 4/12
436/436 [==============================] - 701s 2s/step - loss: 1.4671 - val_loss: 4.2011
— tr_f1: 0.1639126149249142 — tr_recall: 0.2745093543653705 — tr_precision 0.22917283151889162
— val_f1: 0.19105428685209727 — val_recall: 0.29497614369912994 — val_precision
0.24210512108172508

Epoch 00004: val_loss did not improve from 2.30064
Epoch 5/12
436/436 [==============================] - 705s 2s/step - loss: 1.1964 - val_loss: 1.3529
— tr_f1: 0.527861979363083 — tr_recall: 0.5505548422597212 — tr_precision 0.6140687598701211
— val_f1: 0.6033091843583054 — val_recall: 0.6299934512115258 — val_precision 0.6310830566423926

Epoch 00005: val_loss improved from 2.30064 to 1.35293, saving model to alex.hdf5
Epoch 6/12
436/436 [==============================] - 705s 2s/step - loss: 0.9965 - val_loss: 1.1308
— tr_f1: 0.6034030229903633 — tr_recall: 0.6083776595744681 — tr_precision 0.6935810161081081
— val_f1: 0.6706194801673072 — val_recall: 0.6814482177939938 — val_precision 0.7207266240433567

Epoch 00006: val_loss improved from 1.35293 to 1.13078, saving model to alex.hdf5
Epoch 7/12
436/436 [==============================] - 669s 2s/step - loss: 0.8369 - val_loss: 1.1711
— tr_f1: 0.5903085283565213 — tr_recall: 0.606726889214967 — tr_precision 0.6972064850561409
— val_f1: 0.6632083981090762 — val_recall: 0.6748994293198616 — val_precision 0.7362316703992434

Epoch 00007: val_loss did not improve from 1.13078
Epoch 8/12
436/436 [==============================] - 656s 2s/step - loss: 0.7327 - val_loss: 0.9796
— tr_f1: 0.6132305433678955 — tr_recall: 0.6179612986060161 — tr_precision 0.7406479703524679
— val_f1: 0.7260839874819438 — val_recall: 0.7266348582655066 — val_precision 0.7903157377408839

Epoch 00008: val_loss improved from 1.13078 to 0.97958, saving model to alex.hdf5
Epoch 9/12
436/436 [==============================] - 661s 2s/step - loss: 0.6231 - val_loss: 0.9481
— tr_f1: 0.6780350059519091 — tr_recall: 0.6759904622157007 — tr_precision 0.7664630232429769
— val_f1: 0.7566980790154872 — val_recall: 0.7614369912994667 — val_precision 0.8163182077929911

Epoch 00009: val_loss improved from 0.97958 to 0.94815, saving model to alex.hdf5
Epoch 10/12
436/436 [==============================] - 652s 1s/step - loss: 0.5719 - val_loss: 0.6988
— tr_f1: 0.7891083483694066 — tr_recall: 0.7923468451944241 — tr_precision 0.8170239464055828
— val_f1: 0.811549952402577 — val_recall: 0.8181307886612406 — val_precision 0.8318699216485904
```

```
Epoch 00010: val_loss improved from 0.94815 to 0.69885, saving model to alex.hdf5
Epoch 11/12
436/436 [==============================] - 667s 2s/step - loss: 0.5151 - val_loss: 0.6414
— tr_f1: 0.716782722518031 — tr_recall: 0.702998899486427 — tr_precision 0.8049831724171319
— val_f1: 0.8137781135181998 — val_recall: 0.8144821779399383 — val_precision 0.8528130199779145

Epoch 00011: val_loss improved from 0.69885 to 0.64136, saving model to alex.hdf5
Epoch 12/12
436/436 [==============================] - 659s 2s/step - loss: 0.4568 - val_loss: 1.2110
— tr_f1: 0.7043169070939382 — tr_recall: 0.7038013573000733 — tr_precision 0.7713208884206278
— val_f1: 0.7137711894105045 — val_recall: 0.7109177659275892 — val_precision 0.778888928517803

Epoch 00012: val_loss did not improve from 0.64136
```

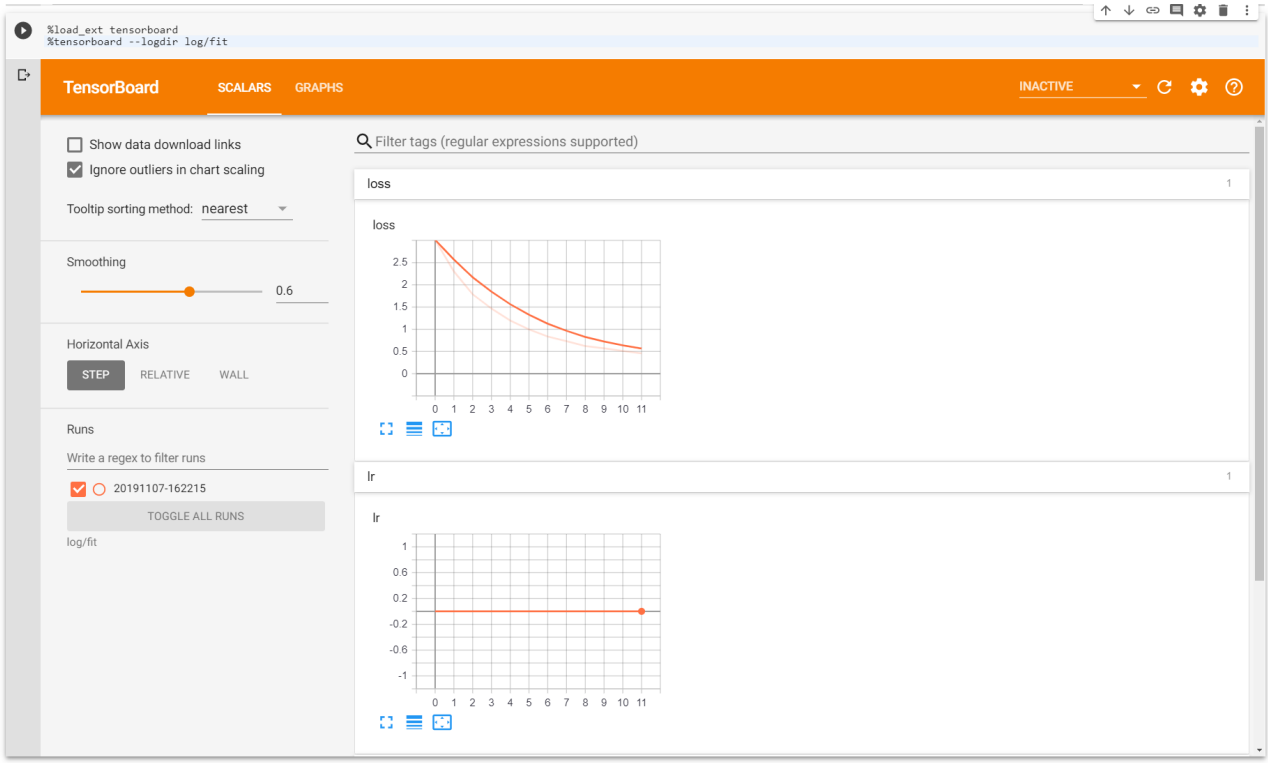
In [0]:

```
# tensorboard output
%load_ext tensorboard
%tensorboard --logdir log/fit
```

In [0]:

```
#tensorbord output screenshot
from IPython.display import Image
Image('1.png',height=600,width=800)
```

Out[0]:

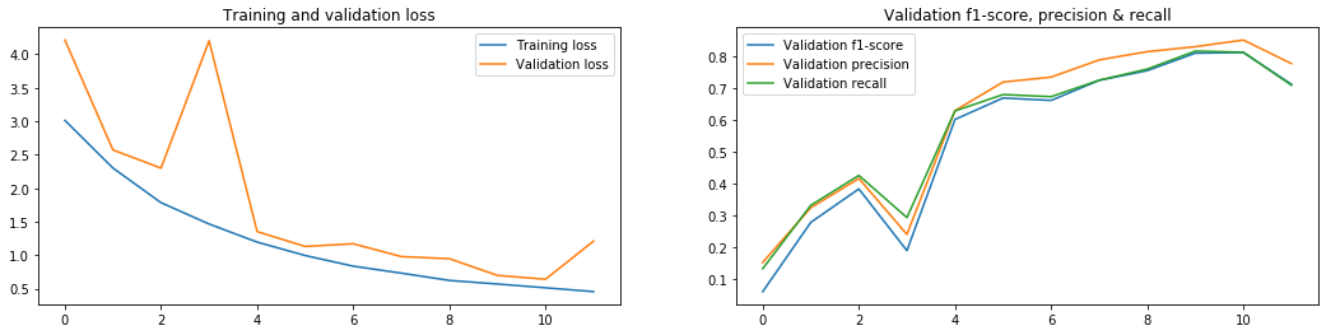


In [0]:

```
#plotting tr and test loss and various metrices on train and test data

"""creating a dataframe from history.history & storing val_f1,val_precision and val_recall from me
tric in dataframe
and then plotting the various metrics and loss."""

h_df = pd.DataFrame(history.history)

h_df['val_f1'] = metric.val_f1s
h_df['val_precision'] = metric.val_precisions
h_df['val_recall'] = metric.val_recalls

epochs = range(len(h_df['val_f1']))
```

```
plt.figure()
fig, ax = plt.subplots(1,2,figsize=(18,4))

ax[0].plot(epochs,h_df['loss'], label='Training loss')
ax[0].plot(epochs,h_df['val_loss'], label='Validation loss')
ax[0].set_title('Training and validation loss')
ax[0].legend()


ax[1].plot(epochs,h_df['val_f1'],label='Validation f1-score')
ax[1].plot(epochs,h_df['val_precision'],label='Validation precision')
ax[1].plot(epochs,h_df['val_recall'],label='Validation recall')
ax[1].set_title('Validation f1-score, precision & recall')
ax[1].legend()

plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



In [0]:

```
#showing the saved csv(csvlogger)
alex_csv=pd.read_csv("alex.csv")
alex_csv
```

Out[0]:

	epoch	loss	lr	tr_f1s	tr_precision	tr_recall	val_f1s	val_loss	val_precision	val_recall
0	0	3.013008	0.001	0.056146	0.120294	0.131603	0.062283	4.212793	0.154126	0.134437
1	1	2.301743	0.001	0.229677	0.315949	0.283887	0.279888	2.571985	0.325930	0.333520
2	2	1.784991	0.001	0.396878	0.426499	0.438280	0.384957	2.300637	0.417762	0.427355
3	3	1.465780	0.001	0.163913	0.229173	0.274509	0.191054	4.201081	0.242105	0.294976
4	4	1.196070	0.001	0.527862	0.614069	0.550555	0.603309	1.352928	0.631083	0.629993
5	5	0.995535	0.001	0.603403	0.693581	0.608378	0.670619	1.130777	0.720727	0.681448
6	6	0.836863	0.001	0.590309	0.697206	0.606727	0.663208	1.171070	0.736232	0.674899
7	7	0.732321	0.001	0.613231	0.740648	0.617961	0.726084	0.979582	0.790316	0.726635
8	8	0.623344	0.001	0.678035	0.766463	0.675990	0.756698	0.948146	0.816318	0.761437
9	9	0.570095	0.001	0.789108	0.817024	0.792347	0.811550	0.698848	0.831870	0.818131
10	10	0.513993	0.001	0.716783	0.804983	0.702999	0.813778	0.641360	0.852813	0.814482
11	11	0.456604	0.001	0.704317	0.771321	0.703801	0.713771	1.211002	0.778889	0.710918

In [0]:

```
# Loading the best saved model
model_alex = load_model("alex.hdf5")
```

In [0]:

```
# compute predictions
```

```
'''we need to reset the test_generator before whenever  calling the predict_generator. This is imp
ortant,
if we forget to reset the test_generator ,we will get outputs in a weird order.
and then predicting using the saved model.
predict_generator will give the prob for each class so we will choose the max prob using np.argmax
and this will
give the pred_class.
also we will get the true class using test_gen.classes'''

test_generator.reset()

predictions = model_alex.predict_generator(generator=test_generator)
y_pred = [np.argmax(probas) for probas in predictions]
y_test = test_generator.classes
```

In [0]:

```
#sanity check
from sklearn import metrics as m
print("Precision_weighted:",m.precision_score(y_test, y_pred , average="weighted")*100)
print("Recall_weighted:",m.recall_score(y_test, y_pred , average="weighted")*100)
print("F1_weighted:",m.f1_score(y_test, y_pred , average="weighted")*100)
```

```
Precision_weighted: 85.28130199779145
Recall_weighted: 81.44821779399382
F1_weighted: 81.37781135181999
```

In [0]:

```
#getting the predicted class for test data

'''
y_pred has the predicted labels,
but we can't simply tell what the predictions are, because all we can see is numbers like 0,1,4,1,
0,6…
and most importantly we need to map the predicted labels with their unique ids such
as filenames to find out what we predicted for which image.'''

labels_map = (train_generator.class_indices)
labels = dict((v,k) for k,v in labels_map.items())
predict = [labels[k] for k in y_pred]

#storing the results in dataframe.
filenames=test_generator.filenames
results=pd.DataFrame({"Filename":filenames,
                      "Predictions":predict})
```

In [0]:

```
#dict of class & its labels
labels_map
```

Out[0]:

```
{'Apple___Apple_scab': 0,
 'Apple___Black_rot': 1,
 'Apple___Cedar_apple_rust': 2,
 'Apple___healthy': 3,
 'Blueberry___healthy': 4,
 'Cherry_(including_sour)___Powdery_mildew': 5,
 'Cherry_(including_sour)___healthy': 6,
 'Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot': 7,
 'Corn_(maize)___Common_rust_': 8,
 'Corn_(maize)___Northern_Leaf_Blight': 9,
 'Corn_(maize)___healthy': 10,
 'Grape___Black_rot': 11,
 'Grape___Esca_(Black_Measles)': 12,
 'Grape___Leaf_blight_(Isariopsis_Leaf_Spot)': 13,
 'Grape___healthy': 14,
 'Orange___Haunglongbing_(Citrus_greening)': 15,
 'Peach___Bacterial_spot': 16,
 'Peach___healthy': 17,
 'Pepper, bell   Bacterial spot': 18,
```

```
 'Pepper,_bell___healthy': 19,
 'Potato___Early_blight': 20,
 'Potato___Late_blight': 21,
 'Potato___healthy': 22,
 'Raspberry___healthy': 23,
 'Soybean___healthy': 24,
 'Squash___Powdery_mildew': 25,
 'Strawberry___Leaf_scorch': 26,
 'Strawberry___healthy': 27,
 'Tomato___Bacterial_spot': 28,
 'Tomato___Early_blight': 29,
 'Tomato___Late_blight': 30,
 'Tomato___Leaf_Mold': 31,
 'Tomato___Septoria_leaf_spot': 32,
 'Tomato___Spider_mites Two-spotted_spider_mite': 33,
 'Tomato___Target_Spot': 34,
 'Tomato___Tomato_Yellow_Leaf_Curl_Virus': 35,
 'Tomato___Tomato_mosaic_virus': 36,
 'Tomato___healthy': 37}
```

In [0]:

```
#showing some data from results
results.head()
```

Out[0]:

	Filename	Predictions
0	Apple___Apple_scab/01f3deaa-6143-4b6c-9c22-620...	Corn_(maize)___healthy
1	Apple___Apple_scab/029424b0-0ef5-491b-9ef5-069...	Apple___Apple_scab
2	Apple___Apple_scab/058d5e64-2c57-45ba-94cb-ac8...	Cherry_(including_sour)___Powdery_mildew
3	Apple___Apple_scab/0631708e-5bac-4611-8ff9-6d5...	Apple___Apple_scab
4	Apple___Apple_scab/0672ab32-9fce-41f3-ae69-e39...	Apple___Apple_scab

this model is Not very good at predicting the class

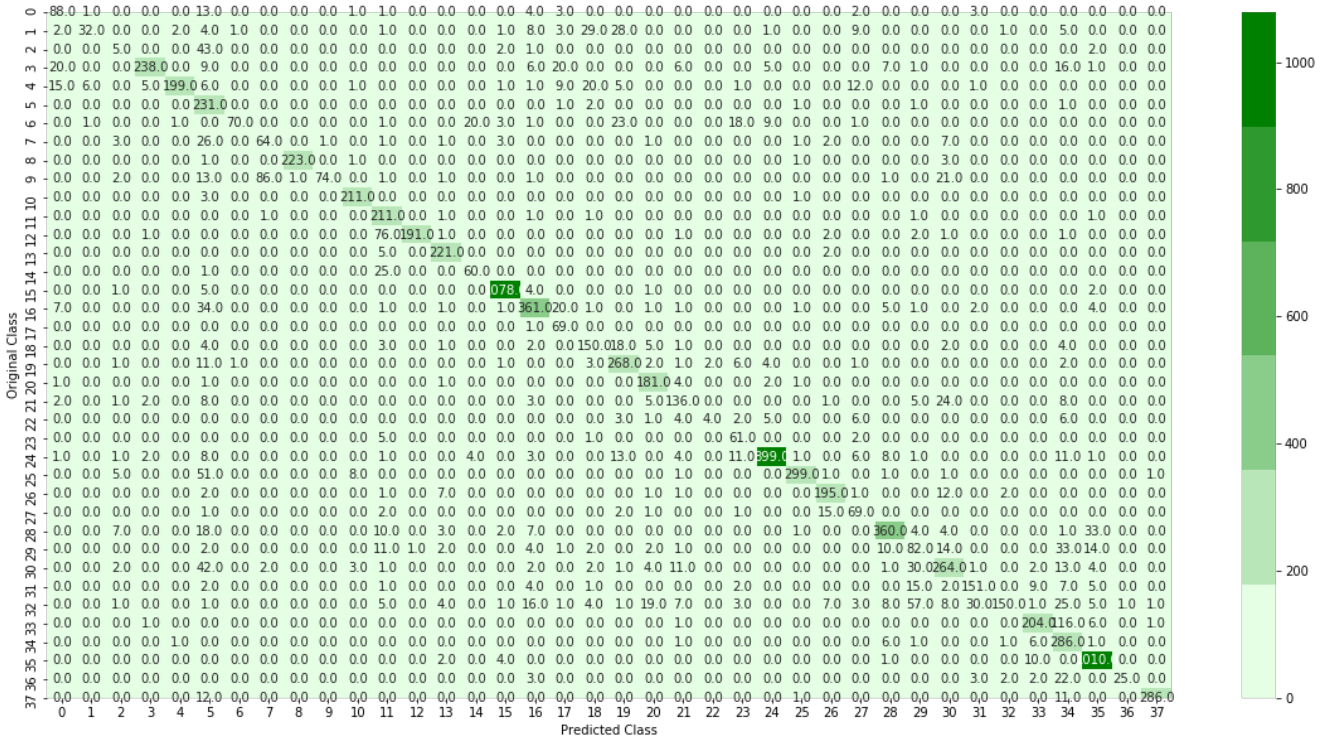
In [0]:

```
#confusion matrix

from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y,predict_y):
    C = confusion_matrix(test_y, predict_y)

    print("Number of misclassified images-",(len(test_y)-np.trace(C)))
    print("% of misclassified images-",(len(test_y)-np.trace(C))*100/len(test_y))

    labels = [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,
32,33,34,35,36,37]
    cmap=sns.light_palette("green")

    print("-"*50, "Confusion matrix", "-"*50)
    plt.figure(figsize=(20,10))
    sns.heatmap(C,annot=True, cmap=cmap,fmt=".1f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

In [0]:

```
plot_confusion_matrix(y_test,y_pred)
```

```
Number of misclassified images- 1983
% of misclassified images- 18.551782206006173
---------------------------------------------------- Confusion matrix ------------------------------
----------------
```



Number of misclasiification is high for this model.

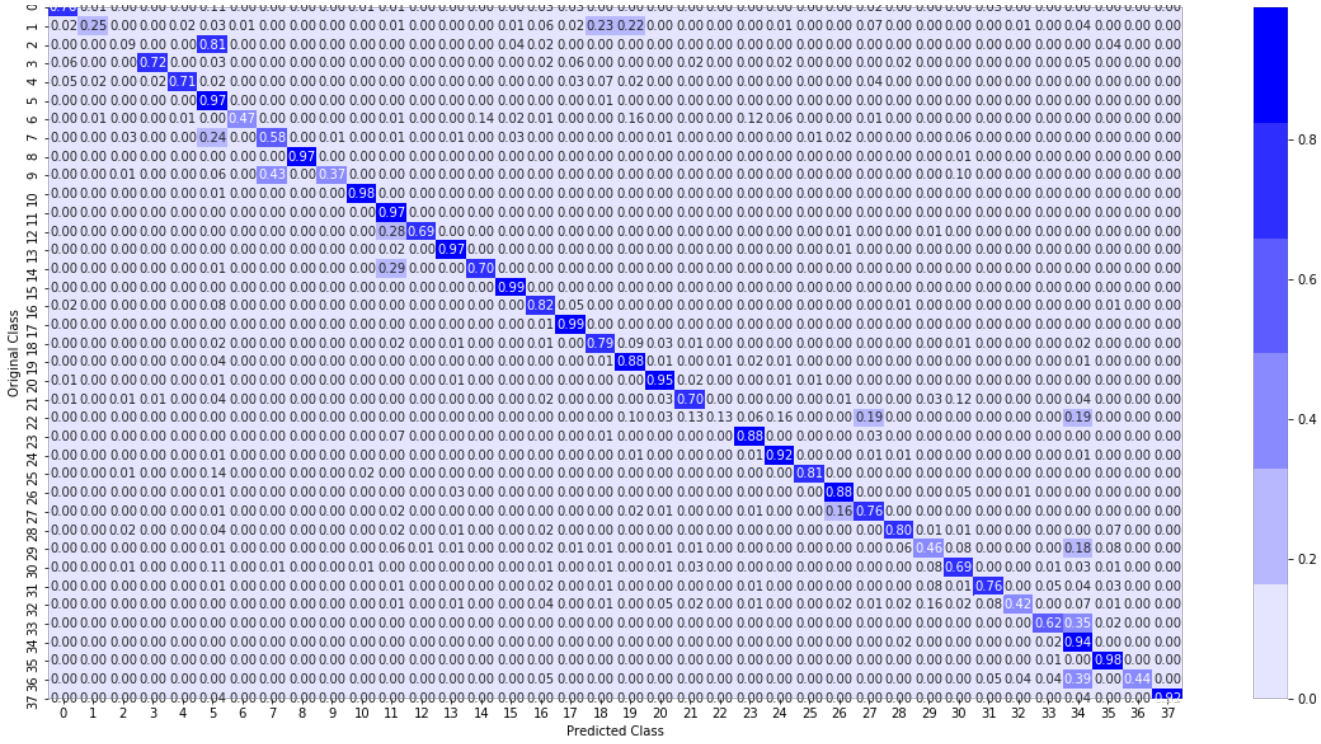
In [0]:

```
def plot_recall_matrix(test_y,predict_y):
    C = confusion_matrix(test_y, predict_y)
    A =(((C.T)/(C.sum(axis=1))).T)

    """
    divide each element of the confusion matrix with the sum of elements in that column

    C = [[1, 2],
         [3, 4]]
    C.T = [[1, 3],
           [2, 4]]
    C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to rows in two
diamensional array
    C.sum(axix =1) = [[3, 7]]
    ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
                               [2/3, 4/7]]

    ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
                                 [3/7, 4/7]]
    sum of row elements = 1"""

    labels = [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,
32,33,34,35,36,37]
    cmap=sns.light_palette("blue")
    # representing A in heatmap format
    print("-"*50, "Recall matrix"    , "-"*50)
    plt.figure(figsize=(20,10))
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".2f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of rows in recall matrix",A.sum(axis=1))
```

In [0]:

```
plot_recall_matrix(y_test,y_pred)
```

```
---------------------------------------------------- Recall matrix ----------------------------------
-------------
```




```
Sum of rows in recall matrix [1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

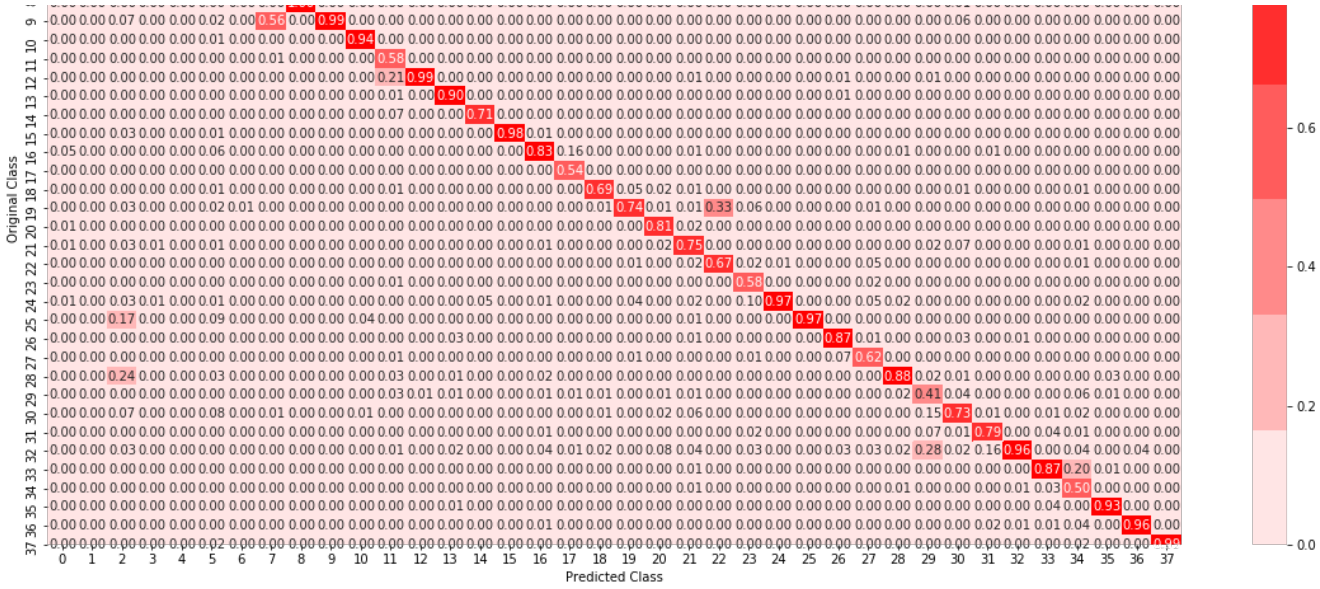
In [0]:

```
def plot_precision_matrix(test_y,predict_y):
    C = confusion_matrix(test_y, predict_y)
    B =(C/C.sum(axis=0))

    '''
    divide each element of the confusion matrix with the sum of elements in that row
    C = [[1, 2],
         [3, 4]]
     C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to rows in two
diamensional array
     C.sum(axix =0) = [[4, 6]]
     (C/C.sum(axis=0)) = [[1/4, 2/6],
                          [3/4, 4/6]]
    '''

    labels = [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,
32,33,34,35,36,37]
    cmap=sns.light_palette("red")
    print("-"*50, "Precision matrix", "-"*50)
    plt.figure(figsize=(20,10))
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".2f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of columns in precision matrix",B.sum(axis=0))
```

In [0]:

```
plot_precision_matrix(y_test,y_pred)
```

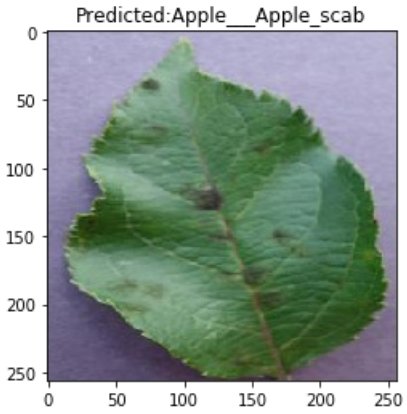
```
-------------------------------------------------- Precision matrix --------------------------------
----------------
```




```
Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

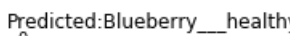
In [0]:

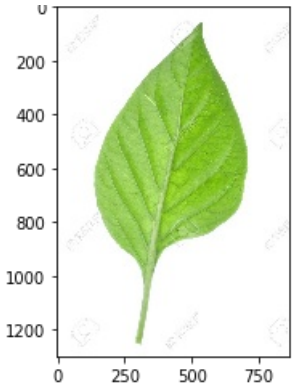
```
#final function for alexnet model
#predicting for a single image

'''pred_img function will take the image and then with help of alex_model predict the class and la
bels will
help to map the class name and then plot the image with the title showing the predicted class'''

def pred_img(file):
    np_image = Image.open(file)
    np_image = np.array(np_image).astype('float32')/255
    np_image = transform.resize(np_image, (256, 256, 3))
    image = np.expand_dims(np_image, axis=0)
    pred=model_alex.predict_classes(image)
    clas=labels[pred[0]]
    plt.imshow(plt.imread(file))
    plt.title("Predicted:"+str(clas))
    plt.show()

#correct prediction
pred_img("apple_scab.jpg")
```



In [0]:

```
#predicting for a single image
#incorrect prediction
pred_img("pepper.jpg")
```





Inception V3 model

(Inception Layer) is a combination of all those layers (namely, 1×1 Convolutional layer, 3×3 Convolutional layer, 5×5 Convolutional layer) with their output filter banks concatenated into a single output vector forming the input of the next stage.

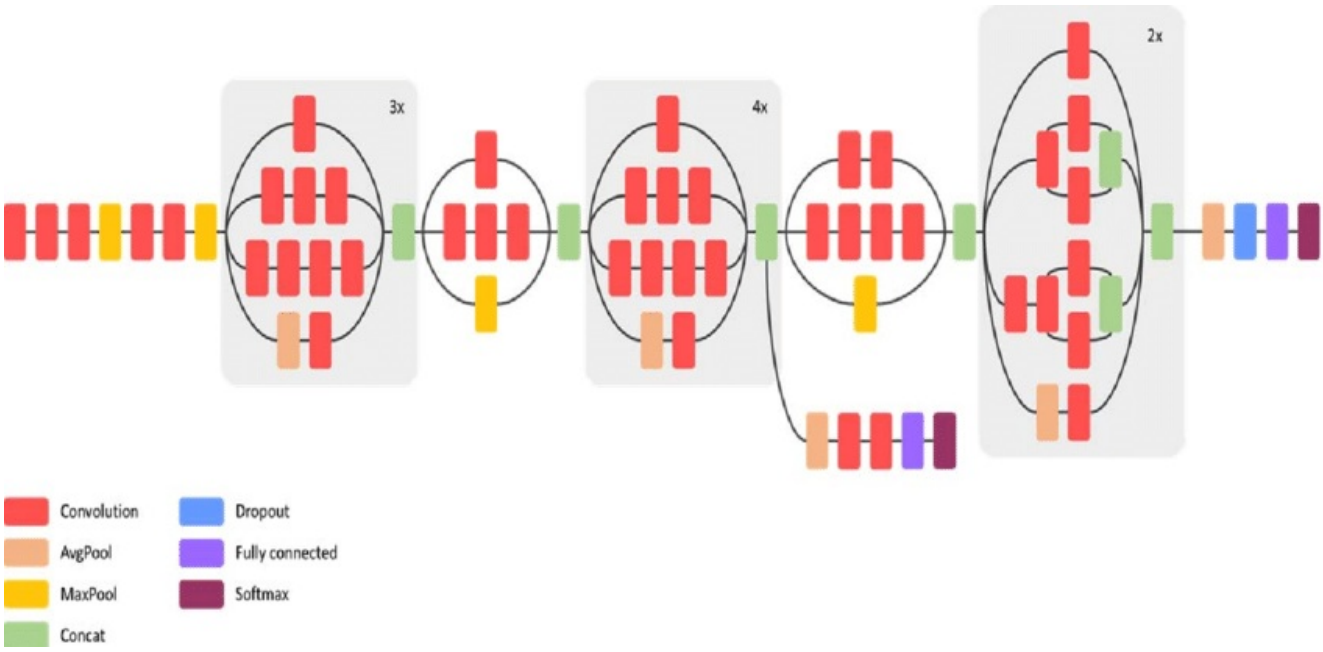
There is 1×1 Convolutional layer before applying another layer, which is mainly used for dimensionality reduction

A parallel Max Pooling layer, which provides another option to the inception layer.

In [0]:

```
from IPython.display import Image
Image('inception.png')
```

Out[0]:



In [0]:

```
# this part will prevent tensorflow to allocate all the avaliable GPU Memory
# backend
import tensorflow as tf
from keras import backend as k

# Don't pre-allocate memory; allocate as-needed
config = tf.ConfigProto()
config.gpu_options.allow_growth = True

# Create a session with the above options specified.
k.tensorflow_backend.set_session(tf.Session(config=config))
```

Image Augmentations techniques are methods of artificially increasing the variations of images in our data-set by using

horizontal/vertical flips, rotations, variations in brightness of images, horizontal/vertical shifts etc and this image augmentation is performed by ImageDataGenerator.

In [0]:

```
from keras.applications.inception_v3 import InceptionV3, preprocess_input

# Specify data generator inputs
train_datagen = ImageDataGenerator(preprocessing_function=preprocess_input,
    rotation_range=30,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True)

test_datagen = ImageDataGenerator(preprocessing_function=preprocess_input)
```

here we are using keras flow from directory to get the train and test data.

Remember to set shuffle=False in test_generator otherwise there will randomness while predicting.

In [0]:

```
width,height,depth= 299, 299 ,3
batch =64

# Create data generators
train_generator = train_datagen.flow_from_directory(
    TRAIN_DIR,
    target_size=(width,height),
    batch_size=batch)

test_generator = test_datagen.flow_from_directory(
    TEST_DIR,
    target_size=(width,height),
    batch_size=batch,
    shuffle=False
    )
```

```
Found 43616 images belonging to 38 classes.
Found 10689 images belonging to 38 classes.
```

Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task.

Here we are using inception v3 model which is trained on imagenet dataset and modifying the last few layers according to our needs.

In [0]:

```
#Get Inception model without final layer
base_model = InceptionV3(weights='imagenet', include_top=False)

# Add new fully connected layer to base model
x = base_model.output

x = GlobalAveragePooling2D()(x)

x = Dense(1024, activation='relu')(x)

x = Dropout(rate=0.5)(x)

output = Dense(38, activation='softmax')(x)
model = Model(input=base_model.input, output=output)
```

In [0]:

```
# Compile model

"""Compile defines the loss function, the optimizer and the metrics."""
```

```
model.compile(optimizer=Adam(lr=0.001),loss='categorical_crossentropy')
```

In [0]:

```
#it will show the layers used and no. of parameters after each layer
model.summary()
```

```
Model: "model_1"
_________________________________________________________________________________________________
Layer (type)                 Output Shape              Param #     Connected to
=================================================================================================
input_1 (InputLayer)         (None, None, None, 3 0
_________________________________________________________________________________________________
conv2d_1 (Conv2D)            (None, None, None, 3 864         input_1[0][0]
_________________________________________________________________________________________________
batch_normalization_1 (BatchNor (None, None, None, 3 96          conv2d_1[0][0]
_________________________________________________________________________________________________
activation_1 (Activation)    (None, None, None, 3 0           batch_normalization_1[0][0]
_________________________________________________________________________________________________
conv2d_2 (Conv2D)            (None, None, None, 3 9216        activation_1[0][0]
_________________________________________________________________________________________________
batch_normalization_2 (BatchNor (None, None, None, 3 96          conv2d_2[0][0]
_________________________________________________________________________________________________
activation_2 (Activation)    (None, None, None, 3 0           batch_normalization_2[0][0]
_________________________________________________________________________________________________
conv2d_3 (Conv2D)            (None, None, None, 6 18432       activation_2[0][0]
_________________________________________________________________________________________________
batch_normalization_3 (BatchNor (None, None, None, 6 192         conv2d_3[0][0]
_________________________________________________________________________________________________
activation_3 (Activation)    (None, None, None, 6 0           batch_normalization_3[0][0]
_________________________________________________________________________________________________
max_pooling2d_1 (MaxPooling2D)  (None, None, None, 6 0           activation_3[0][0]
_________________________________________________________________________________________________
conv2d_4 (Conv2D)            (None, None, None, 8 5120        max_pooling2d_1[0][0]
_________________________________________________________________________________________________
batch_normalization_4 (BatchNor (None, None, None, 8 240         conv2d_4[0][0]
_________________________________________________________________________________________________
activation_4 (Activation)    (None, None, None, 8 0           batch_normalization_4[0][0]
_________________________________________________________________________________________________
conv2d_5 (Conv2D)            (None, None, None, 1 138240      activation_4[0][0]
_________________________________________________________________________________________________
batch_normalization_5 (BatchNor (None, None, None, 1 576         conv2d_5[0][0]
_________________________________________________________________________________________________
activation_5 (Activation)    (None, None, None, 1 0           batch_normalization_5[0][0]
_________________________________________________________________________________________________
max_pooling2d_2 (MaxPooling2D)  (None, None, None, 1 0           activation_5[0][0]
_________________________________________________________________________________________________
conv2d_9 (Conv2D)            (None, None, None, 6 12288       max_pooling2d_2[0][0]
_________________________________________________________________________________________________
batch_normalization_9 (BatchNor (None, None, None, 6 192         conv2d_9[0][0]
_________________________________________________________________________________________________
activation_9 (Activation)    (None, None, None, 6 0           batch_normalization_9[0][0]
_________________________________________________________________________________________________
conv2d_7 (Conv2D)            (None, None, None, 4 9216        max_pooling2d_2[0][0]
_________________________________________________________________________________________________
conv2d_10 (Conv2D)           (None, None, None, 9 55296       activation_9[0][0]
_________________________________________________________________________________________________
batch_normalization_7 (BatchNor (None, None, None, 4 144         conv2d_7[0][0]
_________________________________________________________________________________________________
batch_normalization_10 (BatchNo (None, None, None, 9 288         conv2d_10[0][0]
_________________________________________________________________________________________________
activation_7 (Activation)    (None, None, None, 4 0           batch_normalization_7[0][0]
_________________________________________________________________________________________________
activation_10 (Activation)   (None, None, None, 9 0           batch_normalization_10[0][0]
_________________________________________________________________________________________________
average_pooling2d_1 (AveragePoo (None, None, None, 1 0           max_pooling2d_2[0][0]
_________________________________________________________________________________________________
conv2d_6 (Conv2D)            (None, None, None, 6 12288       max_pooling2d_2[0][0]
_________________________________________________________________________________________________
conv2d_8 (Conv2D)            (None, None, None, 6 76800       activation_7[0][0]
_________________________________________________________________________________________________
conv2d_11 (Conv2D)           (None, None, None, 9 82944       activation_10[0][0]
_________________________________________________________________________________________________
conv2d_12 (Conv2D)           (None, None, None, 3 6144        average_pooling2d_1[0][0]
_________________________________________________________________________________________________
batch_normalization_6 (BatchNor (None, None, None, 6 192         conv2d_6[0][0]
```

batch_normalization_6 (BatchNor	(None, None, None, 6	192	conv2d_6[0][0]
batch_normalization_8 (BatchNor	(None, None, None, 6	192	conv2d_8[0][0]
batch_normalization_11 (BatchNo	(None, None, None, 9	288	conv2d_11[0][0]
batch_normalization_12 (BatchNo	(None, None, None, 3	96	conv2d_12[0][0]
activation_6 (Activation)	(None, None, None, 6	0	batch_normalization_6[0][0]
activation_8 (Activation)	(None, None, None, 6	0	batch_normalization_8[0][0]
activation_11 (Activation)	(None, None, None, 9	0	batch_normalization_11[0][0]
activation_12 (Activation)	(None, None, None, 3	0	batch_normalization_12[0][0]
mixed0 (Concatenate)	(None, None, None, 2	0	activation_6[0][0] activation_8[0][0] activation_11[0][0] activation_12[0][0]
conv2d_16 (Conv2D)	(None, None, None, 6	16384	mixed0[0][0]
batch_normalization_16 (BatchNo	(None, None, None, 6	192	conv2d_16[0][0]
activation_16 (Activation)	(None, None, None, 6	0	batch_normalization_16[0][0]
conv2d_14 (Conv2D)	(None, None, None, 4	12288	mixed0[0][0]
conv2d_17 (Conv2D)	(None, None, None, 9	55296	activation_16[0][0]
batch_normalization_14 (BatchNo	(None, None, None, 4	144	conv2d_14[0][0]
batch_normalization_17 (BatchNo	(None, None, None, 9	288	conv2d_17[0][0]
activation_14 (Activation)	(None, None, None, 4	0	batch_normalization_14[0][0]
activation_17 (Activation)	(None, None, None, 9	0	batch_normalization_17[0][0]
average_pooling2d_2 (AveragePoo	(None, None, None, 2	0	mixed0[0][0]
conv2d_13 (Conv2D)	(None, None, None, 6	16384	mixed0[0][0]
conv2d_15 (Conv2D)	(None, None, None, 6	76800	activation_14[0][0]
conv2d_18 (Conv2D)	(None, None, None, 9	82944	activation_17[0][0]
conv2d_19 (Conv2D)	(None, None, None, 6	16384	average_pooling2d_2[0][0]
batch_normalization_13 (BatchNo	(None, None, None, 6	192	conv2d_13[0][0]
batch_normalization_15 (BatchNo	(None, None, None, 6	192	conv2d_15[0][0]
batch_normalization_18 (BatchNo	(None, None, None, 9	288	conv2d_18[0][0]
batch_normalization_19 (BatchNo	(None, None, None, 6	192	conv2d_19[0][0]
activation_13 (Activation)	(None, None, None, 6	0	batch_normalization_13[0][0]
activation_15 (Activation)	(None, None, None, 6	0	batch_normalization_15[0][0]
activation_18 (Activation)	(None, None, None, 9	0	batch_normalization_18[0][0]
activation_19 (Activation)	(None, None, None, 6	0	batch_normalization_19[0][0]
mixed1 (Concatenate)	(None, None, None, 2	0	activation_13[0][0] activation_15[0][0] activation_18[0][0] activation_19[0][0]
conv2d_23 (Conv2D)	(None, None, None, 6	18432	mixed1[0][0]
batch_normalization_23 (BatchNo	(None, None, None, 6	192	conv2d_23[0][0]
activation_23 (Activation)	(None, None, None, 6	0	batch_normalization_23[0][0]
conv2d_21 (Conv2D)	(None, None, None, 4	13824	mixed1[0][0]

conv2d_24 (Conv2D)	(None, None, None, 9	55296	activation_23[0][0]
batch_normalization_21 (BatchNo	(None, None, None, 4	144	conv2d_21[0][0]
batch_normalization_24 (BatchNo	(None, None, None, 9	288	conv2d_24[0][0]
activation_21 (Activation)	(None, None, None, 4	0	batch_normalization_21[0][0]
activation_24 (Activation)	(None, None, None, 9	0	batch_normalization_24[0][0]
average_pooling2d_3 (AveragePoo	(None, None, None, 2	0	mixed1[0][0]
conv2d_20 (Conv2D)	(None, None, None, 6	18432	mixed1[0][0]
conv2d_22 (Conv2D)	(None, None, None, 6	76800	activation_21[0][0]
conv2d_25 (Conv2D)	(None, None, None, 9	82944	activation_24[0][0]
conv2d_26 (Conv2D)	(None, None, None, 6	18432	average_pooling2d_3[0][0]
batch_normalization_20 (BatchNo	(None, None, None, 6	192	conv2d_20[0][0]
batch_normalization_22 (BatchNo	(None, None, None, 6	192	conv2d_22[0][0]
batch_normalization_25 (BatchNo	(None, None, None, 9	288	conv2d_25[0][0]
batch_normalization_26 (BatchNo	(None, None, None, 6	192	conv2d_26[0][0]
activation_20 (Activation)	(None, None, None, 6	0	batch_normalization_20[0][0]
activation_22 (Activation)	(None, None, None, 6	0	batch_normalization_22[0][0]
activation_25 (Activation)	(None, None, None, 9	0	batch_normalization_25[0][0]
activation_26 (Activation)	(None, None, None, 6	0	batch_normalization_26[0][0]
mixed2 (Concatenate)	(None, None, None, 2	0	activation_20[0][0] activation_22[0][0] activation_25[0][0] activation_26[0][0]
conv2d_28 (Conv2D)	(None, None, None, 6	18432	mixed2[0][0]
batch_normalization_28 (BatchNo	(None, None, None, 6	192	conv2d_28[0][0]
activation_28 (Activation)	(None, None, None, 6	0	batch_normalization_28[0][0]
conv2d_29 (Conv2D)	(None, None, None, 9	55296	activation_28[0][0]
batch_normalization_29 (BatchNo	(None, None, None, 9	288	conv2d_29[0][0]
activation_29 (Activation)	(None, None, None, 9	0	batch_normalization_29[0][0]
conv2d_27 (Conv2D)	(None, None, None, 3	995328	mixed2[0][0]
conv2d_30 (Conv2D)	(None, None, None, 9	82944	activation_29[0][0]
batch_normalization_27 (BatchNo	(None, None, None, 3	1152	conv2d_27[0][0]
batch_normalization_30 (BatchNo	(None, None, None, 9	288	conv2d_30[0][0]
activation_27 (Activation)	(None, None, None, 3	0	batch_normalization_27[0][0]
activation_30 (Activation)	(None, None, None, 9	0	batch_normalization_30[0][0]
max_pooling2d_3 (MaxPooling2D)	(None, None, None, 2	0	mixed2[0][0]
mixed3 (Concatenate)	(None, None, None, 7	0	activation_27[0][0] activation_30[0][0] max_pooling2d_3[0][0]
conv2d_35 (Conv2D)	(None, None, None, 1	98304	mixed3[0][0]
batch_normalization_35 (BatchNo	(None, None, None, 1	384	conv2d_35[0][0]
activation_35 (Activation)	(None, None, None, 1	0	batch_normalization_35[0][0]

conv2d_36 (Conv2D)	(None, None, None, 1	114688	activation_35[0][0]
batch_normalization_36 (BatchNo	(None, None, None, 1	384	conv2d_36[0][0]
activation_36 (Activation)	(None, None, None, 1	0	batch_normalization_36[0][0]
conv2d_32 (Conv2D)	(None, None, None, 1	98304	mixed3[0][0]
conv2d_37 (Conv2D)	(None, None, None, 1	114688	activation_36[0][0]
batch_normalization_32 (BatchNo	(None, None, None, 1	384	conv2d_32[0][0]
batch_normalization_37 (BatchNo	(None, None, None, 1	384	conv2d_37[0][0]
activation_32 (Activation)	(None, None, None, 1	0	batch_normalization_32[0][0]
activation_37 (Activation)	(None, None, None, 1	0	batch_normalization_37[0][0]
conv2d_33 (Conv2D)	(None, None, None, 1	114688	activation_32[0][0]
conv2d_38 (Conv2D)	(None, None, None, 1	114688	activation_37[0][0]
batch_normalization_33 (BatchNo	(None, None, None, 1	384	conv2d_33[0][0]
batch_normalization_38 (BatchNo	(None, None, None, 1	384	conv2d_38[0][0]
activation_33 (Activation)	(None, None, None, 1	0	batch_normalization_33[0][0]
activation_38 (Activation)	(None, None, None, 1	0	batch_normalization_38[0][0]
average_pooling2d_4 (AveragePoo	(None, None, None, 7	0	mixed3[0][0]
conv2d_31 (Conv2D)	(None, None, None, 1	147456	mixed3[0][0]
conv2d_34 (Conv2D)	(None, None, None, 1	172032	activation_33[0][0]
conv2d_39 (Conv2D)	(None, None, None, 1	172032	activation_38[0][0]
conv2d_40 (Conv2D)	(None, None, None, 1	147456	average_pooling2d_4[0][0]
batch_normalization_31 (BatchNo	(None, None, None, 1	576	conv2d_31[0][0]
batch_normalization_34 (BatchNo	(None, None, None, 1	576	conv2d_34[0][0]
batch_normalization_39 (BatchNo	(None, None, None, 1	576	conv2d_39[0][0]
batch_normalization_40 (BatchNo	(None, None, None, 1	576	conv2d_40[0][0]
activation_31 (Activation)	(None, None, None, 1	0	batch_normalization_31[0][0]
activation_34 (Activation)	(None, None, None, 1	0	batch_normalization_34[0][0]
activation_39 (Activation)	(None, None, None, 1	0	batch_normalization_39[0][0]
activation_40 (Activation)	(None, None, None, 1	0	batch_normalization_40[0][0]
mixed4 (Concatenate)	(None, None, None, 7	0	activation_31[0][0] activation_34[0][0] activation_39[0][0] activation_40[0][0]
conv2d_45 (Conv2D)	(None, None, None, 1	122880	mixed4[0][0]
batch_normalization_45 (BatchNo	(None, None, None, 1	480	conv2d_45[0][0]
activation_45 (Activation)	(None, None, None, 1	0	batch_normalization_45[0][0]
conv2d_46 (Conv2D)	(None, None, None, 1	179200	activation_45[0][0]
batch_normalization_46 (BatchNo	(None, None, None, 1	480	conv2d_46[0][0]
activation_46 (Activation)	(None, None, None, 1	0	batch_normalization_46[0][0]
conv2d_42 (Conv2D)	(None, None, None, 1	122880	mixed4[0][0]
conv2d_47 (Conv2D)	(None, None, None, 1	179200	activation_46[0][0]

```
batch_normalization_42 (BatchNo (None, None, None, 1 480         conv2d_42[0][0]
batch_normalization_47 (BatchNo (None, None, None, 1 480         conv2d_47[0][0]
activation_42 (Activation)      (None, None, None, 1 0           batch_normalization_42[0][0]
activation_47 (Activation)      (None, None, None, 1 0           batch_normalization_47[0][0]
conv2d_43 (Conv2D)              (None, None, None, 1 179200      activation_42[0][0]
conv2d_48 (Conv2D)              (None, None, None, 1 179200      activation_47[0][0]
batch_normalization_43 (BatchNo (None, None, None, 1 480         conv2d_43[0][0]
batch_normalization_48 (BatchNo (None, None, None, 1 480         conv2d_48[0][0]
activation_43 (Activation)      (None, None, None, 1 0           batch_normalization_43[0][0]
activation_48 (Activation)      (None, None, None, 1 0           batch_normalization_48[0][0]
average_pooling2d_5 (AveragePoo (None, None, None, 7 0           mixed4[0][0]
conv2d_41 (Conv2D)              (None, None, None, 1 147456      mixed4[0][0]
conv2d_44 (Conv2D)              (None, None, None, 1 215040      activation_43[0][0]
conv2d_49 (Conv2D)              (None, None, None, 1 215040      activation_48[0][0]
conv2d_50 (Conv2D)              (None, None, None, 1 147456      average_pooling2d_5[0][0]
batch_normalization_41 (BatchNo (None, None, None, 1 576         conv2d_41[0][0]
batch_normalization_44 (BatchNo (None, None, None, 1 576         conv2d_44[0][0]
batch_normalization_49 (BatchNo (None, None, None, 1 576         conv2d_49[0][0]
batch_normalization_50 (BatchNo (None, None, None, 1 576         conv2d_50[0][0]
activation_41 (Activation)      (None, None, None, 1 0           batch_normalization_41[0][0]
activation_44 (Activation)      (None, None, None, 1 0           batch_normalization_44[0][0]
activation_49 (Activation)      (None, None, None, 1 0           batch_normalization_49[0][0]
activation_50 (Activation)      (None, None, None, 1 0           batch_normalization_50[0][0]
mixed5 (Concatenate)            (None, None, None, 7 0           activation_41[0][0]
                                                                 activation_44[0][0]
                                                                 activation_49[0][0]
                                                                 activation_50[0][0]
conv2d_55 (Conv2D)              (None, None, None, 1 122880      mixed5[0][0]
batch_normalization_55 (BatchNo (None, None, None, 1 480         conv2d_55[0][0]
activation_55 (Activation)      (None, None, None, 1 0           batch_normalization_55[0][0]
conv2d_56 (Conv2D)              (None, None, None, 1 179200      activation_55[0][0]
batch_normalization_56 (BatchNo (None, None, None, 1 480         conv2d_56[0][0]
activation_56 (Activation)      (None, None, None, 1 0           batch_normalization_56[0][0]
conv2d_52 (Conv2D)              (None, None, None, 1 122880      mixed5[0][0]
conv2d_57 (Conv2D)              (None, None, None, 1 179200      activation_56[0][0]
batch_normalization_52 (BatchNo (None, None, None, 1 480         conv2d_52[0][0]
batch_normalization_57 (BatchNo (None, None, None, 1 480         conv2d_57[0][0]
activation_52 (Activation)      (None, None, None, 1 0           batch_normalization_52[0][0]
activation_57 (Activation)      (None, None, None, 1 0           batch_normalization_57[0][0]
conv2d_53 (Conv2D)              (None, None, None, 1 179200      activation_52[0][0]
```

conv2d_58 (Conv2D)	(None, None, None, 1	179200	activation_57[0][0]
batch_normalization_53 (BatchNo	(None, None, None, 1	480	conv2d_53[0][0]
batch_normalization_58 (BatchNo	(None, None, None, 1	480	conv2d_58[0][0]
activation_53 (Activation)	(None, None, None, 1	0	batch_normalization_53[0][0]
activation_58 (Activation)	(None, None, None, 1	0	batch_normalization_58[0][0]
average_pooling2d_6 (AveragePoo	(None, None, None, 7	0	mixed5[0][0]
conv2d_51 (Conv2D)	(None, None, None, 1	147456	mixed5[0][0]
conv2d_54 (Conv2D)	(None, None, None, 1	215040	activation_53[0][0]
conv2d_59 (Conv2D)	(None, None, None, 1	215040	activation_58[0][0]
conv2d_60 (Conv2D)	(None, None, None, 1	147456	average_pooling2d_6[0][0]
batch_normalization_51 (BatchNo	(None, None, None, 1	576	conv2d_51[0][0]
batch_normalization_54 (BatchNo	(None, None, None, 1	576	conv2d_54[0][0]
batch_normalization_59 (BatchNo	(None, None, None, 1	576	conv2d_59[0][0]
batch_normalization_60 (BatchNo	(None, None, None, 1	576	conv2d_60[0][0]
activation_51 (Activation)	(None, None, None, 1	0	batch_normalization_51[0][0]
activation_54 (Activation)	(None, None, None, 1	0	batch_normalization_54[0][0]
activation_59 (Activation)	(None, None, None, 1	0	batch_normalization_59[0][0]
activation_60 (Activation)	(None, None, None, 1	0	batch_normalization_60[0][0]
mixed6 (Concatenate)	(None, None, None, 7	0	activation_51[0][0] activation_54[0][0] activation_59[0][0] activation_60[0][0]
conv2d_65 (Conv2D)	(None, None, None, 1	147456	mixed6[0][0]
batch_normalization_65 (BatchNo	(None, None, None, 1	576	conv2d_65[0][0]
activation_65 (Activation)	(None, None, None, 1	0	batch_normalization_65[0][0]
conv2d_66 (Conv2D)	(None, None, None, 1	258048	activation_65[0][0]
batch_normalization_66 (BatchNo	(None, None, None, 1	576	conv2d_66[0][0]
activation_66 (Activation)	(None, None, None, 1	0	batch_normalization_66[0][0]
conv2d_62 (Conv2D)	(None, None, None, 1	147456	mixed6[0][0]
conv2d_67 (Conv2D)	(None, None, None, 1	258048	activation_66[0][0]
batch_normalization_62 (BatchNo	(None, None, None, 1	576	conv2d_62[0][0]
batch_normalization_67 (BatchNo	(None, None, None, 1	576	conv2d_67[0][0]
activation_62 (Activation)	(None, None, None, 1	0	batch_normalization_62[0][0]
activation_67 (Activation)	(None, None, None, 1	0	batch_normalization_67[0][0]
conv2d_63 (Conv2D)	(None, None, None, 1	258048	activation_62[0][0]
conv2d_68 (Conv2D)	(None, None, None, 1	258048	activation_67[0][0]
batch_normalization_63 (BatchNo	(None, None, None, 1	576	conv2d_63[0][0]
batch_normalization_68 (BatchNo	(None, None, None, 1	576	conv2d_68[0][0]
activation_63 (Activation)	(None, None, None, 1	0	batch_normalization_63[0][0]
activation_68 (Activation)	(None, None, None, 1	0	batch_normalization_68[0][0]

average_pooling2d_7 (AveragePoo	(None, None, None, 7	0	mixed6[0][0]
conv2d_61 (Conv2D)	(None, None, None, 1	147456	mixed6[0][0]
conv2d_64 (Conv2D)	(None, None, None, 1	258048	activation_63[0][0]
conv2d_69 (Conv2D)	(None, None, None, 1	258048	activation_68[0][0]
conv2d_70 (Conv2D)	(None, None, None, 1	147456	average_pooling2d_7[0][0]
batch_normalization_61 (BatchNo	(None, None, None, 1	576	conv2d_61[0][0]
batch_normalization_64 (BatchNo	(None, None, None, 1	576	conv2d_64[0][0]
batch_normalization_69 (BatchNo	(None, None, None, 1	576	conv2d_69[0][0]
batch_normalization_70 (BatchNo	(None, None, None, 1	576	conv2d_70[0][0]
activation_61 (Activation)	(None, None, None, 1	0	batch_normalization_61[0][0]
activation_64 (Activation)	(None, None, None, 1	0	batch_normalization_64[0][0]
activation_69 (Activation)	(None, None, None, 1	0	batch_normalization_69[0][0]
activation_70 (Activation)	(None, None, None, 1	0	batch_normalization_70[0][0]
mixed7 (Concatenate)	(None, None, None, 7	0	activation_61[0][0] activation_64[0][0] activation_69[0][0] activation_70[0][0]
conv2d_73 (Conv2D)	(None, None, None, 1	147456	mixed7[0][0]
batch_normalization_73 (BatchNo	(None, None, None, 1	576	conv2d_73[0][0]
activation_73 (Activation)	(None, None, None, 1	0	batch_normalization_73[0][0]
conv2d_74 (Conv2D)	(None, None, None, 1	258048	activation_73[0][0]
batch_normalization_74 (BatchNo	(None, None, None, 1	576	conv2d_74[0][0]
activation_74 (Activation)	(None, None, None, 1	0	batch_normalization_74[0][0]
conv2d_71 (Conv2D)	(None, None, None, 1	147456	mixed7[0][0]
conv2d_75 (Conv2D)	(None, None, None, 1	258048	activation_74[0][0]
batch_normalization_71 (BatchNo	(None, None, None, 1	576	conv2d_71[0][0]
batch_normalization_75 (BatchNo	(None, None, None, 1	576	conv2d_75[0][0]
activation_71 (Activation)	(None, None, None, 1	0	batch_normalization_71[0][0]
activation_75 (Activation)	(None, None, None, 1	0	batch_normalization_75[0][0]
conv2d_72 (Conv2D)	(None, None, None, 3	552960	activation_71[0][0]
conv2d_76 (Conv2D)	(None, None, None, 1	331776	activation_75[0][0]
batch_normalization_72 (BatchNo	(None, None, None, 3	960	conv2d_72[0][0]
batch_normalization_76 (BatchNo	(None, None, None, 1	576	conv2d_76[0][0]
activation_72 (Activation)	(None, None, None, 3	0	batch_normalization_72[0][0]
activation_76 (Activation)	(None, None, None, 1	0	batch_normalization_76[0][0]
max_pooling2d_4 (MaxPooling2D)	(None, None, None, 7	0	mixed7[0][0]
mixed8 (Concatenate)	(None, None, None, 1	0	activation_72[0][0] activation_76[0][0] max_pooling2d_4[0][0]
conv2d_81 (Conv2D)	(None, None, None, 4	573440	mixed8[0][0]
batch_normalization_81 (BatchNo	(None, None, None, 4	1344	conv2d_81[0][0]

activation_81 (Activation)	(None, None, None, 4	0	batch_normalization_81[0][0]
conv2d_78 (Conv2D)	(None, None, None, 3	491520	mixed8[0][0]
conv2d_82 (Conv2D)	(None, None, None, 3	1548288	activation_81[0][0]
batch_normalization_78 (BatchNo	(None, None, None, 3	1152	conv2d_78[0][0]
batch_normalization_82 (BatchNo	(None, None, None, 3	1152	conv2d_82[0][0]
activation_78 (Activation)	(None, None, None, 3	0	batch_normalization_78[0][0]
activation_82 (Activation)	(None, None, None, 3	0	batch_normalization_82[0][0]
conv2d_79 (Conv2D)	(None, None, None, 3	442368	activation_78[0][0]
conv2d_80 (Conv2D)	(None, None, None, 3	442368	activation_78[0][0]
conv2d_83 (Conv2D)	(None, None, None, 3	442368	activation_82[0][0]
conv2d_84 (Conv2D)	(None, None, None, 3	442368	activation_82[0][0]
average_pooling2d_8 (AveragePoo	(None, None, None, 1	0	mixed8[0][0]
conv2d_77 (Conv2D)	(None, None, None, 3	409600	mixed8[0][0]
batch_normalization_79 (BatchNo	(None, None, None, 3	1152	conv2d_79[0][0]
batch_normalization_80 (BatchNo	(None, None, None, 3	1152	conv2d_80[0][0]
batch_normalization_83 (BatchNo	(None, None, None, 3	1152	conv2d_83[0][0]
batch_normalization_84 (BatchNo	(None, None, None, 3	1152	conv2d_84[0][0]
conv2d_85 (Conv2D)	(None, None, None, 1	245760	average_pooling2d_8[0][0]
batch_normalization_77 (BatchNo	(None, None, None, 3	960	conv2d_77[0][0]
activation_79 (Activation)	(None, None, None, 3	0	batch_normalization_79[0][0]
activation_80 (Activation)	(None, None, None, 3	0	batch_normalization_80[0][0]
activation_83 (Activation)	(None, None, None, 3	0	batch_normalization_83[0][0]
activation_84 (Activation)	(None, None, None, 3	0	batch_normalization_84[0][0]
batch_normalization_85 (BatchNo	(None, None, None, 1	576	conv2d_85[0][0]
activation_77 (Activation)	(None, None, None, 3	0	batch_normalization_77[0][0]
mixed9_0 (Concatenate)	(None, None, None, 7	0	activation_79[0][0] activation_80[0][0]
concatenate_1 (Concatenate)	(None, None, None, 7	0	activation_83[0][0] activation_84[0][0]
activation_85 (Activation)	(None, None, None, 1	0	batch_normalization_85[0][0]
mixed9 (Concatenate)	(None, None, None, 2	0	activation_77[0][0] mixed9_0[0][0] concatenate_1[0][0] activation_85[0][0]
conv2d_90 (Conv2D)	(None, None, None, 4	917504	mixed9[0][0]
batch_normalization_90 (BatchNo	(None, None, None, 4	1344	conv2d_90[0][0]
activation_90 (Activation)	(None, None, None, 4	0	batch_normalization_90[0][0]
conv2d_87 (Conv2D)	(None, None, None, 3	786432	mixed9[0][0]
conv2d_91 (Conv2D)	(None, None, None, 3	1548288	activation_90[0][0]
batch_normalization_87 (BatchNo	(None, None, None, 3	1152	conv2d_87[0][0]
batch_normalization_91 (BatchNo	(None, None, None, 3	1152	conv2d_91[0][0]

```
activation_87 (Activation)      (None, None, None, 3 0           batch_normalization_87[0][0]
activation_91 (Activation)      (None, None, None, 3 0           batch_normalization_91[0][0]
conv2d_88 (Conv2D)              (None, None, None, 3 442368      activation_87[0][0]
conv2d_89 (Conv2D)              (None, None, None, 3 442368      activation_87[0][0]
conv2d_92 (Conv2D)              (None, None, None, 3 442368      activation_91[0][0]
conv2d_93 (Conv2D)              (None, None, None, 3 442368      activation_91[0][0]
average_pooling2d_9 (AveragePoo (None, None, None, 2 0           mixed9[0][0]
conv2d_86 (Conv2D)              (None, None, None, 3 655360      mixed9[0][0]
batch_normalization_88 (BatchNo (None, None, None, 3 1152        conv2d_88[0][0]
batch_normalization_89 (BatchNo (None, None, None, 3 1152        conv2d_89[0][0]
batch_normalization_92 (BatchNo (None, None, None, 3 1152        conv2d_92[0][0]
batch_normalization_93 (BatchNo (None, None, None, 3 1152        conv2d_93[0][0]
conv2d_94 (Conv2D)              (None, None, None, 1 393216      average_pooling2d_9[0][0]
batch_normalization_86 (BatchNo (None, None, None, 3 960         conv2d_86[0][0]
activation_88 (Activation)      (None, None, None, 3 0           batch_normalization_88[0][0]
activation_89 (Activation)      (None, None, None, 3 0           batch_normalization_89[0][0]
activation_92 (Activation)      (None, None, None, 3 0           batch_normalization_92[0][0]
activation_93 (Activation)      (None, None, None, 3 0           batch_normalization_93[0][0]
batch_normalization_94 (BatchNo (None, None, None, 1 576         conv2d_94[0][0]
activation_86 (Activation)      (None, None, None, 3 0           batch_normalization_86[0][0]
mixed9_1 (Concatenate)          (None, None, None, 7 0           activation_88[0][0]
                                                                 activation_89[0][0]
concatenate_2 (Concatenate)     (None, None, None, 7 0           activation_92[0][0]
                                                                 activation_93[0][0]
activation_94 (Activation)      (None, None, None, 1 0           batch_normalization_94[0][0]
mixed10 (Concatenate)           (None, None, None, 2 0           activation_86[0][0]
                                                                 mixed9_1[0][0]
                                                                 concatenate_2[0][0]
                                                                 activation_94[0][0]
global_average_pooling2d_1 (Glo (None, 2048)         0           mixed10[0][0]
dense_1 (Dense)                 (None, 1024)         2098176     global_average_pooling2d_1[0][0]
dropout_1 (Dropout)             (None, 1024)         0           dense_1[0][0]
dense_2 (Dense)                 (None, 38)           38950       dropout_1[0][0]
==================================================================================================
Total params: 23,939,910
Trainable params: 23,905,478
Non-trainable params: 34,432
__________________________________________________________________________________________________
```

As F1_score,precision and recall are not readily available in Keras to be used as metric so we introduce it via keras callback.

we create class Metrics and define attributes train_data,val_data and batch size using init method and to get the attributes of parent class (callback) we will use super() keyword.

now we define on_train_begin method in which we will have f1,precision and recall for train and val data whose entry will be written by later method.

and then we have on_epoch_end method in which we will calculate weighted f1 score,precision and recall (using sklearn function) for train and val data after end of each epoch and print it.

In [0]:

```
#https://github.com/keras-team/keras/issues/10472

import itertools
class Metrics(Callback):

        def __init__(self,tr_data, val_data, batch_size):
            super().__init__()
            self.train_data=tr_data
            self.validation_data = val_data
            self.batch_size = batch_size

        def on_train_begin(self, logs={}):
            self.tr_f1s=[]
            self.tr_recalls=[]
            self.tr_precisions=[]

            self.val_f1s = []
            self.val_recalls = []
            self.val_precisions = []

        def on_epoch_end(self, epoch, logs={}):

            batch_tr=len(self.train_data)
            total_tr=batch_tr*self.batch_size

            tr_pred= []
            tr_true= []

            for batch in range(batch_tr):
                xtr,ytr=next(self.train_data)

                tr_pred_batch=np.zeros((len(xtr)))
                tr_true_batch=np.zeros((len(ytr)))

                tr_pred_batch=np.argmax(np.asarray(self.model.predict(xtr)),axis=-1)
                tr_true_batch=np.argmax(ytr,axis=-1)

                tr_pred.append(tr_pred_batch)
                tr_true.append(tr_true_batch)

            tr_pred = np.asarray(list(itertools.chain.from_iterable(tr_pred)))
            tr_true = np.asarray(list(itertools.chain.from_iterable(tr_true)))


            _tr_f1 = f1_score(tr_true, tr_pred,average="weighted")
            _tr_precision = precision_score(tr_true, tr_pred,average="weighted")
            _tr_recall = recall_score(tr_true, tr_pred,average="weighted")

            self.tr_f1s.append(_tr_f1)
            self.tr_recalls.append(_tr_recall)
            self.tr_precisions.append(_tr_precision)

            logs['tr_f1s']= _tr_f1
            logs["tr_recall"]= _tr_recall
            logs["tr_precision"]= _tr_precision

            print("— tr_f1: {} — tr_recall: {} — tr_precision {}".format(_tr_f1, _tr_recall, _tr_pr
ecision))

            batches = len(self.validation_data)
            total = batches * self.batch_size

            val_pred = []
            val_true = []

            for batch in range(batches):

                xVal, yVal = next(self.validation_data)

                val_pred_batch = np.zeros((len(xVal)))
                val_true_batch = np.zeros((len(xVal)))
```

```
                val_pred_batch = np.argmax(np.asarray(self.model.predict(xVal)), axis=-1)
                val_true_batch = np.argmax(yVal,axis=-1)


                val_pred.append(val_pred_batch)
                val_true.append(val_true_batch)


            val_pred = np.asarray(list(itertools.chain.from_iterable(val_pred)))
            val_true = np.asarray(list(itertools.chain.from_iterable(val_true)))


            _val_f1 = f1_score(val_true, val_pred,average="weighted")
            _val_precision = precision_score(val_true, val_pred,average="weighted")
            _val_recall = recall_score(val_true, val_pred,average="weighted")

            self.val_f1s.append(_val_f1)
            self.val_recalls.append(_val_recall)
            self.val_precisions.append(_val_precision)

            logs['val_f1s']= _val_f1
            logs["val_recall"]= _val_recall
            logs["val_precision"]= _val_precision

            print("— val_f1: {} — val_recall: {} — val_precision {}".format(
                 _val_f1, _val_recall, _val_precision))

            return

metric=Metrics(train_generator,test_generator,batch_size=64)
```

In [0]:

```
# Load the TensorBoard notebook extension
from keras.callbacks import TensorBoard
import datetime


"""Tensorboard is the interface used to visualize the graph and
 other tools to understand, debug, and optimize the model. """

#https://www.tensorflow.org/tensorboard/r1/summaries

log_dir="logs1/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensor = TensorBoard(log_dir=log_dir)

'''The ModelCheckpoint callback class allows to define where to checkpoint the model weights,
   how the file should named and under what circumstances to make a checkpoint of the model'''

path="inception"+'.hdf5'

checkpoint = ModelCheckpoint(path,
                             monitor='val_loss',
                             mode='min',
                             verbose=1,
                             save_best_only=True)

'''ReduceLROnPlateau callback monitors a quantity and if no improvement is seen for
   a 'patience' number of epochs, the learning rate is reduced. '''

reduce_lr = ReduceLROnPlateau(monitor='val_loss',
                              factor=0.2,
                              patience=4,
                              cooldown=5)

'''CSVLogger Callback store epoch results to a csv file.'''

filepath = "inception" + ".csv"

csv_log = CSVLogger(filepath)
```

In [0]:

```
# Fit transfer learning model
history = model.fit_generator(train_generator,epochs=15,
```

```
    steps_per_epoch=500,
    validation_data=test_generator,
    validation_steps=180,
    callbacks=[metric,checkpoint,reduce_lr,csv_log,tensor])
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow_core/python/ops/math_grad.py:1424: where (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please us
e tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is deprecated. Please use tf
.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1122: The name t
f.summary.merge_all is deprecated. Please use tf.compat.v1.summary.merge_all instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1125: The name t
f.summary.FileWriter is deprecated. Please use tf.compat.v1.summary.FileWriter instead.

Epoch 1/15
500/500 [==============================] - 681s 1s/step - loss: 0.5855 - val_loss: 0.8404
— tr_f1: 0.7761149969451141 — tr_recall: 0.781502201027146 — tr_precision 0.8441304239260359
— val_f1: 0.797748037062383 — val_recall: 0.8055009823182712 — val_precision 0.8547548684078947

Epoch 00001: val_loss improved from inf to 0.84041, saving model to inception.hdf5
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1265: The name t
f.Summary is deprecated. Please use tf.compat.v1.Summary instead.

Epoch 2/15
500/500 [==============================] - 643s 1s/step - loss: 0.2306 - val_loss: 0.6656
— tr_f1: 0.8211018767038183 — tr_recall: 0.8324238811445341 — tr_precision 0.8691871740350082
— val_f1: 0.8360716813297451 — val_recall: 0.8491907568528394 — val_precision 0.8819815090640326

Epoch 00002: val_loss improved from 0.84041 to 0.66565, saving model to inception.hdf5
Epoch 3/15
500/500 [==============================] - 648s 1s/step - loss: 0.1558 - val_loss: 0.6771
— tr_f1: 0.8714617131342741 — tr_recall: 0.870208180484226 — tr_precision 0.9021018321481544
— val_f1: 0.8716838199066823 — val_recall: 0.8731406118439518 — val_precision 0.9054167983415603

Epoch 00003: val_loss did not improve from 0.66565
Epoch 4/15
500/500 [==============================] - 642s 1s/step - loss: 0.1425 - val_loss: 0.6214
— tr_f1: 0.8751718872748133 — tr_recall: 0.8816947909024211 — tr_precision 0.90622124655336
— val_f1: 0.8880725163919656 — val_recall: 0.8949387220507063 — val_precision 0.9153931229864534

Epoch 00004: val_loss improved from 0.66565 to 0.62141, saving model to inception.hdf5
Epoch 5/15
500/500 [==============================] - 649s 1s/step - loss: 0.1170 - val_loss: 1.0897
— tr_f1: 0.752962728248012 — tr_recall: 0.7462399119589141 — tr_precision 0.8837173693659899
— val_f1: 0.7972052438331243 — val_recall: 0.7940873795490692 — val_precision 0.8984250620182035

Epoch 00005: val_loss did not improve from 0.62141
Epoch 6/15
500/500 [==============================] - 647s 1s/step - loss: 0.1249 - val_loss: 0.9104
— tr_f1: 0.7573391919124156 — tr_recall: 0.7352118488628027 — tr_precision 0.8742363901460685
— val_f1: 0.8275957297853737 — val_recall: 0.8158854897558238 — val_precision 0.8987643293763337

Epoch 00006: val_loss did not improve from 0.62141
Epoch 7/15
500/500 [==============================] - 671s 1s/step - loss: 0.0972 - val_loss: 0.1145
— tr_f1: 0.9668747904839661 — tr_recall: 0.9667094644167278 — tr_precision 0.9688965017210402
— val_f1: 0.969862306041764 — val_recall: 0.9696884647768734 — val_precision 0.9719922855375893

Epoch 00007: val_loss improved from 0.62141 to 0.11453, saving model to inception.hdf5
Epoch 8/15
500/500 [==============================] - 653s 1s/step - loss: 0.0875 - val_loss: 0.1554
— tr_f1: 0.9493398319223824 — tr_recall: 0.9497890682318415 — tr_precision 0.956631780789561
— val_f1: 0.9552907015753793 — val_recall: 0.9562166713443727 — val_precision 0.961582408104522

Epoch 00008: val_loss did not improve from 0.11453
Epoch 9/15
```

```
500/500 [==============================] - 648s 1s/step - loss: 0.0746 - val_loss: 0.6901
— tr_f1: 0.8009620787664998 — tr_recall: 0.8063554658840792 — tr_precision 0.8743015123208766
— val_f1: 0.8227567963561434 — val_recall: 0.8275797548882028 — val_precision 0.8909902380443993

Epoch 00009: val_loss did not improve from 0.11453
Epoch 10/15
500/500 [==============================] - 641s 1s/step - loss: 0.0925 - val_loss: 0.7005
— tr_f1: 0.8536594345473701 — tr_recall: 0.8549385546588408 — tr_precision 0.895779946613781
— val_f1: 0.856863671652333 — val_recall: 0.8585461689587426 — val_precision 0.9031717141928106

Epoch 00010: val_loss did not improve from 0.11453
Epoch 11/15
500/500 [==============================] - 647s 1s/step - loss: 0.0744 - val_loss: 0.1326
— tr_f1: 0.9496590636664521 — tr_recall: 0.9528384079236977 — tr_precision 0.9574921549916592
— val_f1: 0.9627779219481386 — val_recall: 0.9644494339975676 — val_precision 0.9673845009580758

Epoch 00011: val_loss did not improve from 0.11453
Epoch 12/15
500/500 [==============================] - 651s 1s/step - loss: 0.0267 - val_loss: 0.0153
— tr_f1: 0.9967213094110056 — tr_recall: 0.996721386647102 — tr_precision 0.9967350084518196
— val_f1: 0.9960512384799619 — val_recall: 0.9960707269155207 — val_precision 0.9961153297834764

Epoch 00012: val_loss improved from 0.11453 to 0.01529, saving model to inception.hdf5
Epoch 13/15
500/500 [==============================] - 674s 1s/step - loss: 0.0158 - val_loss: 0.0147
— tr_f1: 0.9969125402279495 — tr_recall: 0.9969048055759354 — tr_precision 0.9969488339018625
— val_f1: 0.995319260611341 — val_recall: 0.9953222939470484 — val_precision 0.9953584780198139

Epoch 00013: val_loss improved from 0.01529 to 0.01467, saving model to inception.hdf5
Epoch 14/15
500/500 [==============================] - 674s 1s/step - loss: 0.0143 - val_loss: 0.0110
— tr_f1: 0.9976628856237537 — tr_recall: 0.9976614086573734 — tr_precision 0.9976717367010709
— val_f1: 0.9961550850960847 — val_recall: 0.9961642810365796 — val_precision 0.9961839334165086

Epoch 00014: val_loss improved from 0.01467 to 0.01097, saving model to inception.hdf5
Epoch 15/15
500/500 [==============================] - 672s 1s/step - loss: 0.0146 - val_loss: 0.0105
— tr_f1: 0.9980834909169878 — tr_recall: 0.9980741012472487 — tr_precision 0.9981273318608376
— val_f1: 0.9965394729175071 — val_recall: 0.9965384975208158 — val_precision 0.9965617342949289

Epoch 00015: val_loss improved from 0.01097 to 0.01054, saving model to inception.hdf5
```

In [0]:

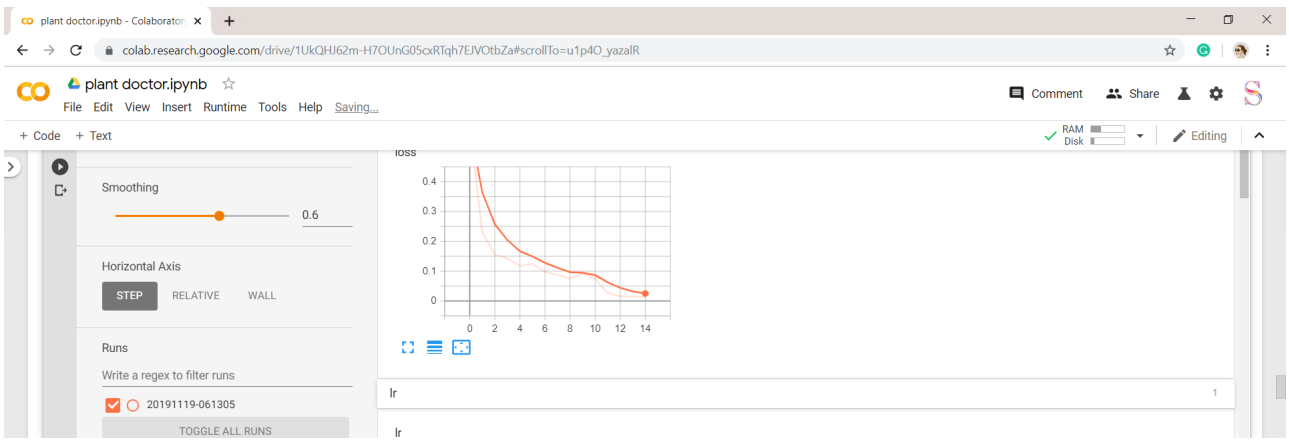
```
#tensorboard output
%reload_ext tensorboard
%tensorboard --logdir logs1/fit
```

```
Reusing TensorBoard on port 6006 (pid 457), started 0:00:59 ago. (Use '!kill 457' to kill it.)
```

In [1]:

```
#tensorboard output screenshot
from IPython.display import Image
Image('1.png',height=600,width=800)
```

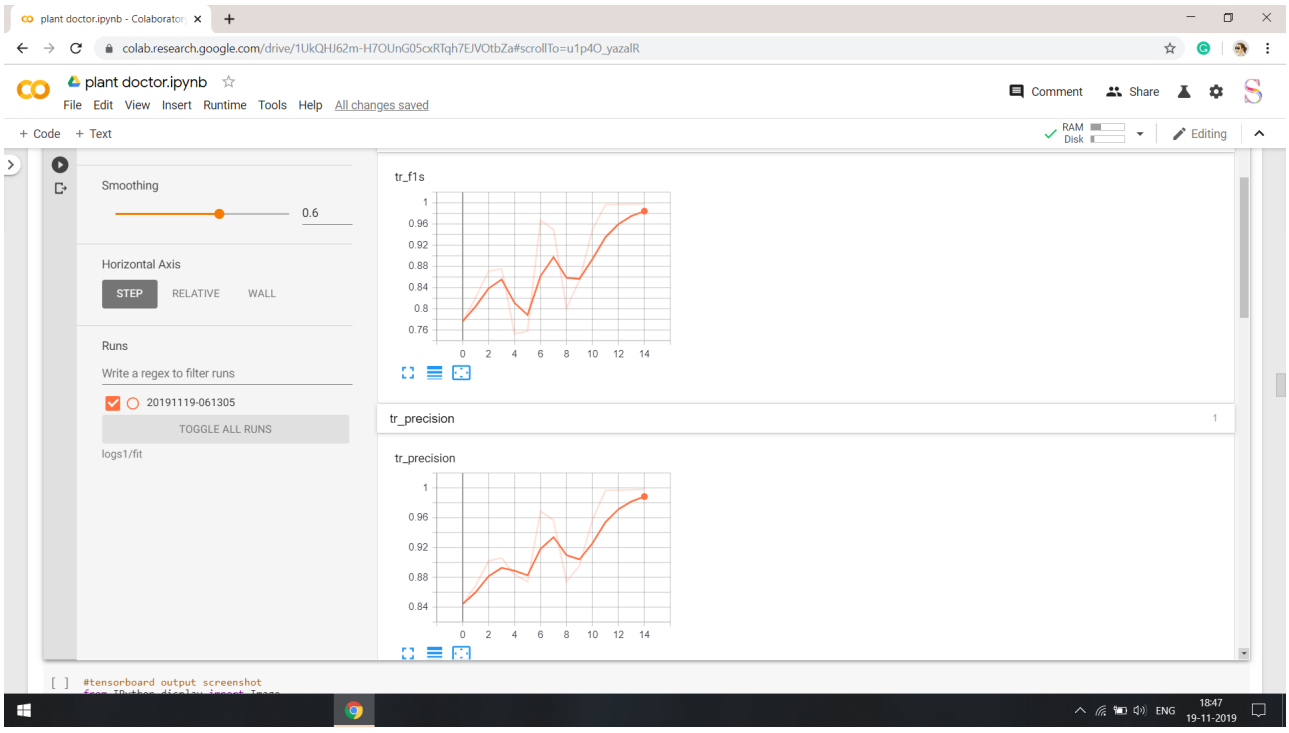
Out[1]:



In [2]:

```
#tensorboard output screenshot
from IPython.display import Image
Image('2.png',height=600,width=800)
```

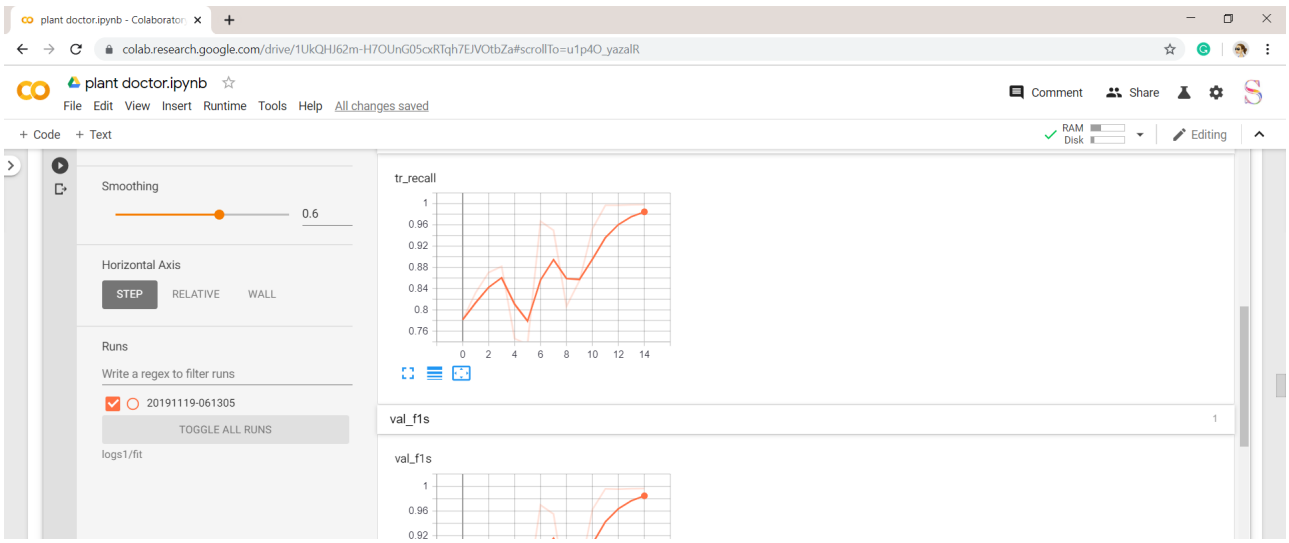
Out[2]:

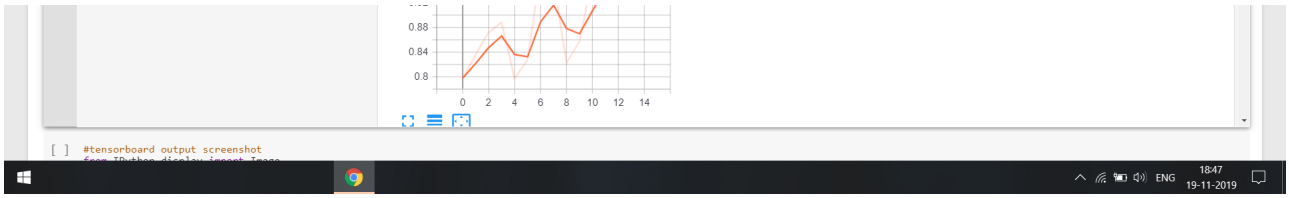


In [3]:

```
#tensorboard output screenshot
from IPython.display import Image
Image('3.png',height=600,width=800)
```

Out[3]:

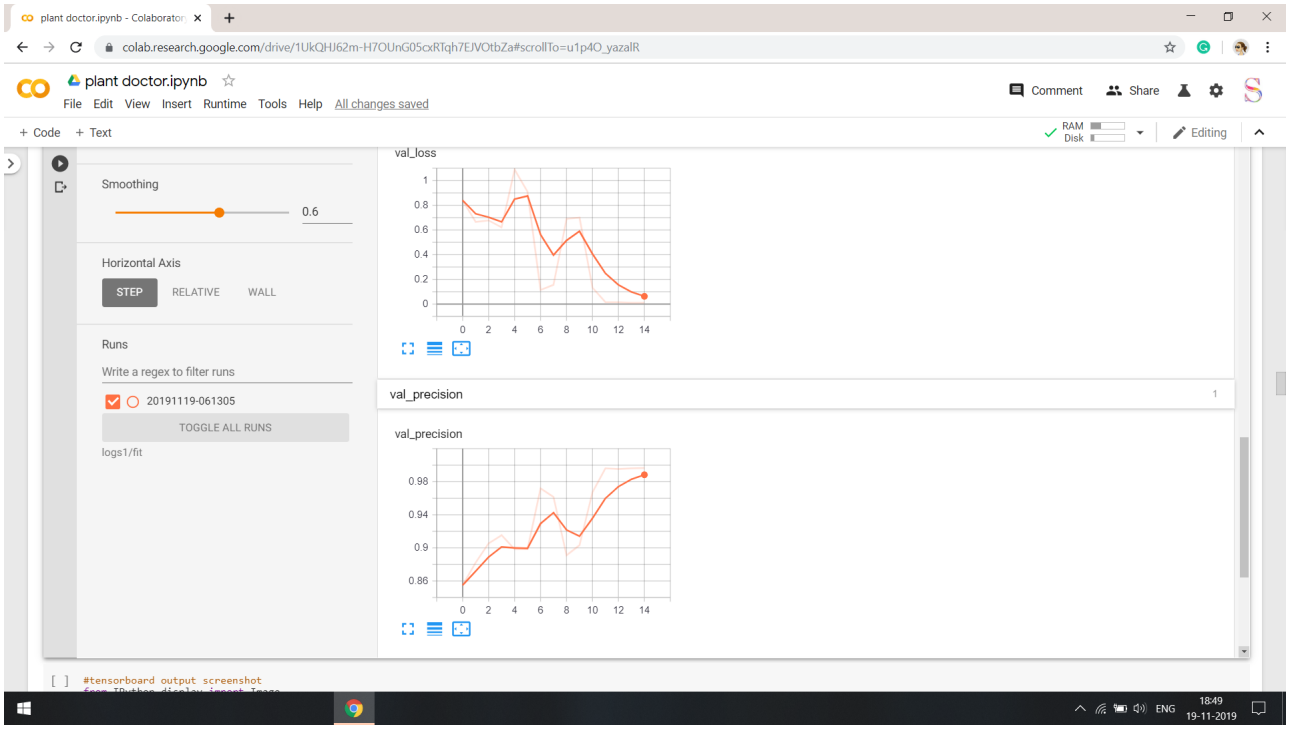




In [4]:

```
#tensorboard output screenshot
from IPython.display import Image
Image('4.png',height=600,width=800)
```

Out[4]:

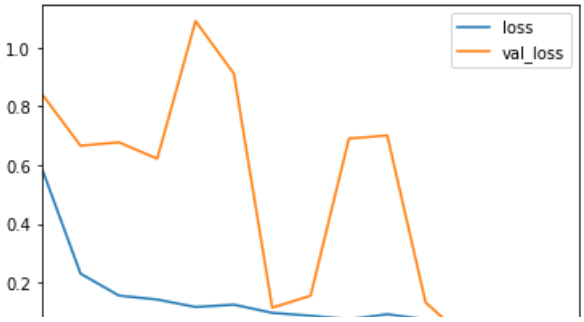


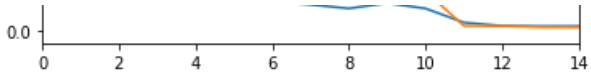
In [0]:

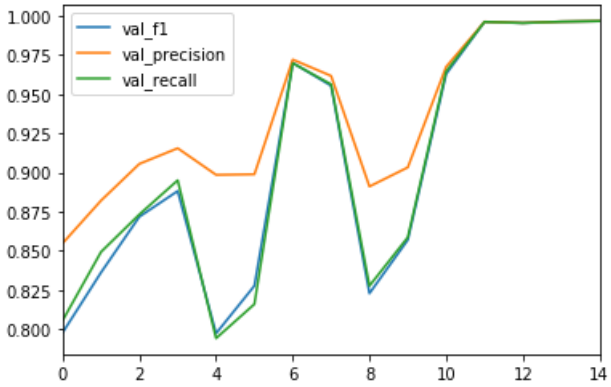
```
#plotting train and test loss and various metrices on train and test data

"""creating a dataframe from history.history & storing val_f1,val_precision and val_recall from me
tric in dataframe
and then plotting the various metrics and loss."""

history_df = pd.DataFrame(history.history)
history_df['val_f1'] = metric.val_f1s
history_df['val_precision'] = metric.val_precisions
history_df['val_recall'] = metric.val_recalls
history_df[['loss', 'val_loss']].plot()
history_df[['val_f1', 'val_precision', 'val_recall']].plot()
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcdcce810b8>
```







In [0]:

```
##showing the saved csv(csvlogger)
inc_csv=pd.read_csv("inception.csv")
inc_csv
```

Out[0]:

	epoch	loss	lr	tr_f1s	tr_precision	tr_recall	val_f1s	val_loss	val_precision	val_recall
0	0	0.585630	0.0010	0.776115	0.844130	0.781502	0.797748	0.840412	0.854755	0.805501
1	1	0.230530	0.0010	0.821102	0.869187	0.832424	0.836072	0.665645	0.881982	0.849191
2	2	0.155807	0.0010	0.871462	0.902102	0.870208	0.871684	0.677144	0.905417	0.873141
3	3	0.142413	0.0010	0.875172	0.906221	0.881695	0.888073	0.621408	0.915393	0.894939
4	4	0.116933	0.0010	0.752963	0.883717	0.746240	0.797205	1.089696	0.898425	0.794087
5	5	0.124896	0.0010	0.757339	0.874236	0.735212	0.827596	0.910436	0.898764	0.815885
6	6	0.097096	0.0010	0.966875	0.968897	0.966709	0.969862	0.114534	0.971992	0.969688
7	7	0.087260	0.0010	0.949340	0.956632	0.949789	0.955291	0.155415	0.961582	0.956217
8	8	0.074648	0.0010	0.800962	0.874302	0.806355	0.822757	0.690063	0.890990	0.827580
9	9	0.092456	0.0010	0.853659	0.895780	0.854939	0.856864	0.700496	0.903172	0.858546
10	10	0.074440	0.0010	0.949659	0.957492	0.952838	0.962778	0.132649	0.967385	0.964449
11	11	0.026743	0.0002	0.996721	0.996735	0.996721	0.996051	0.015287	0.996115	0.996071
12	12	0.015550	0.0002	0.996913	0.996949	0.996905	0.995319	0.014670	0.995358	0.995322
13	13	0.014286	0.0002	0.997663	0.997672	0.997661	0.996155	0.010967	0.996184	0.996164
14	14	0.014573	0.0002	0.998083	0.998127	0.998074	0.996539	0.010538	0.996562	0.996538

In [0]:

```
# Loading the saved best model
inc_model = load_model("inception.hdf5")
```

In [0]:

```
# compute predictions

'''we need to reset the test_generator before whenever  calling the predict_generator. This is imp
ortant,
if we forget to reset the test_generator then we will get outputs in a weird order.
and then predicting using the saved model.
predict_generator will give the prob for each class so we will choose the max prob using np.argmax
and this will
give the pred_class.
also we will get the true class using test generator.classes'''
```

```
test_generator.reset()

predictions = inc_model.predict_generator(generator=test_generator)
y_pred = [np.argmax(probas) for probas in predictions]
y_test = test_generator.classes
```

In [0]:

```
#sanity check
from sklearn import metrics as m

print("Precision_weighted:",m.precision_score(y_test, y_pred , average="weighted")*100)
print("Recall_weighted:",m.recall_score(y_test, y_pred , average="weighted")*100)
print("F1_weighted:",m.f1_score(y_test, y_pred , average="weighted")*100)
```

```
Precision_weighted: 99.6561734294929
Recall_weighted: 99.65384975208158
F1_weighted: 99.65394729175071
```

In [0]:

```
#getting the predicted class for test data

'''
y_pred has the predicted labels,
but we can't simply tell what the predictions are, because all we can see is numbers like 0,1,4,1,
0,6…
and most importantly we need to map the predicted labels with their unique ids such
as filenames to find out what we predicted for which image.'''

labels_map = (train_generator.class_indices)
labels = dict((v,k) for k,v in labels_map.items())
predict = [labels[k] for k in y_pred]

#storing the results in dataframe
filenames=test_generator.filenames
results=pd.DataFrame({"Filename":filenames,"Predictions":predict})
```

In [0]:

```
#dict of class & its labels
labels_map
```

Out[0]:

```
{'Apple___Apple_scab': 0,
 'Apple___Black_rot': 1,
 'Apple___Cedar_apple_rust': 2,
 'Apple___healthy': 3,
 'Blueberry___healthy': 4,
 'Cherry_(including_sour)___Powdery_mildew': 5,
 'Cherry_(including_sour)___healthy': 6,
 'Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot': 7,
 'Corn_(maize)___Common_rust_': 8,
 'Corn_(maize)___Northern_Leaf_Blight': 9,
 'Corn_(maize)___healthy': 10,
 'Grape___Black_rot': 11,
 'Grape___Esca_(Black_Measles)': 12,
 'Grape___Leaf_blight_(Isariopsis_Leaf_Spot)': 13,
 'Grape___healthy': 14,
 'Orange___Haunglongbing_(Citrus_greening)': 15,
 'Peach___Bacterial_spot': 16,
 'Peach___healthy': 17,
 'Pepper,_bell___Bacterial_spot': 18,
 'Pepper,_bell___healthy': 19,
 'Potato___Early_blight': 20,
 'Potato___Late_blight': 21,
 'Potato___healthy': 22,
 'Raspberry___healthy': 23,
 'Soybean___healthy': 24,
 'Squash___Powdery_mildew': 25,
 'Strawberry___Leaf_scorch': 26,
```

```
 'Strawberry___healthy': 27,
 'Tomato___Bacterial_spot': 28,
 'Tomato___Early_blight': 29,
 'Tomato___Late_blight': 30,
 'Tomato___Leaf_Mold': 31,
 'Tomato___Septoria_leaf_spot': 32,
 'Tomato___Spider_mites Two-spotted_spider_mite': 33,
 'Tomato___Target_Spot': 34,
 'Tomato___Tomato_Yellow_Leaf_Curl_Virus': 35,
 'Tomato___Tomato_mosaic_virus': 36,
 'Tomato___healthy': 37}
```

In [0]:

```
#displaying the result of test data as dataframe
results.head()
```

Out[0]:

	Filename	Predictions
0	Apple___Apple_scab/03354abb-aa1c-4f9d-a1ef-9f4...	Apple___Apple_scab
1	Apple___Apple_scab/03eccb1a-0368-4ac7-9f48-754...	Apple___Apple_scab
2	Apple___Apple_scab/0672ab32-9fce-41f3-ae69-e39...	Apple___Apple_scab
3	Apple___Apple_scab/0a14783a-838a-4d4f-a671-ff9...	Apple___Apple_scab
4	Apple___Apple_scab/0ea78733-9404-4536-8793-a10...	Apple___Apple_scab

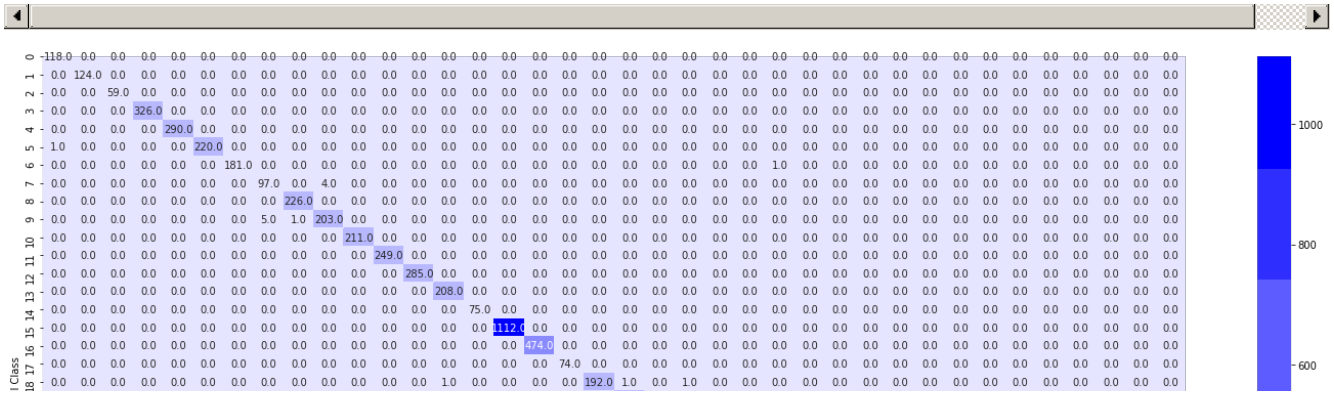
In [0]:

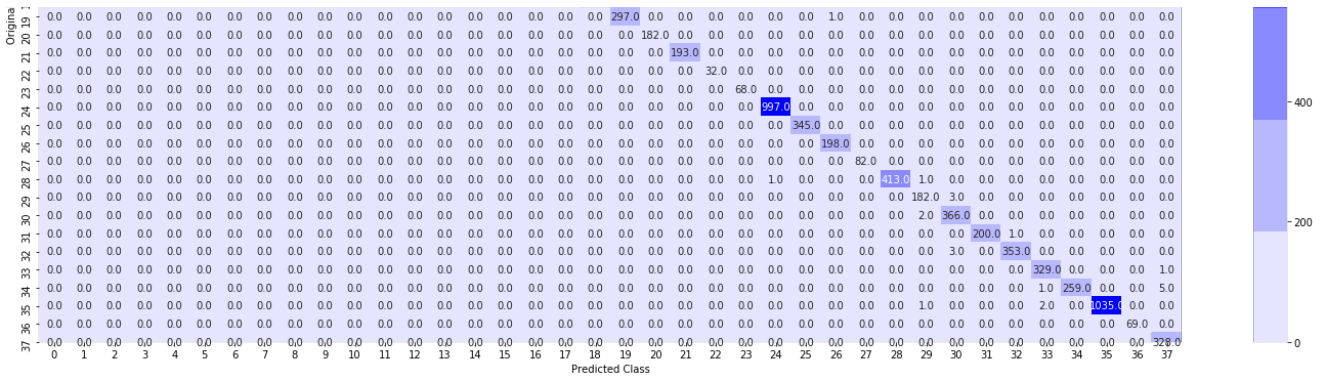
```
#confusion matrix
from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y,predict_y):
    C = confusion_matrix(test_y, predict_y)

    print("Number of misclassified images-",(len(test_y)-np.trace(C)))
    print("% of misclassified images-",(len(test_y)-np.trace(C))*100/len(test_y))

    labels = [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,
32,33,34,35,36,37]
    cmap=sns.light_palette("blue")
    print("-"*50, "Confusion matrix", "-"*50)
    plt.figure(figsize=(25,12))
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".1f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

In [0]:

```
plot_confusion_matrix(y_test,y_pred)
```

```
Number of misclassified images- 37
% of misclassified images- 0.3461502479184208
---------------------------------------------------- Confusion matrix ------------------------------
----------------
```





some of images from class 7 gets predicted as class 9 and vice versa.

class 32 is predicted as class 30 in some cases.

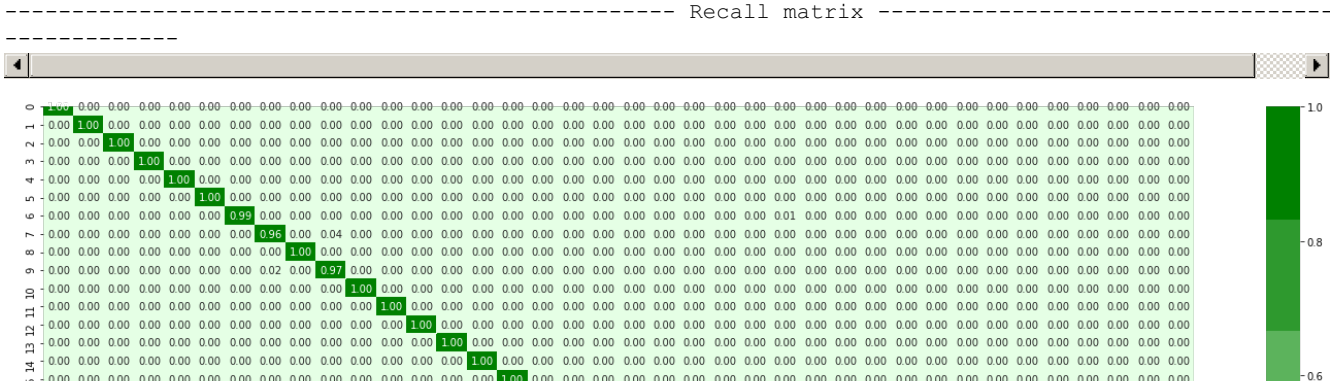
class 34 gets predicted as 33,37 in some cases.

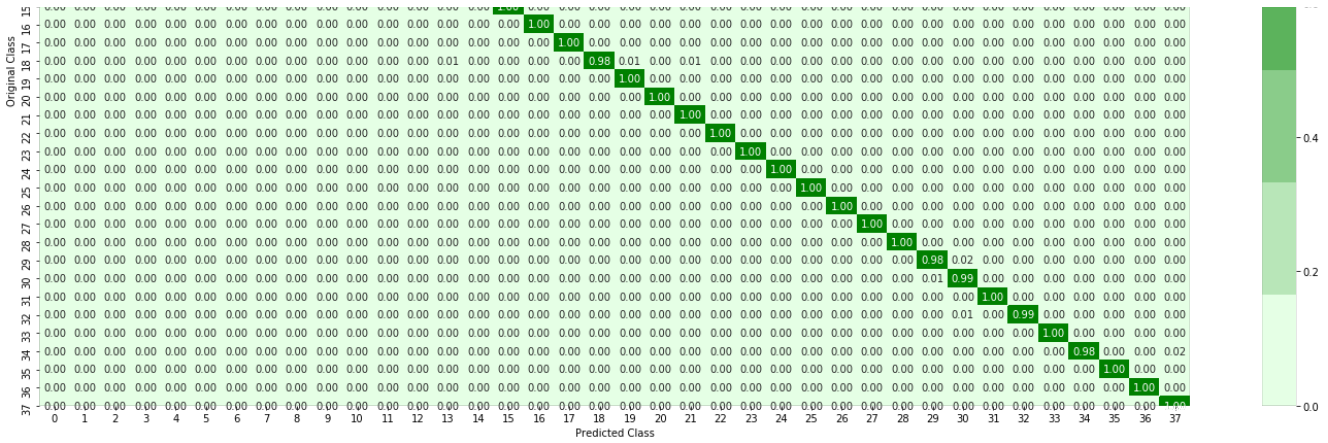
In [0]:

```
def plot_recall_matrix(test_y,predict_y):
    C = confusion_matrix(test_y, predict_y)
    A =(((C.T)/(C.sum(axis=1))).T)

    """
    divide each element of the confusion matrix with the sum of elements in that column

    C = [[1, 2],
         [3, 4]]
    C.T = [[1, 3],
           [2, 4]]
    C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to rows in two
diamensional array
    C.sum(axix =1) = [[3, 7]]
    ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
                               [2/3, 4/7]]

    ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
                                 [3/7, 4/7]]
    sum of row elements = 1"""


    labels = [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,
32,33,34,35,36,37]
    cmap=sns.light_palette("green")
    print("-"*50, "Recall matrix", "-"*50)
    plt.figure(figsize=(25,12))
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".2f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of rows in recall matrix",A.sum(axis=1))
```

In [0]:

```
plot_recall_matrix(y_test,y_pred)
```






```
Sum of rows in recall matrix [1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

recall for class 7,9 is not good as compared to others

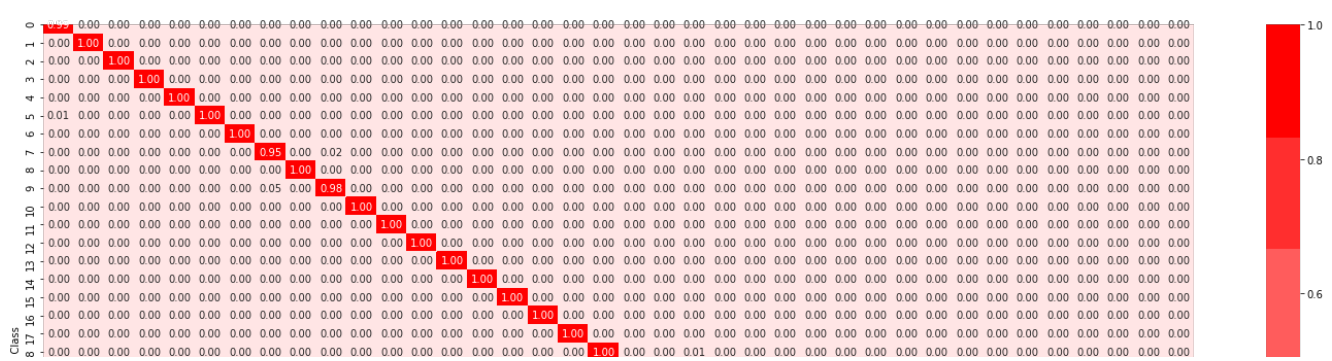
In [0]:

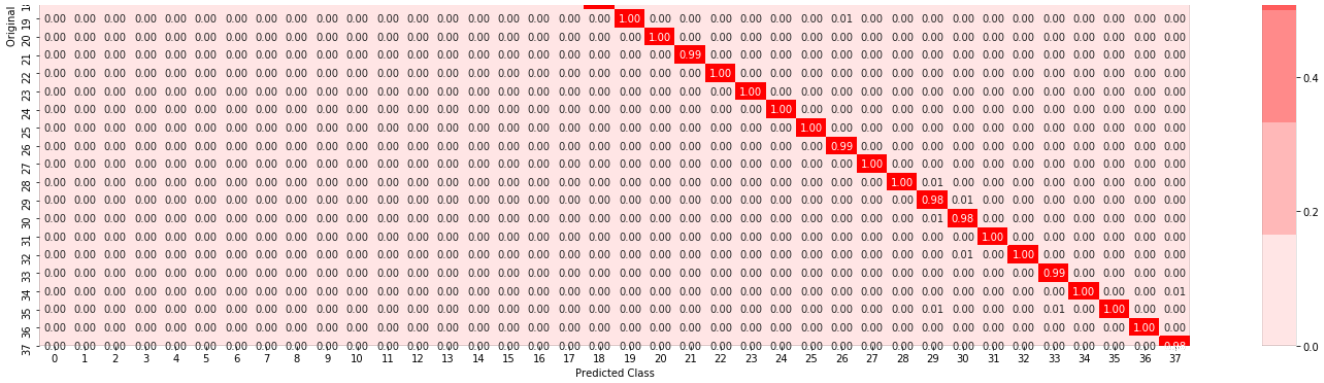
```
def plot_precision_matrix(test_y,predict_y):
    C = confusion_matrix(test_y, predict_y)
    B =(C/C.sum(axis=0))

    '''
    divide each element of the confusion matrix with the sum of elements in that row
    C = [[1, 2],
         [3, 4]]
     C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to rows in two
diamensional array
     C.sum(axix =0) = [[4, 6]]
     (C/C.sum(axis=0)) = [[1/4, 2/6],
                          [3/4, 4/6]]
    '''


    labels = [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,
32,33,34,35,36,37]
    cmap=sns.light_palette("red")
    print("-"*50, "Precision matrix", "-"*50)
    plt.figure(figsize=(25,12))
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".2f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of columns in precision matrix",B.sum(axis=0))
```

In [0]:

```
plot_precision_matrix(y_test,y_pred)
```

```
---------------------------------------------------- Precision matrix -----------------------------------
----------------
```



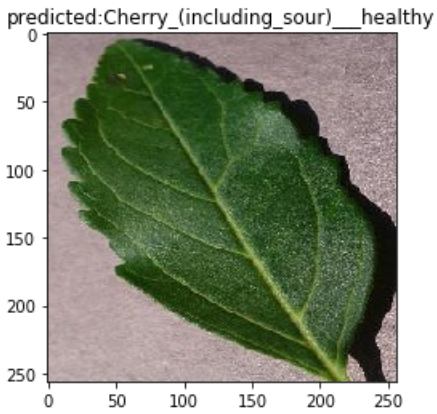



```
Sum of columns in precision matrix [1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

presicion for class 7,9 ,29 & 30 is not good as compared to others.

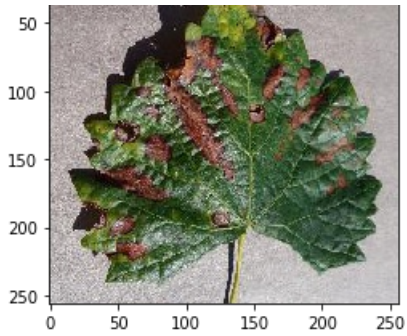
In [0]:

```
#final function which will take raw input image from used and predict the class
#predicting for a single image
#correct prediction


'''pred_img function will take the image and then with help of inc_model predict the class and lab
els will
help to map the class name and then plot the image with the title showing the predicted class'''


def pred_img(file):
    np_image = Image.open(filename)
    np_image = np.array(np_image).astype('float32')/255
    np_image = transform.resize(np_image, (299, 299, 3))
    image = np.expand_dims(np_image, axis=0)
    pred=inc_model.predict(image)
    k=np.argmax(pred,axis=1)
    clas=labels[k[0]]
    plt.imshow(plt.imread(file))
    plt.title("predicted:"+str(clas))
    plt.show()


pred_img("cherry_healthy.JPG")
```



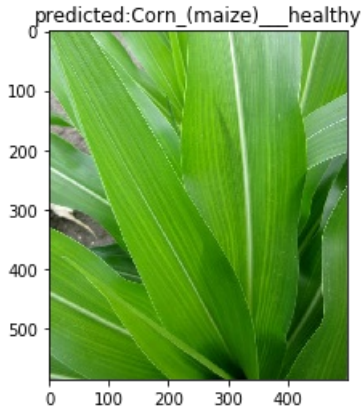
In [0]:

```
#correctly classified
pred_img("grape_measles.png")
```



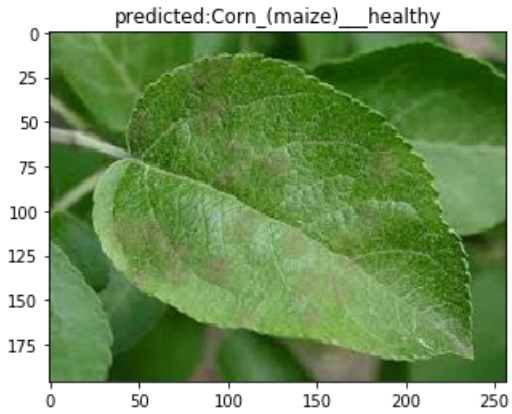
In [0]:

```
#correctly classified
pred_img("corn_healthy.jpg")
```



In [0]:

```
#incorrect prediction
pred_img("apple_scab.jpg")
```



FAST AI library

Let's use the fast ai library to do the disease detection from starting.

Reference-https://towardsdatascience.com/fastai-image-classification-32d626da20

In [ ]:

```
%reload_ext autoreload
%autoreload 2
%matplotlib inline

from fastai import *
from fastai.vision import *
```

```
from fastai.metrics import error_rate,FBeta
from fastai.callbacks import *
```

ImageDataBunch.from_folder can be used to load data that has the following structure.

data-dir

-Train

-Class1

-Class2
-...

-Valid

-Class1

-Class2

-...

In [0]:

```
#loading the data
data = ImageDataBunch.from_folder(path=data_dir, train='train', valid='test', ds_tfms=get_transforms(), size=256, bs=64).normalize(imagenet_stats)
```

In [0]:

```
#class in data

'''we can use the data object to get more information about data.'''

data.classes
```

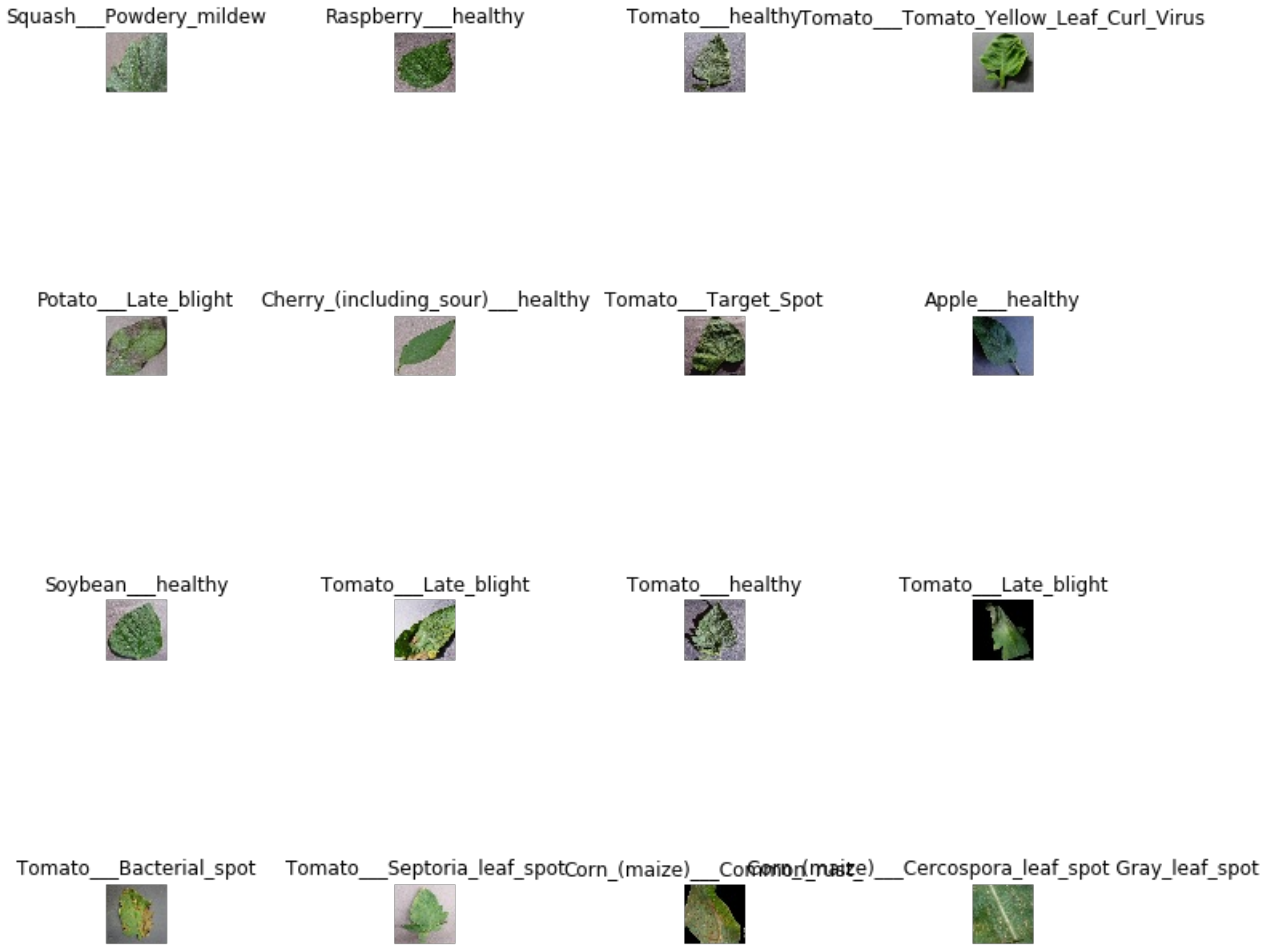
Out[0]:

```
['Apple___Apple_scab',
 'Apple___Black_rot',
 'Apple___Cedar_apple_rust',
 'Apple___healthy',
 'Blueberry___healthy',
 'Cherry_(including_sour)___Powdery_mildew',
 'Cherry_(including_sour)___healthy',
 'Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot',
 'Corn_(maize)___Common_rust_',
 'Corn_(maize)___Northern_Leaf_Blight',
 'Corn_(maize)___healthy',
 'Grape___Black_rot',
 'Grape___Esca_(Black_Measles)',
 'Grape___Leaf_blight_(Isariopsis_Leaf_Spot)',
 'Grape___healthy',
 'Orange___Haunglongbing_(Citrus_greening)',
 'Peach___Bacterial_spot',
 'Peach___healthy',
 'Pepper,_bell___Bacterial_spot',
 'Pepper,_bell___healthy',
 'Potato___Early_blight',
 'Potato___Late_blight',
 'Potato___healthy',
 'Raspberry___healthy',
 'Soybean___healthy',
 'Squash___Powdery_mildew',
 'Strawberry___Leaf_scorch',
 'Strawberry___healthy',
 'Tomato___Bacterial_spot',
 'Tomato___Early_blight',
 'Tomato___Late_blight',
 'Tomato___Leaf_Mold',
 'Tomato___Septoria_leaf_spot',
```

```
 'Tomato___Spider_mites Two-spotted_spider_mite',
 'Tomato___Target_Spot',
 'Tomato___Tomato_Yellow_Leaf_Curl_Virus',
 'Tomato___Tomato_mosaic_virus',
 'Tomato___healthy']
```

In [0]:

```
#show a random batch of images using the show_batch method.

data.show_batch(rows=4, figsize=(10,10))
```



ResNet architecture-

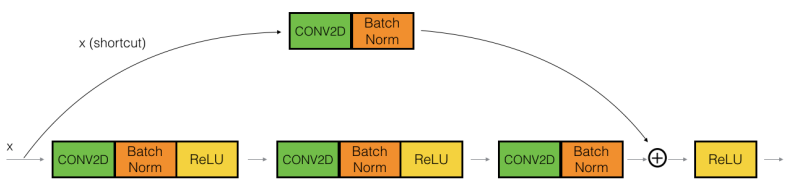
One of the problems ResNets solve is the famous vanishing gradient. Its key idea is to use **Skip Connection**.

With ResNets, the gradients can flow directly through the skip connections backwards from later layers to initial filters.

In [0]:

```
#resnet architecture
from IPython.display import Image
Image('resnet.png',width=500,height=200)
```

Out[0]:



In [0]:

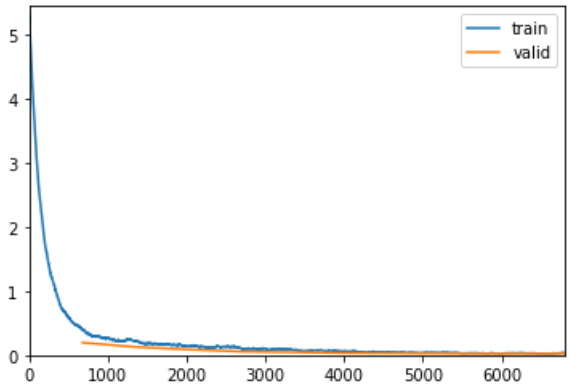
```
#transfer learning using resnet34

'''there is cnn learner in fastai lib which needs two arguments, the data, and the architecture,
but also supports many other parameters that can be used to customize the model for a given proble
m '''

learn = cnn_learner(data, models.resnet34, metrics=[Precision(average="weighted"),Recall(average="w
eighted"),FBeta(average="weighted")], callback_fns=ShowGraph)
```

```
Downloading: "https://download.pytorch.org/models/resnet34-333f7ec4.pth" to
/root/.cache/torch/checkpoints/resnet34-333f7ec4.pth
100%|██████████| 83.3M/83.3M [00:02<00:00, 43.1MB/s]
```

In [0]:

```
#fit the model

'''To train the layers we can use the fit or fit_one_cycle method.
The fit method is the "normal" way of training a neural net with a constant learning rate,
whilst the fit_one_cycle method uses something called the 1 cycle policy,
which basically changes the learning rate over time to achieve better results.'''


learn.fit_one_cycle(10,callbacks=[callbacks.SaveModelCallback(learn, every='epoch',
monitor='valid_loss')])
```

epoch	train_loss	valid_loss	precision	recall	f_beta	time
0	0.394207	0.195391	0.940988	0.939751	0.939120	08:58
1	0.216652	0.126474	0.963197	0.961081	0.960252	08:57
2	0.143612	0.087872	0.974770	0.972308	0.972123	08:56
3	0.095625	0.054442	0.983672	0.983254	0.983113	08:54
4	0.078488	0.044941	0.987827	0.986996	0.986921	08:56
5	0.058806	0.031343	0.991168	0.991112	0.991097	08:55
6	0.043090	0.029424	0.991899	0.991393	0.991369	08:55
7	0.035417	0.023828	0.993365	0.993264	0.993255	08:55
8	0.030950	0.022818	0.993615	0.993545	0.993538	08:56
9	0.029865	0.023229	0.993650	0.993545	0.993534	08:57



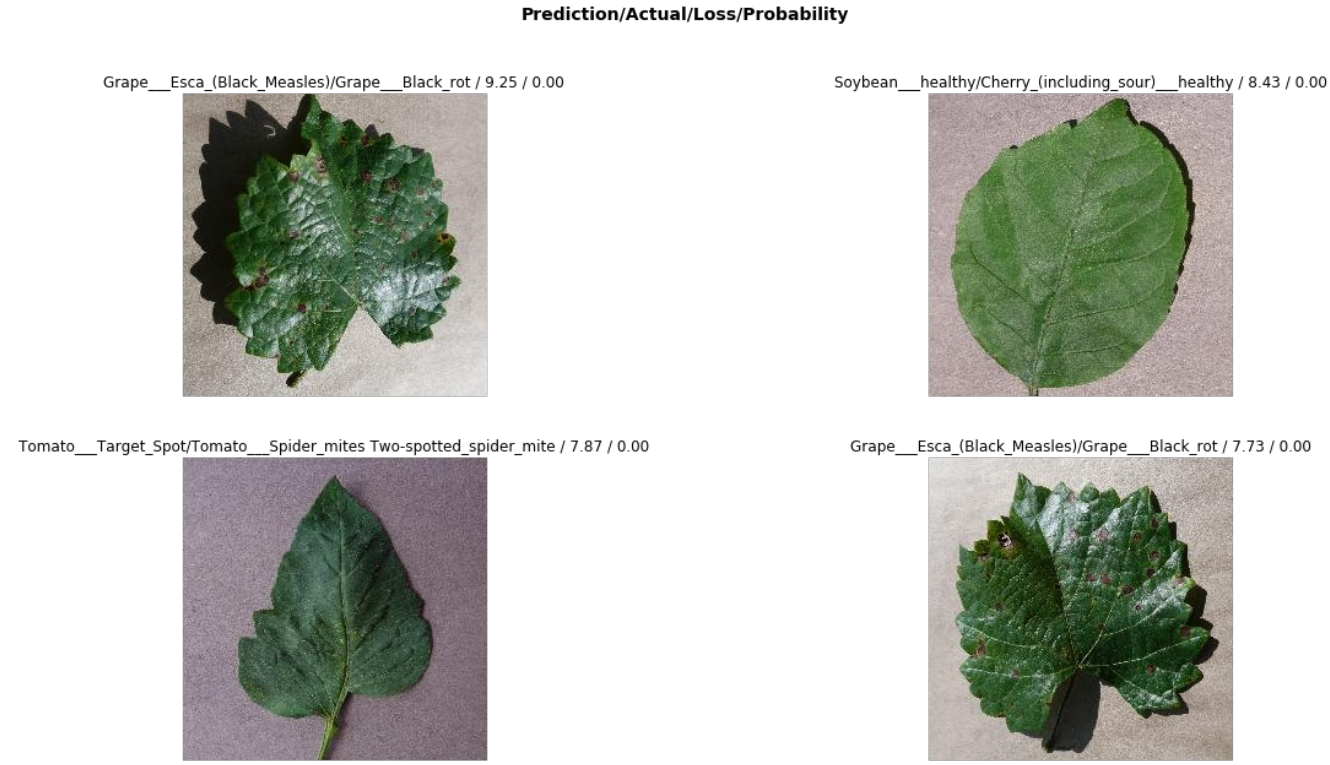
In [0]:

```
#to interpret the results

'''we can use FastAIs ClassificationInterpretation class to interpret our results.
To create an interpretation object we need to call the from_learner method and pass it our learner
/model.
```

```
Then we can use methods like plot_confusion_matrix, plot_top_losses or most_confused.'''

ip= ClassificationInterpretation.from_learner(learn)
```

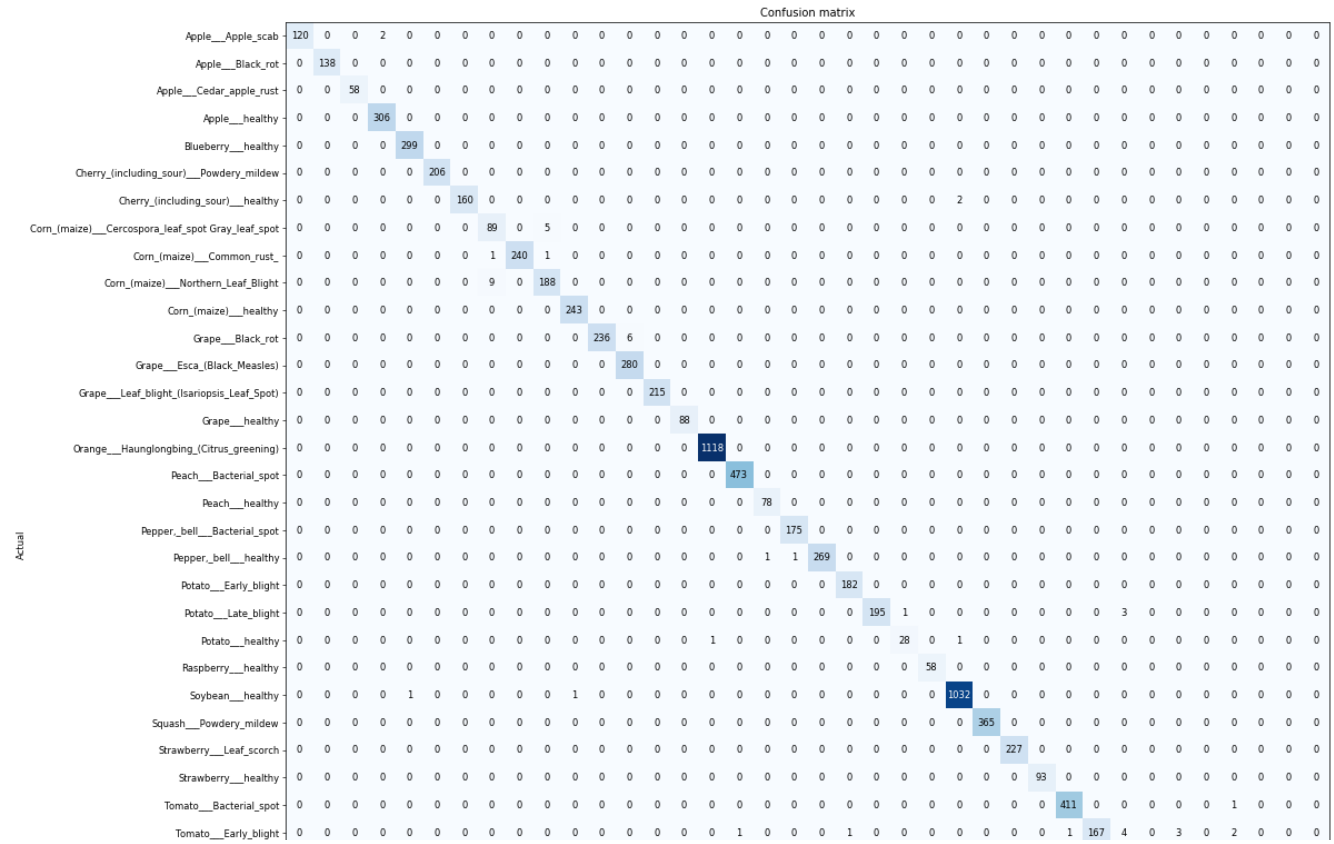
In [0]:

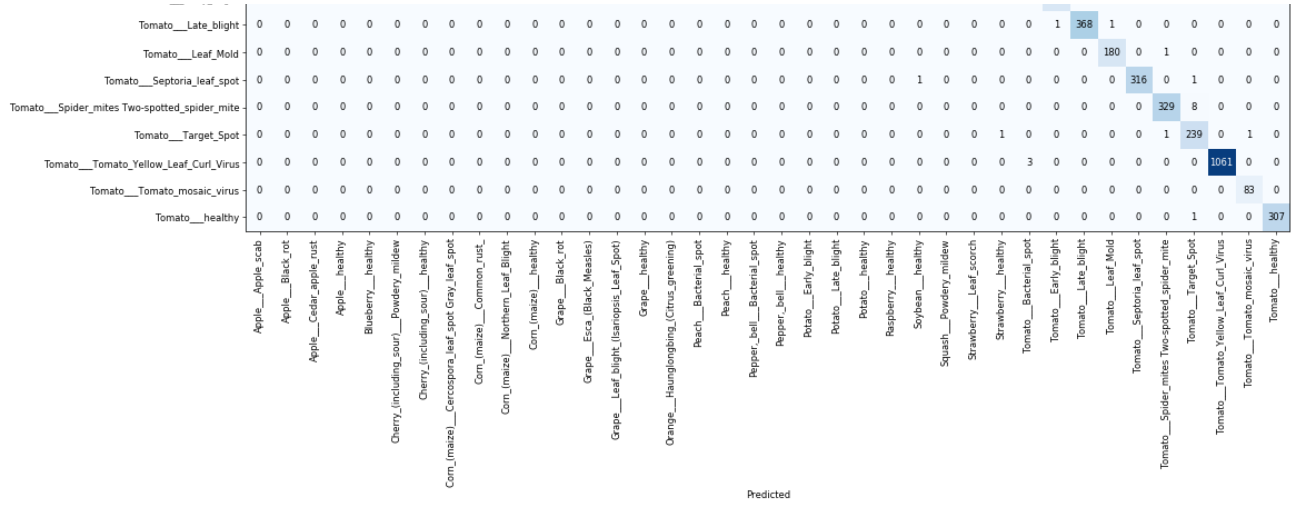
```
#plot top losses
ip.plot_top_losses(4, figsize=(20,10))
```



In [0]:

```
#confusion matrix
ip.plot_confusion_matrix(figsize=(20,20), dpi=60)
```





In [0]:

```
#confused prediction(misclassified prediction)
mis=ip.most_confused(min_val=1)
mis
```

Out[0]:

```
[('Corn_(maize)___Northern_Leaf_Blight',
  'Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot',
  9),
 ('Tomato___Spider_mites Two-spotted_spider_mite', 'Tomato___Target_Spot', 8),
 ('Grape___Black_rot', 'Grape___Esca_(Black_Measles)', 6),
 ('Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot',
  'Corn_(maize)___Northern_Leaf_Blight',
  5),
 ('Tomato___Early_blight', 'Tomato___Late_blight', 4),
 ('Potato___Late_blight', 'Tomato___Late_blight', 3),
 ('Tomato___Early_blight', 'Tomato___Septoria_leaf_spot', 3),
 ('Tomato___Tomato_Yellow_Leaf_Curl_Virus', 'Tomato___Bacterial_spot', 3),
 ('Apple___Apple_scab', 'Apple___healthy', 2),
 ('Cherry_(including_sour)___healthy', 'Soybean___healthy', 2),
 ('Tomato___Early_blight', 'Tomato___Target_Spot', 2),
 ('Corn_(maize)___Common_rust_',
  'Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot',
  1),
 ('Corn_(maize)___Common_rust_', 'Corn_(maize)___Northern_Leaf_Blight', 1),
 ('Pepper,_bell___healthy', 'Peach___healthy', 1),
 ('Pepper,_bell___healthy', 'Pepper,_bell___Bacterial_spot', 1),
 ('Potato___Late_blight', 'Potato___healthy', 1),
 ('Potato___healthy', 'Orange___Haunglongbing_(Citrus_greening)', 1),
 ('Potato___healthy', 'Soybean___healthy', 1),
 ('Soybean___healthy', 'Blueberry___healthy', 1),
 ('Soybean___healthy', 'Corn_(maize)___healthy', 1),
 ('Tomato___Bacterial_spot', 'Tomato___Target_Spot', 1),
 ('Tomato___Early_blight', 'Peach___Bacterial_spot', 1),
 ('Tomato___Early_blight', 'Potato___Early_blight', 1),
 ('Tomato___Early_blight', 'Tomato___Bacterial_spot', 1),
 ('Tomato___Late_blight', 'Tomato___Early_blight', 1),
 ('Tomato___Late_blight', 'Tomato___Leaf_Mold', 1),
 ('Tomato___Leaf_Mold', 'Tomato___Spider_mites Two-spotted_spider_mite', 1),
 ('Tomato___Septoria_leaf_spot', 'Soybean___healthy', 1),
 ('Tomato___Septoria_leaf_spot', 'Tomato___Target_Spot', 1),
 ('Tomato___Target_Spot', 'Strawberry___healthy', 1),
 ('Tomato___Target_Spot', 'Tomato___Spider_mites Two-spotted_spider_mite', 1),
 ('Tomato___Target_Spot', 'Tomato___Tomato_mosaic_virus', 1),
 ('Tomato___healthy', 'Tomato___Target_Spot', 1)]
```

these are some classes which are mispredicted as other classes-

Corn_ Northern_Leaf_Blight gets predicted as Corn __ Cercospora_leaf_spot Gray_leaf_spot and vice versa.

Tomato_**Spider_mites Two-spotted_spider*mite gets predicted as Tomato*** Target_Spot

Grape_**Black*rot gets predicted as Grape*** Esca_(Black_Measles)

Tomato_**Early*blight gets predicted as Tomato*** Late_blight

Potato_**Late*blight gets predicted as Tomato*** Late_blight

Tomato_**Early*blight gets predicted as Tomato*** Septoria_leaf_spot

Tomato_**Tomato_Yellow_Leaf_Curl *Virus gets predicted as Tomato*** Bacterial_spot

Apple_**Apple*scab gets predicted as Apple*** healthy

Cherry_(including *sour)* healthy gets predicted as Soybean __ healthy

Tomato_**Early*blight gets predicted as Tomato*** Target_Spot

In [0]:

```
#total misclassified image

l=[]
for i in mis:
    l.append(i[2])
print("total misclassified image:",sum(l))
```

```
total misclassified image: 69
```

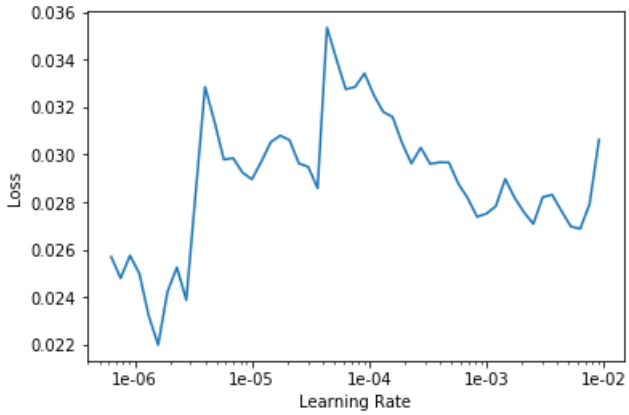
In [0]:

```
#learning rate finder

'''To find the perfect learning rates we can use the lr_find and recorder.plot methods
 which create a plot that relates the learning rate with the loss.
'''

learn.lr_find()
```

```
LR Finder is complete, type {learner_name}.recorder.plot() to see the graph.
```

In [0]:

```
#plot of loss vs lr
learn.recorder.plot()
```



In [0]:

```
#saving the model in the pkl file

learn.export('resnet.pkl')
```

In [0]:

```
#final Function which takes raw image from user and gives the output class.

'''pred_img function takes the image and with help of save model we will use it to predict the cla
ss and
the predicted class will be shown title of the image'''

def pred_img(file):
    img=open_image(file)
    cat,_,_=learn.predict(img)
    return img.show(title="predicted:"+str(cat))
```

In [0]:

```
##prediction on image downloaded from google
#correct prediction
pred_img("corn.jpg")
```

In [0]:

```
#prediction on image downloaded from google
#incorrect prediction
pred_img("scab.jpg")
```

Result

In [0]:

```
from prettytable import PrettyTable
x=PrettyTable()

print("RESULTS")
x.field_names=["Value","AlexNet model","Inception model","Resnet34"]
x.add_row(["No. of misclassified image",1983,37,69])
x.add_row(["Loss",0.6361,0.01538,0.02322])
x.add_row(["Precision_weighted",85.2813,99.6561,99.3650])
x.add_row(["Recall_weighted",81.4482,99.6538,99.3545])
x.add_row(["F1_weighted",81.3778,99.6539,99.3545])

print(x)
```

```
RESULTS
+---------------------------+---------------+-----------------+----------+
|           Value           | AlexNet model | Inception model | Resnet34 |
+---------------------------+---------------+-----------------+----------+
| No. of misclassified image |      1983     |        37       |    69    |
```

No. of Misclassified Image	1905	37	69
Loss	0.6361	0.01538	0.02322
Precision_weighted	85.2813	99.6561	99.365
Recall_weighted	81.4482	99.6538	99.3545
F1_weighted	81.3778	99.6539	99.3545
+----------------------------+----------------+------------------+----------+

Steps-

1-Load the data and explore it to understand which also helps in knowing how to split the data.

2-split the data into train and test.

3-try various models to get which works best.

4-plot the confusion matrix and analyse it.

5-report loss and other metrics of each models.