HarvestGuard

This project focuses on Leaf Disease Classification using an Afrocentric dataset. The dataset is specifically curated to represent diverse agricultural scenarios across various African regions. It comprises annotated photos of leaves from a variety of crops, showcasing both healthy specimens and those affected by diseases. The goal is to develop a classification system leveraging machine learning techniques to accurately identify and categorize crop diseases based on the subtle symptoms observed in the annotated images. By using an Afrocentric dataset, the project aims to enhance the effectiveness of disease classification models tailored to the unique agricultural landscape of Africa (Responsible AI Lab, 2023)

```
# Import libraries
!pip install opendatasets
import pandas as pd
import cv2
import json
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import opendatasets as od
import glob
import os
import pathlib
import PIL
from PIL import Image
import PIL.Image
import PIL.ImageShow
from google.colab.patches import cv2_imshow
import numpy as np
from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.model_selection import train_test_split
import pickle
from tensorflow import keras
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import opendatasets as od
import re
import pathlib
import imgaug as ia
ia.seed(1)
# imgaug uses matplotlib backend for displaying images
%matplotlib inline
from imgaug.augmentables.bbs import BoundingBox, BoundingBoxesOnImage
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing.image import img_to_array
```

```python
from imgaug import augmenters as iaa
# imageio library will be used for image input/output
import imageio
import PIL
from PIL import Image
import PIL.Image
import PIL.ImageShow
from google.colab.patches import cv2_imshow
import xml.etree.ElementTree as ET
from os import listdir
from sklearn.preprocessing import LabelBinarizer
from keras.layers import MaxPooling2D
from keras.layers import Activation, Flatten, Dropout, Dense
from keras import backend as K
from keras.preprocessing.image import ImageDataGenerator
from keras.optimizers.legacy import Adam
from keras.preprocessing import image
from tensorflow.keras.preprocessing.image import img_to_array
from keras.models import Sequential
from tensorflow.compat.v1.keras.layers import BatchNormalization
from keras.layers import Conv2D
import matplotlib.pyplot as plt
import xml.etree.ElementTree as ET
from tensorflow.keras.applications import VGG16
from tensorflow.keras.layers import Input
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Input
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.preprocessing.image import load_img
from sklearn.utils import class_weight
import shutil
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=DeprecationWarning)
```

```
Requirement already satisfied: opendatasets in
/usr/local/lib/python3.10/dist-packages (0.1.22)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-
packages (from opendatasets) (4.66.1)
Requirement already satisfied: kaggle in
/usr/local/lib/python3.10/dist-packages (from opendatasets) (1.5.16)
Requirement already satisfied: click in
/usr/local/lib/python3.10/dist-packages (from opendatasets) (8.1.7)
Requirement already satisfied: six>=1.10 in
/usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets)
(1.16.0)
```

```
Requirement already satisfied: certifi in
/usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets)
(2023.11.17)
Requirement already satisfied: python-dateutil in
/usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets)
(2.8.2)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets)
(2.31.0)
Requirement already satisfied: python-slugify in
/usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets)
(8.0.1)
Requirement already satisfied: urllib3 in
/usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets)
(2.0.7)
Requirement already satisfied: bleach in
/usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets)
(6.1.0)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.10/dist-packages (from bleach->kaggle-
>opendatasets) (0.5.1)
Requirement already satisfied: text-unidecode>=1.3 in
/usr/local/lib/python3.10/dist-packages (from python-slugify->kaggle-
>opendatasets) (1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->kaggle-
>opendatasets) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->kaggle-
>opendatasets) (3.6)
```

Afrocentric (African) Crop Dataset

The Afrocentric Crop Disease dataset on Kaggle.The dataset includes annotated images of crops from Ghana, categorizing them based on disease types. Each category contains information on disease categories, image sizes, bounding boxes, and sample images

```
# Download datset from Kaggle to notebook directory
od.download('https://www.kaggle.com/datasets/responsibleailab/crop-disease-ghana')
```

```
Skipping, found downloaded files in "./crop-disease-ghana" (use
force=True to force download)
```

```
# Print out test image
test_img =
'/content/crop-disease-ghana/input/Tomato/Tomato__Early_Blight/images/20230518_134246.jpg'
```

```
test_img = cv2.imread(test_img)
#cv2_imshow(test_img)

def display_image(test_img):
    h, w = test_img.shape[0:2]
    neww = 300
    newh = int(neww*(h/w))
    test_img = cv2.resize(test_img, (neww, newh))
    cv2_imshow(test_img)
    cv2.waitKey(0)

display_image(test_img)
```

```
# Show files in directory
os.listdir('/content/crop-disease-ghana/input')
```

```
['Pepper',
 'Tomato',
 'Corn',
 'dataset_labels.csv',
 'label_map.pbtxt',
 'catyegory_index.pbtxt',
 'label_map.txt',
 'label_map.json']

# Read csv file with data labels
labels_df =
pd.read_csv('/content/crop-disease-ghana/input/dataset_labels.csv')
labels_df.head()

              filename                    disease  crop  width  height
depth  \
0  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3
1  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3
2  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3
3  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3
4  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3

          xmin         ymin         xmax         ymax  \
0  2052.653343   695.836619  2210.117161   785.809054
1  1110.682288   901.086237  1228.780152   982.623756
2  1647.746382   912.332791  1791.150930  1002.305226
3  2491.302550  1275.034169  2589.717436  1367.818243
4  3326.423156  1255.352699  3410.778773  1339.701857

                                            ann_path  \
0  input\Corn\Corn__Cercospora_Leaf_Spot\annotati...
1  input\Corn\Corn__Cercospora_Leaf_Spot\annotati...
2  input\Corn\Corn__Cercospora_Leaf_Spot\annotati...
3  input\Corn\Corn__Cercospora_Leaf_Spot\annotati...
4  input\Corn\Corn__Cercospora_Leaf_Spot\annotati...

                                            img_path
0  input\Corn\Corn__Cercospora_Leaf_Spot\images\2...
1  input\Corn\Corn__Cercospora_Leaf_Spot\images\2...
2  input\Corn\Corn__Cercospora_Leaf_Spot\images\2...
3  input\Corn\Corn__Cercospora_Leaf_Spot\images\2...
4  input\Corn\Corn__Cercospora_Leaf_Spot\images\2...

# Create new column combining width and height column
labels_df['shape'] = 0
```

```
shape_lst = []
for i in range(len(labels_df)):
  shape_lst.append((labels_df['width'][i],labels_df['height'][i]))

labels_df['shape'] = shape_lst
labels_df['shape'].value_counts()
```

```
(4032, 3024)    19548
(4080, 1836)    13500
(1920, 1280)    12418
(4080, 3060)     9007
(720, 480)       1473
(4000, 3000)     1123
(6720, 4480)      552
(1920, 2560)      428
(2560, 1920)      210
(2576, 1932)      102
Name: shape, dtype: int64
```

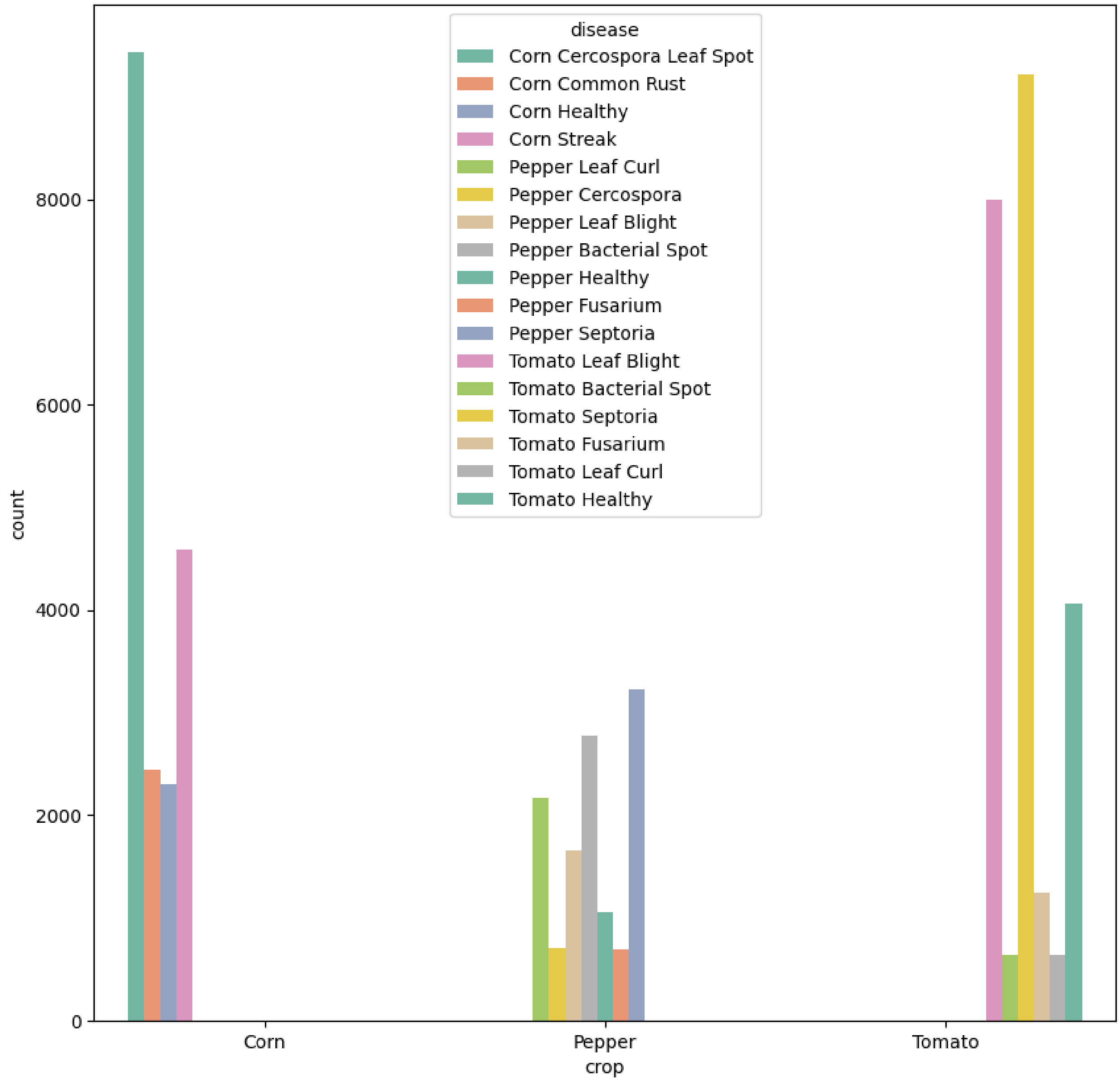
Addressing rare catagories of diseases

```
# Merge similar classes
labels_df.replace(['Pepper Late Blight','Pepper Early Blight'],'Pepper
Leaf Blight',inplace = True)
labels_df.replace(['Tomato Late Blight','Tomato Early Blight'],'Tomato
Leaf Blight',inplace = True)

# Drop labels with too little data or multiple diseases
labels_df = labels_df[labels_df['disease'] != 'Tomato Mosaic']
labels_df = labels_df[labels_df['disease'] != 'Corn Northern Leaf
Blight']
labels_df = labels_df[labels_df['disease'] != 'Pepper Leaf Mosaic']
labels_df['disease'].value_counts()
```

```
Corn Cercospora Leaf Spot    9431
Tomato Septoria              9211
Tomato Leaf Blight           7993
Corn Streak                  4591
Tomato Healthy               4066
Pepper Septoria              3222
Pepper Bacterial Spot        2780
Corn Common Rust             2434
Corn Healthy                 2304
Pepper Leaf Curl             2175
Pepper Leaf Blight           1660
Tomato Fusarium              1238
Pepper Healthy               1049
Pepper Cercospora             704
Pepper Fusarium               696
Tomato Leaf Curl              641
```

```
Tomato Bacterial Spot         639
Name: disease, dtype: int64

# Fix img path
loc_path = '/content/crop-disease-ghana/'
new_img = []
for txt in labels_df['img_path']:
  n = loc_path + txt.replace('\\','/')
  new_img.append(n)
labels_df['img_path'] = new_img
labels_df['img_path'][0]

{"type":"string"}

# Fix annotation path
loc_path = '/content/crop-disease-ghana/'
new_ann = []
for txt in labels_df['ann_path']:
  a = loc_path + txt.replace('\\','/')
  new_ann.append(a)
labels_df['ann_path'] = new_ann
labels_df['ann_path'][0]

{"type":"string"}

# Labels for categories
labels = {}
lab_len = len(np.unique(labels_df['disease']))
for j,i in zip(np.unique(labels_df['disease']),range(1,lab_len + 1)):
  labels[j] = i
print(labels)

{'Corn Cercospora Leaf Spot': 1, 'Corn Common Rust': 2, 'Corn
Healthy': 3, 'Corn Streak': 4, 'Pepper Bacterial Spot': 5, 'Pepper
Cercospora': 6, 'Pepper Fusarium': 7, 'Pepper Healthy': 8, 'Pepper
Leaf Blight': 9, 'Pepper Leaf Curl': 10, 'Pepper Septoria': 11,
'Tomato Bacterial Spot': 12, 'Tomato Fusarium': 13, 'Tomato Healthy':
14, 'Tomato Leaf Blight': 15, 'Tomato Leaf Curl': 16, 'Tomato
Septoria': 17}

# Use categorical labels to make new target column
enc_labels = []
for i in labels_df['disease']:
  for k,v in labels.items():
    if i == k :
      enc_labels.append(labels[i])
labels_df['label'] = enc_labels
labels_df.head()

              filename                    disease  crop  width  height
depth  \
```

```
0  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3
1  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3
2  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3
3  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3
4  20230524_104642.jpg  Corn Cercospora Leaf Spot  Corn   4080    1836
3

          xmin         ymin         xmax         ymax  \
0  2052.653343   695.836619  2210.117161   785.809054
1  1110.682288   901.086237  1228.780152   982.623756
2  1647.746382   912.332791  1791.150930  1002.305226
3  2491.302550  1275.034169  2589.717436  1367.818243
4  3326.423156  1255.352699  3410.778773  1339.701857

                                            ann_path  \
0  /content/crop-disease-ghana/input/Corn/Corn__C...
1  /content/crop-disease-ghana/input/Corn/Corn__C...
2  /content/crop-disease-ghana/input/Corn/Corn__C...
3  /content/crop-disease-ghana/input/Corn/Corn__C...
4  /content/crop-disease-ghana/input/Corn/Corn__C...

                                            img_path         shape
label
0  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
1  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
2  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
3  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
4  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1

# Crop type and disease distribution
plt.figure(figsize = (10,10))
sns.countplot(x = labels_df['crop'],hue = labels_df['disease'],palette
= 'Set2')

<Axes: xlabel='crop', ylabel='count'>
```

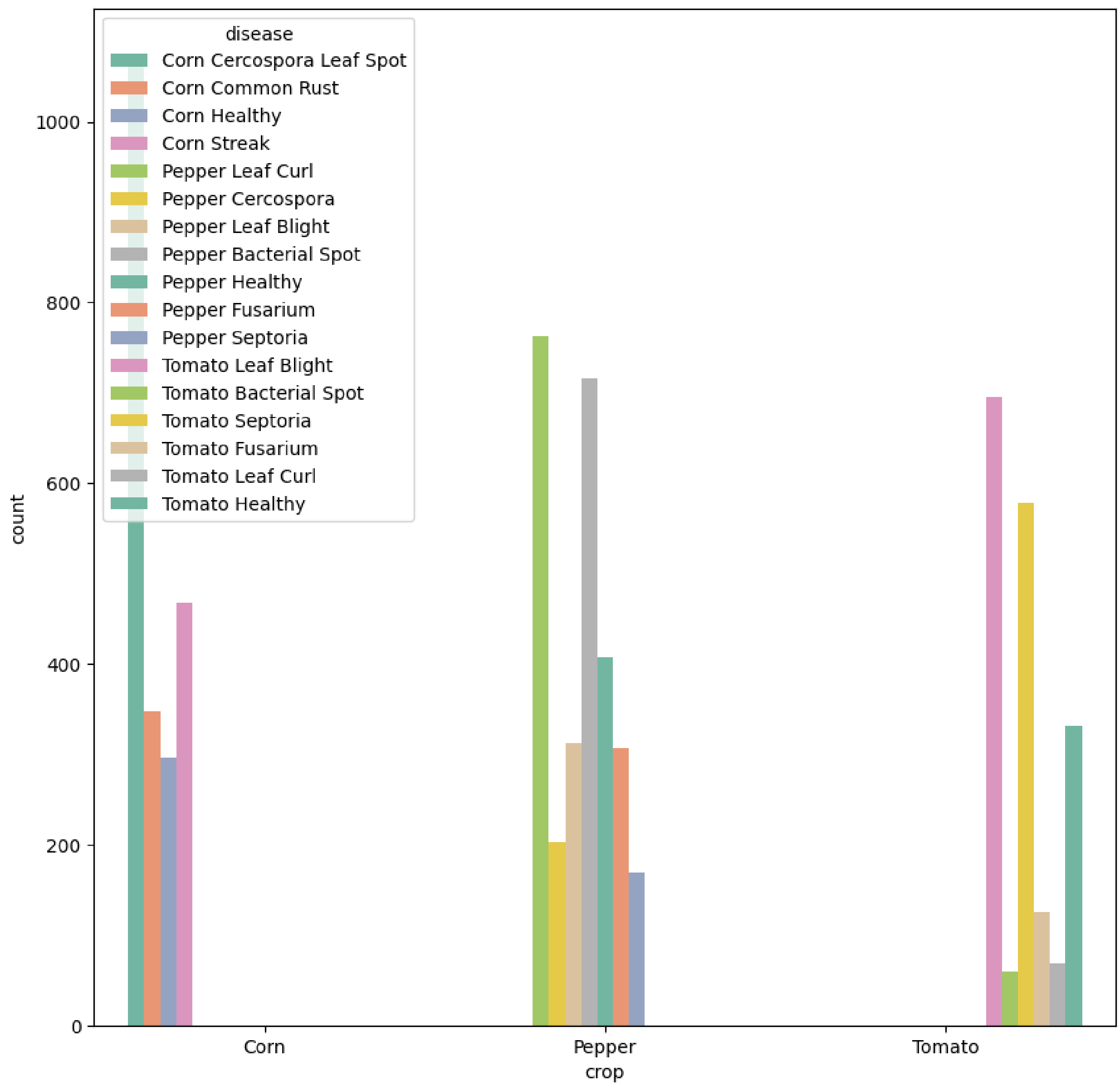



```
# Drop duplicates
no_duplicates = labels_df.drop_duplicates(subset =
'img_path',ignore_index=True)
no_duplicates.reset_index()
no_duplicates.shape
```

```
(6919, 14)
```

```
# Crop type and disease distribution
plt.figure(figsize = (10,10))
sns.countplot(x = no_duplicates['crop'],hue =
no_duplicates['disease'],palette = 'Set2')
```

```
<Axes: xlabel='crop', ylabel='count'>
```




```
# Disease value counts
no_duplicates['disease'].value_counts()
```

```
Corn Cercospora Leaf Spot    1072
Pepper Leaf Curl              763
Pepper Bacterial Spot         716
Tomato Leaf Blight            696
Tomato Septoria               579
Corn Streak                   467
Pepper Healthy                408
Corn Common Rust              348
Tomato Healthy                331
Pepper Leaf Blight            312
```

```
Pepper Fusarium                306
Corn Healthy                   296
Pepper Cercospora              203
Pepper Septoria                169
Tomato Fusarium                126
Tomato Leaf Curl                68
Tomato Bacterial Spot           59
Name: disease, dtype: int64
```

Data Analysis

Graph shows class imbalance in selected dataset. There are catagories such as Corn Cercospora Leaf, Pepper Lead Curl, Pepper Bacteria Spot and others are contributing to majority of sample data. This will lead us in our next section where we addressed class imbalances.

Data Augmentation

In order to address class imbalance problem, there should be a combination of resampling and data augmentation.

```
# Modifed from:
# https://medium.com/@a.karazhay/guide-augment-images-and-multiple-
bounding-boxes-for-deep-learning-in-4-steps-with-the-notebook-
9b263e414dac
# Augments bounding box coordiantes along with their respective images

# Function to convert BoundingBoxesOnImage object into DataFrame
def bbs_obj_to_df(bbs_object):
#  Convert bounding box object to array
    bbs_array = bbs_object.to_xyxy_array()
    # Convert array into a DataFrame ['xmin', 'ymin', 'xmax', 'ymax']
columns
    df_bbs = pd.DataFrame(bbs_array, columns=['xmin', 'ymin', 'xmax',
'ymax'])
    return df_bbs

def image_aug(df,aug_images_path, image_prefix, augmentor,ref_df):
    # Create data frame to store augmented image info
    aug_bbs_xy = pd.DataFrame(columns=labels_df.columns)
    grouped = df.groupby('filename')
    # Group data by filename
    for filename,i in zip(df['filename'].unique(),range(len(df))):
        group_df = grouped.get_group(filename)
        group_df = group_df.reset_index()
        group_df = group_df.drop(['index'], axis=1)
        # Read image
        image = imageio.imread(ref_df['img_path'][i])
        # Find bounding box coordinates put and put them into an array
```

```
        bb_array = group_df.drop(['filename', 'disease', 'crop',
'width', 'height', 'depth',
                                  'ann_path',
'img_path','label','shape'], axis=1).values
    #  Pass bounding box coordinates to Img Aug
        bbs = BoundingBoxesOnImage.from_xyxy_array(bb_array,
shape=image.shape)

        # Apply augmentation on image and on the bounding boxes
        image_aug, bbs_aug = augmentor(image=image,
bounding_boxes=bbs)
        # Disregard boxes which have fallen out of image
        bbs_aug = bbs_aug.remove_out_of_image()
        # Clip  boxes which are partially outside of image
        bbs_aug = bbs_aug.clip_out_of_image()

      # Don't perform any actions with the image if there are no
bounding boxes left in it
        if re.findall('Image...', str(bbs_aug)) == ['Image([]']:
            pass
        else:
            # Write augmented image to a file
            os.chdir(aug_images_path)
            name = image_prefix+'_'+filename
            cv2.imwrite(name, image_aug)
            # Create a data frame with augmented values of image width
and height
            info_df = group_df.drop(['xmin', 'ymin', 'xmax', 'ymax'],
axis=1)
            for index, _ in info_df.iterrows():
                info_df.at[index, 'width'] = image_aug.shape[1]
                info_df.at[index, 'height'] = image_aug.shape[0]
            # Rename filenames by adding the predifined prefix
            info_df['filename'] = info_df['filename'].apply(lambda x:
image_prefix+'_'+x)
            # Create a data frame with augmented bounding boxes
coordinates using the function we created earlier
            bbs_df = bbs_obj_to_df(bbs_aug)
            # Concat all new augmented info into new data frame
            aug_df = pd.concat([info_df, bbs_df], axis=1)
            # Append rows to aug_bbs_xy data frame
            aug_bbs_xy = pd.concat([aug_bbs_xy, aug_df])

    # Return dataframe with updated images and bounding boxes
annotations
    aug_bbs_xy = aug_bbs_xy.reset_index()
    aug_bbs_xy = aug_bbs_xy.drop(['index'], axis=1)
    return aug_bbs_xy
```

```
# Augmentors to use
aug_flip = iaa.Sequential([
    iaa.Fliplr(1)
])
aug_rotate = iaa.Sequential([
    iaa.Affine(rotate=(-60, 60))
])

aug_blur = iaa.Sequential([
    iaa.GaussianBlur(sigma=(2.0, 3.0))
])

aug_noise = iaa.Sequential([
  iaa.AdditiveGaussianNoise(scale=(0.03*255, 0.05*255))
])

# Going to augment rare classes the append augmented data to labels_df
tlc_df = labels_df[labels_df['disease']=='Tomato Leaf
Curl'].reset_index()
tbs_df = labels_df[labels_df['disease']=='Tomato Bacterial
Spot'].reset_index()
pc_df = labels_df[labels_df['disease']=='Pepper
Cercospora'].reset_index()
ps_df = labels_df[labels_df['disease']=='Pepper
Septoria'].reset_index()
tf_df = labels_df[labels_df['disease']=='Tomato
Fusarium'].reset_index()

# Make folders to store augmented images
!mkdir Tomato_Leaf_Curl_Aug
!mkdir Tomato_Bacterial_Spot_Aug
!mkdir Pepper_Cercospora_Aug
!mkdir Pepper_Septoria_Aug
!mkdir Tomato_Fusarium_Aug

# Create augmented data set
def make_aug(df,aug_dir):
  aug_list = [aug_flip,aug_rotate,aug_blur,aug_noise]

  aug_df = image_aug(df[labels_df.columns],
                   aug_dir, 'flip', aug_list[0],df)
  label = ['rotate','blur','noise']
  for a,n in zip(aug_list[1:],label):
    aug_df = aug_df.append(image_aug(df[labels_df.columns],
                   aug_dir, n, a,df))
  # Drop rows with null
  aug_df = aug_df.dropna()
  return aug_df
```

```
# Make augmented datasets
tlc_aug =
make_aug(tlc_df,'/content/Tomato_Leaf_Curl_Aug').reset_index()
tbs_aug =
make_aug(tbs_df,'/content/Tomato_Bacterial_Spot_Aug').reset_index()
pc_aug =
make_aug(pc_df,'/content/Pepper_Cercospora_Aug').reset_index()
ps_aug = make_aug(ps_df,'/content/Pepper_Septoria_Aug').reset_index()
tf_aug = make_aug(tf_df,'/content/Tomato_Fusarium_Aug').reset_index()

tlc_aug.head()
```

```
   index             filename           disease    crop width height
depth  \
0      0  flip_IMG_3011.jpeg  Tomato Leaf Curl  Tomato  4032   3024
3
1      1  flip_IMG_3011.jpeg  Tomato Leaf Curl  Tomato  4032   3024
3
2      2  flip_IMG_3011.jpeg  Tomato Leaf Curl  Tomato  4032   3024
3
3      3  flip_IMG_3011.jpeg  Tomato Leaf Curl  Tomato  4032   3024
3
4      4  flip_IMG_3011.jpeg  Tomato Leaf Curl  Tomato  4032   3024
3

          xmin         ymin         xmax         ymax  \
0  1533.429932  1586.780884  1840.773926  2167.487305
1   618.202393  1597.042847  1096.607178  2033.170288
2  2577.438477   902.496277  2912.614014  1354.034424
3  1315.911865  1372.759277  1736.795410  1517.977295
4  2185.676270  1207.585449  2512.000732  1416.671509

                                            ann_path  \
0  /content/crop-disease-ghana/input/Tomato/Tomat...
1  /content/crop-disease-ghana/input/Tomato/Tomat...
2  /content/crop-disease-ghana/input/Tomato/Tomat...
3  /content/crop-disease-ghana/input/Tomato/Tomat...
4  /content/crop-disease-ghana/input/Tomato/Tomat...

                                            img_path         shape
label
0  /content/crop-disease-ghana/input/Tomato/Tomat...  (4032, 3024)
16
1  /content/crop-disease-ghana/input/Tomato/Tomat...  (4032, 3024)
16
2  /content/crop-disease-ghana/input/Tomato/Tomat...  (4032, 3024)
16
3  /content/crop-disease-ghana/input/Tomato/Tomat...  (4032, 3024)
16
```

```
4  /content/crop-disease-ghana/input/Tomato/Tomat...  (4032, 3024)
16
```

```
# Display augmented image
p = '/content/Tomato_Leaf_Curl_Aug/' + tlc_aug['filename'][0]
test_img=cv2.imread(p)
def display_image(test_img):
    h, w = test_img.shape[0:2]
    neww = 300
    newh = int(neww*(h/w))
    test_img = cv2.resize(test_img, (neww, newh))
    cv2_imshow(test_img)
    cv2.waitKey(0)

display_image(test_img)
```

```
# Replace image paths
tlc_aug['img_path'] = '/content/Tomato_Leaf_Curl_Aug/' +
tlc_aug['filename']
tbs_aug['img_path'] = '/content/Tomato_Bacterial_Spot_Aug/' +
tbs_aug['filename']
pc_aug['img_path'] = '/content/Pepper_Cercospora_Aug/' +
pc_aug['filename']
ps_aug['img_path'] = '/content/Pepper_Septoria_Aug/' +
ps_aug['filename']
tf_aug['img_path'] = '/content/Tomato_Fusarium_Aug/' +
tf_aug['filename']

# Drop index column
tlc_aug = tlc_aug.drop(labels = 'index',axis = 1)
tbs_aug = tbs_aug.drop(labels = 'index',axis = 1)
```

```python
pc_aug = pc_aug.drop(labels = 'index',axis = 1)
ps_aug = ps_aug.drop(labels = 'index',axis = 1)
tf_aug = tf_aug.drop(labels = 'index',axis = 1)

# Append to labels_df
labels_df = labels_df.append(tlc_aug)
labels_df = labels_df.append(tbs_aug)
labels_df = labels_df.append(pc_aug)
labels_df = labels_df.append(ps_aug)
labels_df = labels_df.append(tf_aug)
labels_df = labels_df.reset_index()

labels_df.shape
```

```
(70259, 15)
```

```python
# Drop duplicates
no_duplicates = labels_df.drop_duplicates(subset =
'filename',ignore_index=True)
no_duplicates.shape
```

```
(9191, 15)
```

```python
no_duplicates['disease'].value_counts()
```

```
Pepper Cercospora            1096
Corn Cercospora Leaf Spot    1021
Pepper Septoria               835
Pepper Leaf Curl              760
Pepper Bacterial Spot         706
Tomato Leaf Blight            632
Tomato Fusarium               570
Corn Streak                   467
Tomato Leaf Curl              447
Tomato Bacterial Spot         412
Tomato Septoria               409
Pepper Healthy                366
Tomato Healthy                331
Pepper Leaf Blight            312
Pepper Fusarium               306
Corn Healthy                  280
Corn Common Rust              241
Name: disease, dtype: int64
```

```python
# Create final balanced dataset
balanced = pd.DataFrame(columns = labels_df.columns)
for i in no_duplicates['disease'].unique():
  df = no_duplicates[no_duplicates['disease'] == i]
  if len(df)>200:
    samp = df.sample(n = 200,random_state = 24)
    balanced = balanced.append(samp)
```

```python
  else:
    balanced = balanced.append(df)

# Using less data because of computational constraints
balanced['disease'].value_counts()
```

```
Corn Cercospora Leaf Spot    200
Pepper Fusarium              200
Tomato Leaf Curl             200
Tomato Fusarium              200
Tomato Septoria              200
Tomato Bacterial Spot        200
Tomato Leaf Blight           200
Pepper Septoria              200
Pepper Healthy               200
Corn Common Rust             200
Pepper Bacterial Spot        200
Pepper Leaf Blight           200
Pepper Cercospora            200
Pepper Leaf Curl             200
Corn Streak                  200
Corn Healthy                 200
Tomato Healthy               200
Name: disease, dtype: int64
```

```python
# Create final balanced df
balanced_df = pd.DataFrame(columns = balanced.columns)
for i in np.unique(balanced['filename']):
  df = labels_df[labels_df['filename'] == i]
  balanced_df = balanced_df.append(df,ignore_index = True)
#balanced_df = balanced_df.reset_index()
#balanced_df = balanced_df.drop(labels = ['index','level_0'],axis = 1)
balanced_df.head()
```

```
   index                   filename            disease    crop width
height  \
0  21667  2010-01-01%2000.06.21.jpg     Pepper Healthy  Pepper  1920
2560
1  21668  2010-01-01%2000.06.21.jpg     Pepper Healthy  Pepper  1920
2560
2  19004  2010-01-01%2000.11.06.jpg  Pepper Cercospora  Pepper  1920
2560
3  19005  2010-01-01%2000.11.06.jpg  Pepper Cercospora  Pepper  1920
2560
4  19006  2010-01-01%2000.11.06.jpg  Pepper Cercospora  Pepper  1920
2560

  depth        xmin         ymin         xmax         ymax  \
0     3  938.970994  1550.683230  1672.769337  2274.989648
```

```
1     3   281.933702  1781.283644   611.042818  2365.175983
2     3  1199.818892  1273.706070  1272.400568  1334.632588
3     3   952.734375  1139.371672  1015.887784  1173.418530
4     3  1037.791193   993.439830  1091.313920  1037.018104

                                            ann_path  \
0  /content/crop-disease-ghana/input/Pepper/Peppe...
1  /content/crop-disease-ghana/input/Pepper/Peppe...
2  /content/crop-disease-ghana/input/Pepper/Peppe...
3  /content/crop-disease-ghana/input/Pepper/Peppe...
4  /content/crop-disease-ghana/input/Pepper/Peppe...

                                            img_path         shape
label
0  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
8
1  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
8
2  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
6
3  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
6
4  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
6

# Dropping unecessary columns
balanced_df = balanced_df.drop(labels =['index'],axis = 1)
balanced_df.head()

                    filename            disease    crop width height
depth  \
0  2010-01-01%2000.06.21.jpg     Pepper Healthy  Pepper  1920   2560
3
1  2010-01-01%2000.06.21.jpg     Pepper Healthy  Pepper  1920   2560
3
2  2010-01-01%2000.11.06.jpg  Pepper Cercospora  Pepper  1920   2560
3
3  2010-01-01%2000.11.06.jpg  Pepper Cercospora  Pepper  1920   2560
3
4  2010-01-01%2000.11.06.jpg  Pepper Cercospora  Pepper  1920   2560
3

          xmin         ymin         xmax         ymax  \
0   938.970994  1550.683230  1672.769337  2274.989648
1   281.933702  1781.283644   611.042818  2365.175983
2  1199.818892  1273.706070  1272.400568  1334.632588
3   952.734375  1139.371672  1015.887784  1173.418530
4  1037.791193   993.439830  1091.313920  1037.018104

                                            ann_path  \
```

```
0  /content/crop-disease-ghana/input/Pepper/Peppe...
1  /content/crop-disease-ghana/input/Pepper/Peppe...
2  /content/crop-disease-ghana/input/Pepper/Peppe...
3  /content/crop-disease-ghana/input/Pepper/Peppe...
4  /content/crop-disease-ghana/input/Pepper/Peppe...

                                            img_path         shape
label
0  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
8
1  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
8
2  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
6
3  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
6
4  /content/crop-disease-ghana/input/Pepper/Peppe...  (1920, 2560)
6
```

```
df_balanced = pd.DataFrame(columns = labels_df.columns)
for i in np.unique(balanced_df['disease']):
  df = balanced_df[balanced_df['disease'] == i]
  if len(df)>200:
    samp = df.sample(n = 200,random_state = 24)
    df_balanced = df_balanced.append(samp,ignore_index = True)
  else:
    df_balanced = df_balanced.append(df,ignore_index = True)

df_balanced = df_balanced.drop(labels =['index'],axis = 1)
df_balanced.head()
```

```
                 filename                    disease  crop width
height depth  \
0     20230526_114545.jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3
1  20230526_103506(0).jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3
2  20230525_111356(0).jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3
3     20230524_110802.jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3
4     20230526_102705.jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3

          xmin         ymin         xmax         ymax  \
0  2089.895178   897.998932  2172.578616  1003.483405
1  2717.148847   592.949243  2822.641509   672.775330
2  2941.199173  1275.034169  3076.168160  1407.181183
3  2857.733711   753.781004  2941.529745   826.064469
4  2976.603774  1257.216324  3062.138365  1348.446137
```

```
                                            ann_path  \
0  /content/crop-disease-ghana/input/Corn/Corn__C...
1  /content/crop-disease-ghana/input/Corn/Corn__C...
2  /content/crop-disease-ghana/input/Corn/Corn__C...
3  /content/crop-disease-ghana/input/Corn/Corn__C...
4  /content/crop-disease-ghana/input/Corn/Corn__C...

                                            img_path         shape
label
0  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
1  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
2  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
3  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
4  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
```

Multi-class object detection and bounding box regression

A single forward pass of our multi-class object detector will result in:

1. The predicted bounding box coordinates of the object in the image

2. The predicted class label of the object in the image

Model Design

Branch #1: A regression layer set, just like in the single-class object detection case

Branch #2: An additional layer set, this one with a softmax classifier used to predict class labels

```
# Initialize parameters

width=224
height=224
depth= 3
epoch_= 25
BS = 32
default_image_size = tuple((224, 224))
image_size = 0
INIT_LR = 1e-3
```

We use resize and img_to_array method of open cv to ensure that our image size is 224x 224 pixels for training with VGG16 followed by converting to array format

```
def convert_image_to_array(image_dir):

    try:
        image = cv2.imread(image_dir)
        if image is not None :
            image = cv2.resize(image, default_image_size)
            return img_to_array(image)
        else :
            return np.array([])
    except Exception as e:
        print(f"Error : {e}")
        return None
```

```
df_balanced.shape
```

```
(3400, 14)
```

```
# scale the bounding box coordinates relative to the spatial
dimensions of the input image
new_xmin = []
new_ymin = []
new_xmax = []
new_ymax = []

for i in range(df_balanced.shape[0]):
  w=df_balanced['width'][i]
  h=df_balanced['height'][i]
  xmin=df_balanced['xmin'][i]
  ymin=df_balanced['ymin'][i]
  xmax=df_balanced['xmax'][i]
  ymax=df_balanced['ymax'][i]
  new_xmin.append(float(xmin) / w)
  new_ymin.append(float(ymin) / h)
  new_xmax.append(float(xmax) / w)
  new_ymax.append(float(ymax) / h)

df_balanced['xmin'] = new_xmin
df_balanced['ymin'] = new_ymin
df_balanced['xmax'] = new_xmax
df_balanced['ymax'] = new_ymax
df_balanced.head()
```

```
                 filename                    disease  crop width
height depth  \
0     20230526_114545.jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3
1  20230526_103506(0).jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3
```

```
2  20230525_111356(0).jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3
3     20230524_110802.jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3
4     20230526_102705.jpg  Corn Cercospora Leaf Spot  Corn  4080
1836     3

       xmin      ymin      xmax      ymax  \
0  0.512229  0.489106  0.532495  0.546560
1  0.665968  0.322957  0.691824  0.366435
2  0.720882  0.694463  0.753963  0.766439
3  0.700425  0.410556  0.720963  0.449926
4  0.729560  0.684758  0.750524  0.734448

                                            ann_path  \
0  /content/crop-disease-ghana/input/Corn/Corn__C...
1  /content/crop-disease-ghana/input/Corn/Corn__C...
2  /content/crop-disease-ghana/input/Corn/Corn__C...
3  /content/crop-disease-ghana/input/Corn/Corn__C...
4  /content/crop-disease-ghana/input/Corn/Corn__C...

                                            img_path         shape
label
0  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
1  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
2  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
3  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
4  /content/crop-disease-ghana/input/Corn/Corn__C...  (4080, 1836)
1
```

Finally, we populate those four lists that we initialized : (1) image_list (array format), (2) ImagePaths_list (3) label_list(Disease catagories), and (4) bboxes_list(xmin ymin, xmax, ymax co-ordinates)

```
image_list, label_list, bboxes_list, imagePaths_list = [], [], [], []

indx=0
i=0
try:
  for img_dir in df_balanced['img_path']:
  #for i in range(2):
    #img_dir=
f"{root_dir}/{plant_folder}/{plant_disease_folder}/{image}"
    if img_dir.endswith(".jpg") == True or img_dir.endswith(".JPG") ==
True:
      image_list.append(convert_image_to_array(img_dir))
```

```
      imagePaths_list.append(df_balanced['img_path'][indx])
      label_list.append(df_balanced['disease'][indx])
      bboxes_list.append((df_balanced['xmin'][indx],
df_balanced['ymin'][indx], df_balanced['xmax'][indx],
df_balanced['ymax'][indx]))
      indx=indx+1
except Exception as e:
  print(f"Error : {e}")

data, labels, bboxes, imagePaths = [], [], [], []
data = np.array(image_list, dtype="float32") / 255.0
labels = np.array(label_list)
bboxes = np.array(bboxes_list, dtype="float32")
imagePaths = np.array(imagePaths_list)

print (data[0], labels[0], bboxes[0], imagePaths[0])
```

```
[[[0.23921569 0.73333335 0.50980395]
  [0.35686275 0.8156863  0.60784316]
  [0.33333334 0.79607844 0.59607846]
  ...
  [0.         0.36862746 0.23137255]
  [0.         0.3137255  0.14509805]
  [0.         0.2784314  0.10980392]]

 [[0.1254902  0.5921569  0.36078432]
  [0.12941177 0.5882353  0.35686275]
  [0.25490198 0.75686276 0.5411765 ]
  ...
  [0.         0.30980393 0.11764706]
  [0.         0.27450982 0.10588235]
  [0.         0.26666668 0.09411765]]

 [[0.08627451 0.59607846 0.34901962]
  [0.12156863 0.59607846 0.34901962]
  [0.13725491 0.6        0.36862746]
  ...
  [0.         0.27450982 0.10588235]
  [0.         0.26666668 0.10588235]
  [0.         0.24313726 0.08235294]]

 ...

 [[0.5764706  0.73333335 0.60784316]
  [0.49411765 0.69411767 0.54509807]
  [0.39607844 0.62352943 0.4627451 ]
  ...
  [0.1254902  0.22745098 0.25490198]
  [0.08235294 0.19607843 0.21568628]
  [0.07843138 0.19215687 0.21176471]]
```

```
[[0.49019608 0.69803923 0.5529412 ]
  [0.36078432 0.5921569  0.42745098]
  [0.37254903 0.6039216  0.43137255]
  ...
  [0.09019608 0.2        0.22745098]
  [0.09411765 0.20784314 0.22745098]
  [0.10196079 0.20392157 0.22745098]]

 [[0.3137255  0.56078434 0.39607844]
  [0.3529412  0.5882353  0.4117647 ]
  [0.33333334 0.5568628  0.38039216]
  ...
  [0.08235294 0.19607843 0.22352941]
  [0.07843138 0.1882353  0.21568628]
  [0.14901961 0.26666668 0.2901961 ]]] Corn Cercospora Leaf Spot
[0.5122292  0.48910618 0.5324948  0.5465596 ] /content/crop-disease-
ghana/input/Corn/Corn__Cercospora_Leaf_Spot/images/20230526_114545.jpg
```

One-hot encoded labels

```
label_binarizer = LabelBinarizer()
if labels is not None:
  binarylabels = label_binarizer.fit_transform(labels)
  pickle.dump(label_binarizer,open('label_transform.pkl', 'wb'))
  n_classes = len(label_binarizer.classes_)

print(labels.shape)

(2479,)

split = train_test_split(data, binarylabels, bboxes, test_size=0.20,
random_state=42)
# unpack the data split
(trainImages, testImages) = split[:2]
(trainLabels, testLabels) = split[2:4]
(trainBBoxes, testBBoxes) = split[4:6]
#(trainPaths, testPaths) = split[6:]

import os
import tensorflow as tf
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
```

Pre-Trained Model VGG16

VGG16: The CNN architecture to serve as the base network which we'll (1) modify for multi-class bounding box regression and (2) then fine-tune on our dataset

VGG16 network is loaded with weights pre-trained on the ImageNet dataset. We leave off the fully-connected layer head (include_top=False), since we will be constructing a new layer head responsible for multi-output prediction (i.e., class label and bounding box location).

```
# load the VGG16 network, ensuring the head FC layers are left off
vgg = VGG16(weights="imagenet", include_top=False,
input_tensor=Input(shape=(224, 224, 3)))
# freeze all VGG layers so they will *not* be updated during the
# training process
vgg.trainable = False
# flatten the max-pooling output of VGG
flatten = vgg.output
flatten = Flatten()(flatten)
```

Flatten the output of the network so we can construct our new layer

(1) The first branch, bboxHead, is responsible for predicting the bounding box (x, y)-coordinates of the object in the image.

(2) Our second branch, softmaxHead, is responsible for predicting the class label of the detected object

```
# construct a fully-connected layer header to output the predicted
# bounding box coordinates
bboxHead = Dense(128, activation="relu")(flatten)
bboxHead = Dense(64, activation="relu")(bboxHead)
bboxHead = Dense(32, activation="relu")(bboxHead)
bboxHead = Dense(4, activation="sigmoid",   name="bounding_box")
(bboxHead)
# construct a second fully-connected layer head, this one to predict
# the class label
softmaxHead = Dense(512, activation="relu")(flatten)
softmaxHead = Dropout(0.5)(softmaxHead)
softmaxHead = Dense(512, activation="relu")(softmaxHead)
softmaxHead = Dropout(0.5)(softmaxHead)
softmaxHead = Dense(len(label_binarizer.classes_),
activation="softmax", name="class_label")(softmaxHead)
# put together our model which accept an input image and then output
# bounding box coordinates and a class label
modell = Model(
      inputs=vgg.input,
      outputs=(bboxHead, softmaxHead))
```

We are using categorical cross-entropy for our class label branch and mean squared error for our bounding box regression head.

```
# define a dictionary to set the loss methods -- categorical
# cross-entropy for the class label head and mean absolute error
# for the bounding box head
losses = {
      "bounding_box": "mean_squared_error",
      "class_label": "categorical_crossentropy"
```

```
    #"bounding_box": "mean_squared_error",
}
# define a dictionary that specifies the weights per loss (both the
# class label and bounding box outputs will receive equal weight)
lossWeights = {
    "bounding_box": 1.0,
    "class_label": 1.0
    #"bounding_box": 1.0
}
# initialize the optimizer, compile the model, and show the model
# summary
opt = Adam(learning_rate=INIT_LR)
modell.compile(loss=losses, optimizer=opt, metrics=["accuracy"],
loss_weights=lossWeights)
print(modell.summary())
```

```
Model: "model"
______________________________________________________________________
____________________________
 Layer (type)                Output Shape                 Param #
Connected to
======================================================================
============================
 input_1 (InputLayer)        [(None, 224, 224, 3)]        0         []


 block1_conv1 (Conv2D)       (None, 224, 224, 64)         1792
['input_1[0][0]']


 block1_conv2 (Conv2D)       (None, 224, 224, 64)         36928
['block1_conv1[0][0]']


 block1_pool (MaxPooling2D)  (None, 112, 112, 64)         0
['block1_conv2[0][0]']


 block2_conv1 (Conv2D)       (None, 112, 112, 128)        73856
['block1_pool[0][0]']


 block2_conv2 (Conv2D)       (None, 112, 112, 128)        147584
['block2_conv1[0][0]']


 block2_pool (MaxPooling2D)  (None, 56, 56, 128)          0
['block2_conv2[0][0]']
```

```
 block3_conv1 (Conv2D)       (None, 56, 56, 256)          295168
['block2_pool[0][0]']

 block3_conv2 (Conv2D)       (None, 56, 56, 256)          590080
['block3_conv1[0][0]']

 block3_conv3 (Conv2D)       (None, 56, 56, 256)          590080
['block3_conv2[0][0]']

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)          0
['block3_conv3[0][0]']

 block4_conv1 (Conv2D)       (None, 28, 28, 512)          1180160
['block3_pool[0][0]']

 block4_conv2 (Conv2D)       (None, 28, 28, 512)          2359808
['block4_conv1[0][0]']

 block4_conv3 (Conv2D)       (None, 28, 28, 512)          2359808
['block4_conv2[0][0]']

 block4_pool (MaxPooling2D)  (None, 14, 14, 512)          0
['block4_conv3[0][0]']

 block5_conv1 (Conv2D)       (None, 14, 14, 512)          2359808
['block4_pool[0][0]']

 block5_conv2 (Conv2D)       (None, 14, 14, 512)          2359808
['block5_conv1[0][0]']

 block5_conv3 (Conv2D)       (None, 14, 14, 512)          2359808
['block5_conv2[0][0]']

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)            0
['block5_conv3[0][0]']

 flatten (Flatten)           (None, 25088)                0
```

```
['block5_pool[0][0]']

 dense_3 (Dense)              (None, 512)                  1284556
['flatten[0][0]']
                                                           8

 dense (Dense)                (None, 128)                  3211392
['flatten[0][0]']

 dropout (Dropout)            (None, 512)                  0
['dense_3[0][0]']

 dense_1 (Dense)              (None, 64)                   8256
['dense[0][0]']

 dense_4 (Dense)              (None, 512)                  262656
['dropout[0][0]']

 dense_2 (Dense)              (None, 32)                   2080
['dense_1[0][0]']

 dropout_1 (Dropout)          (None, 512)                  0
['dense_4[0][0]']

 bounding_box (Dense)         (None, 4)                    132
['dense_2[0][0]']

 class_label (Dense)          (None, 13)                   6669
['dropout_1[0][0]']

======================================================================
============================
Total params: 31051441 (118.45 MB)
Trainable params: 16336753 (62.32 MB)
Non-trainable params: 14714688 (56.13 MB)
______________________________________________________________________
____________________________
None
```

```
# construct a dictionary for our target training outputs
trainTargets = {
      "bounding_box": trainBBoxes,
      "class_label": trainLabels
      #"bounding_box": trainBBoxes
}
# construct a second dictionary, this one for our target testing
# outputs
testTargets = {
      "bounding_box": testBBoxes,
      "class_label": testLabels
      #"bounding_box": testBBoxes
}
```

Training multi-class object detector

Our architecture has two branches in the layer head — the first branch to predict the bounding box coordinates and the second to predict the class label of the detected object

```
# train the network for bounding box regression and class label
# prediction
print("[INFO] training model...")
H = modell.fit(
      trainImages, trainTargets,
      validation_data=(testImages, testTargets),
      batch_size=BS,
      epochs=50,
      #class_weight=class_weights,
      verbose=1)
```

```
[INFO] training model...
Epoch 1/50
62/62 [==============================] - 19s 139ms/step - loss: 3.0276
- bounding_box_loss: 0.0585 - class_label_loss: 2.9690 -
bounding_box_accuracy: 0.4347 - class_label_accuracy: 0.1906 -
val_loss: 1.9419 - val_bounding_box_loss: 0.0535 -
val_class_label_loss: 1.8884 - val_bounding_box_accuracy: 0.5262 -
val_class_label_accuracy: 0.3407
Epoch 2/50
62/62 [==============================] - 4s 67ms/step - loss: 2.1131 -
bounding_box_loss: 0.0487 - class_label_loss: 2.0644 -
bounding_box_accuracy: 0.4851 - class_label_accuracy: 0.2481 -
val_loss: 1.9010 - val_bounding_box_loss: 0.0539 -
val_class_label_loss: 1.8471 - val_bounding_box_accuracy: 0.5302 -
val_class_label_accuracy: 0.3770
Epoch 3/50
62/62 [==============================] - 4s 65ms/step - loss: 1.9877 -
bounding_box_loss: 0.0459 - class_label_loss: 1.9418 -
```

```
bounding_box_accuracy: 0.4634 - class_label_accuracy: 0.2960 -
val_loss: 1.6535 - val_bounding_box_loss: 0.0586 -
val_class_label_loss: 1.5949 - val_bounding_box_accuracy: 0.4617 -
val_class_label_accuracy: 0.4516
Epoch 4/50
62/62 [==============================] - 4s 69ms/step - loss: 1.8881 -
bounding_box_loss: 0.0455 - class_label_loss: 1.8425 -
bounding_box_accuracy: 0.4912 - class_label_accuracy: 0.3167 -
val_loss: 1.5108 - val_bounding_box_loss: 0.0531 -
val_class_label_loss: 1.4577 - val_bounding_box_accuracy: 0.5323 -
val_class_label_accuracy: 0.5161
Epoch 5/50
62/62 [==============================] - 4s 68ms/step - loss: 1.7252 -
bounding_box_loss: 0.0421 - class_label_loss: 1.6831 -
bounding_box_accuracy: 0.5214 - class_label_accuracy: 0.3732 -
val_loss: 1.5221 - val_bounding_box_loss: 0.0561 -
val_class_label_loss: 1.4659 - val_bounding_box_accuracy: 0.3569 -
val_class_label_accuracy: 0.5181
Epoch 6/50
62/62 [==============================] - 5s 76ms/step - loss: 1.7345 -
bounding_box_loss: 0.0397 - class_label_loss: 1.6948 -
bounding_box_accuracy: 0.5265 - class_label_accuracy: 0.3792 -
val_loss: 1.3897 - val_bounding_box_loss: 0.0550 -
val_class_label_loss: 1.3348 - val_bounding_box_accuracy: 0.4919 -
val_class_label_accuracy: 0.5181
Epoch 7/50
62/62 [==============================] - 5s 81ms/step - loss: 1.6394 -
bounding_box_loss: 0.0369 - class_label_loss: 1.6025 -
bounding_box_accuracy: 0.6031 - class_label_accuracy: 0.4014 -
val_loss: 1.3815 - val_bounding_box_loss: 0.0548 -
val_class_label_loss: 1.3267 - val_bounding_box_accuracy: 0.4133 -
val_class_label_accuracy: 0.5665
Epoch 8/50
62/62 [==============================] - 4s 70ms/step - loss: 1.5505 -
bounding_box_loss: 0.0354 - class_label_loss: 1.5151 -
bounding_box_accuracy: 0.6051 - class_label_accuracy: 0.4216 -
val_loss: 1.3537 - val_bounding_box_loss: 0.0609 -
val_class_label_loss: 1.2928 - val_bounding_box_accuracy: 0.4093 -
val_class_label_accuracy: 0.5403
Epoch 9/50
62/62 [==============================] - 4s 66ms/step - loss: 1.5244 -
bounding_box_loss: 0.0350 - class_label_loss: 1.4895 -
bounding_box_accuracy: 0.6319 - class_label_accuracy: 0.4231 -
val_loss: 1.3108 - val_bounding_box_loss: 0.0566 -
val_class_label_loss: 1.2542 - val_bounding_box_accuracy: 0.5282 -
val_class_label_accuracy: 0.5685
Epoch 10/50
62/62 [==============================] - 4s 67ms/step - loss: 1.5147 -
bounding_box_loss: 0.0329 - class_label_loss: 1.4817 -
```

```
bounding_box_accuracy: 0.6157 - class_label_accuracy: 0.4276 -
val_loss: 1.4049 - val_bounding_box_loss: 0.0595 -
val_class_label_loss: 1.3454 - val_bounding_box_accuracy: 0.4315 -
val_class_label_accuracy: 0.5323
Epoch 11/50
62/62 [==============================] - 5s 79ms/step - loss: 1.4535 -
bounding_box_loss: 0.0318 - class_label_loss: 1.4217 -
bounding_box_accuracy: 0.6490 - class_label_accuracy: 0.4629 -
val_loss: 1.2777 - val_bounding_box_loss: 0.0586 -
val_class_label_loss: 1.2190 - val_bounding_box_accuracy: 0.4980 -
val_class_label_accuracy: 0.5867
Epoch 12/50
62/62 [==============================] - 5s 75ms/step - loss: 1.3957 -
bounding_box_loss: 0.0303 - class_label_loss: 1.3654 -
bounding_box_accuracy: 0.6475 - class_label_accuracy: 0.4584 -
val_loss: 1.2728 - val_bounding_box_loss: 0.0625 -
val_class_label_loss: 1.2103 - val_bounding_box_accuracy: 0.5181 -
val_class_label_accuracy: 0.6149
Epoch 13/50
62/62 [==============================] - 4s 66ms/step - loss: 1.4315 -
bounding_box_loss: 0.0304 - class_label_loss: 1.4011 -
bounding_box_accuracy: 0.6727 - class_label_accuracy: 0.4493 -
val_loss: 1.2688 - val_bounding_box_loss: 0.0632 -
val_class_label_loss: 1.2056 - val_bounding_box_accuracy: 0.5101 -
val_class_label_accuracy: 0.6089
Epoch 14/50
62/62 [==============================] - 5s 80ms/step - loss: 1.3934 -
bounding_box_loss: 0.0307 - class_label_loss: 1.3627 -
bounding_box_accuracy: 0.6803 - class_label_accuracy: 0.4695 -
val_loss: 1.2336 - val_bounding_box_loss: 0.0582 -
val_class_label_loss: 1.1753 - val_bounding_box_accuracy: 0.5242 -
val_class_label_accuracy: 0.6069
Epoch 15/50
62/62 [==============================] - 4s 66ms/step - loss: 1.3835 -
bounding_box_loss: 0.0288 - class_label_loss: 1.3548 -
bounding_box_accuracy: 0.6899 - class_label_accuracy: 0.4755 -
val_loss: 1.3159 - val_bounding_box_loss: 0.0601 -
val_class_label_loss: 1.2559 - val_bounding_box_accuracy: 0.5222 -
val_class_label_accuracy: 0.6230
Epoch 16/50
62/62 [==============================] - 5s 76ms/step - loss: 1.4599 -
bounding_box_loss: 0.0301 - class_label_loss: 1.4298 -
bounding_box_accuracy: 0.6662 - class_label_accuracy: 0.4690 -
val_loss: 1.3568 - val_bounding_box_loss: 0.0620 -
val_class_label_loss: 1.2948 - val_bounding_box_accuracy: 0.4294 -
val_class_label_accuracy: 0.5504
Epoch 17/50
62/62 [==============================] - 4s 70ms/step - loss: 1.3438 -
bounding_box_loss: 0.0278 - class_label_loss: 1.3161 -
```

```
bounding_box_accuracy: 0.6798 - class_label_accuracy: 0.4771 -
val_loss: 1.2291 - val_bounding_box_loss: 0.0632 -
val_class_label_loss: 1.1659 - val_bounding_box_accuracy: 0.5081 -
val_class_label_accuracy: 0.6411
Epoch 18/50
62/62 [==============================] - 4s 67ms/step - loss: 1.3262 -
bounding_box_loss: 0.0265 - class_label_loss: 1.2997 -
bounding_box_accuracy: 0.6949 - class_label_accuracy: 0.4927 -
val_loss: 1.2151 - val_bounding_box_loss: 0.0640 -
val_class_label_loss: 1.1511 - val_bounding_box_accuracy: 0.5202 -
val_class_label_accuracy: 0.6452
Epoch 19/50
62/62 [==============================] - 5s 76ms/step - loss: 1.3230 -
bounding_box_loss: 0.0269 - class_label_loss: 1.2961 -
bounding_box_accuracy: 0.7196 - class_label_accuracy: 0.4987 -
val_loss: 1.1984 - val_bounding_box_loss: 0.0620 -
val_class_label_loss: 1.1364 - val_bounding_box_accuracy: 0.4980 -
val_class_label_accuracy: 0.5847
Epoch 20/50
62/62 [==============================] - 4s 70ms/step - loss: 1.3395 -
bounding_box_loss: 0.0263 - class_label_loss: 1.3132 -
bounding_box_accuracy: 0.7237 - class_label_accuracy: 0.4791 -
val_loss: 1.2191 - val_bounding_box_loss: 0.0620 -
val_class_label_loss: 1.1572 - val_bounding_box_accuracy: 0.5222 -
val_class_label_accuracy: 0.6169
Epoch 21/50
62/62 [==============================] - 5s 78ms/step - loss: 1.4042 -
bounding_box_loss: 0.0262 - class_label_loss: 1.3781 -
bounding_box_accuracy: 0.7126 - class_label_accuracy: 0.4705 -
val_loss: 1.2598 - val_bounding_box_loss: 0.0623 -
val_class_label_loss: 1.1975 - val_bounding_box_accuracy: 0.4899 -
val_class_label_accuracy: 0.6290
Epoch 22/50
62/62 [==============================] - 5s 75ms/step - loss: 1.2860 -
bounding_box_loss: 0.0257 - class_label_loss: 1.2604 -
bounding_box_accuracy: 0.7090 - class_label_accuracy: 0.4801 -
val_loss: 1.1940 - val_bounding_box_loss: 0.0641 -
val_class_label_loss: 1.1299 - val_bounding_box_accuracy: 0.5181 -
val_class_label_accuracy: 0.6431
Epoch 23/50
62/62 [==============================] - 5s 78ms/step - loss: 1.3103 -
bounding_box_loss: 0.0258 - class_label_loss: 1.2845 -
bounding_box_accuracy: 0.7171 - class_label_accuracy: 0.4786 -
val_loss: 1.1831 - val_bounding_box_loss: 0.0635 -
val_class_label_loss: 1.1195 - val_bounding_box_accuracy: 0.4657 -
val_class_label_accuracy: 0.6593
Epoch 24/50
62/62 [==============================] - 5s 75ms/step - loss: 1.3063 -
bounding_box_loss: 0.0259 - class_label_loss: 1.2804 -
```

```
bounding_box_accuracy: 0.7161 - class_label_accuracy: 0.4922 -
val_loss: 1.2153 - val_bounding_box_loss: 0.0638 -
val_class_label_loss: 1.1515 - val_bounding_box_accuracy: 0.4940 -
val_class_label_accuracy: 0.6048
Epoch 25/50
62/62 [==============================] - 5s 80ms/step - loss: 1.3154 -
bounding_box_loss: 0.0270 - class_label_loss: 1.2884 -
bounding_box_accuracy: 0.6904 - class_label_accuracy: 0.4806 -
val_loss: 1.2024 - val_bounding_box_loss: 0.0658 -
val_class_label_loss: 1.1366 - val_bounding_box_accuracy: 0.4456 -
val_class_label_accuracy: 0.6129
Epoch 26/50
62/62 [==============================] - 4s 71ms/step - loss: 1.2792 -
bounding_box_loss: 0.0261 - class_label_loss: 1.2531 -
bounding_box_accuracy: 0.7100 - class_label_accuracy: 0.4952 -
val_loss: 1.2330 - val_bounding_box_loss: 0.0657 -
val_class_label_loss: 1.1673 - val_bounding_box_accuracy: 0.5343 -
val_class_label_accuracy: 0.5645
Epoch 27/50
62/62 [==============================] - 4s 67ms/step - loss: 1.2521 -
bounding_box_loss: 0.0250 - class_label_loss: 1.2272 -
bounding_box_accuracy: 0.7060 - class_label_accuracy: 0.5184 -
val_loss: 1.2538 - val_bounding_box_loss: 0.0672 -
val_class_label_loss: 1.1866 - val_bounding_box_accuracy: 0.5262 -
val_class_label_accuracy: 0.6250
Epoch 28/50
62/62 [==============================] - 4s 67ms/step - loss: 1.2841 -
bounding_box_loss: 0.0259 - class_label_loss: 1.2582 -
bounding_box_accuracy: 0.6944 - class_label_accuracy: 0.5119 -
val_loss: 1.2287 - val_bounding_box_loss: 0.0645 -
val_class_label_loss: 1.1641 - val_bounding_box_accuracy: 0.4637 -
val_class_label_accuracy: 0.5766
Epoch 29/50
62/62 [==============================] - 4s 67ms/step - loss: 1.2416 -
bounding_box_loss: 0.0246 - class_label_loss: 1.2171 -
bounding_box_accuracy: 0.7176 - class_label_accuracy: 0.5275 -
val_loss: 1.2026 - val_bounding_box_loss: 0.0626 -
val_class_label_loss: 1.1401 - val_bounding_box_accuracy: 0.4435 -
val_class_label_accuracy: 0.6391
Epoch 30/50
62/62 [==============================] - 4s 70ms/step - loss: 1.2011 -
bounding_box_loss: 0.0243 - class_label_loss: 1.1769 -
bounding_box_accuracy: 0.7368 - class_label_accuracy: 0.5265 -
val_loss: 1.2844 - val_bounding_box_loss: 0.0644 -
val_class_label_loss: 1.2200 - val_bounding_box_accuracy: 0.5000 -
val_class_label_accuracy: 0.5907
Epoch 31/50
62/62 [==============================] - 5s 76ms/step - loss: 1.1748 -
bounding_box_loss: 0.0251 - class_label_loss: 1.1497 -
```

```
bounding_box_accuracy: 0.7171 - class_label_accuracy: 0.5562 -
val_loss: 1.1911 - val_bounding_box_loss: 0.0633 -
val_class_label_loss: 1.1278 - val_bounding_box_accuracy: 0.4254 -
val_class_label_accuracy: 0.6452
Epoch 32/50
62/62 [==============================] - 5s 75ms/step - loss: 1.1858 -
bounding_box_loss: 0.0250 - class_label_loss: 1.1608 -
bounding_box_accuracy: 0.7141 - class_label_accuracy: 0.5356 -
val_loss: 1.1700 - val_bounding_box_loss: 0.0646 -
val_class_label_loss: 1.1054 - val_bounding_box_accuracy: 0.4516 -
val_class_label_accuracy: 0.6532
Epoch 33/50
62/62 [==============================] - 5s 81ms/step - loss: 1.1598 -
bounding_box_loss: 0.0266 - class_label_loss: 1.1332 -
bounding_box_accuracy: 0.6566 - class_label_accuracy: 0.5451 -
val_loss: 1.2553 - val_bounding_box_loss: 0.0630 -
val_class_label_loss: 1.1923 - val_bounding_box_accuracy: 0.4315 -
val_class_label_accuracy: 0.6028
Epoch 34/50
62/62 [==============================] - 4s 67ms/step - loss: 1.2429 -
bounding_box_loss: 0.0235 - class_label_loss: 1.2194 -
bounding_box_accuracy: 0.7171 - class_label_accuracy: 0.5224 -
val_loss: 1.2956 - val_bounding_box_loss: 0.0639 -
val_class_label_loss: 1.2317 - val_bounding_box_accuracy: 0.5101 -
val_class_label_accuracy: 0.5867
Epoch 35/50
62/62 [==============================] - 5s 75ms/step - loss: 1.2917 -
bounding_box_loss: 0.0237 - class_label_loss: 1.2680 -
bounding_box_accuracy: 0.7252 - class_label_accuracy: 0.5209 -
val_loss: 1.2562 - val_bounding_box_loss: 0.0639 -
val_class_label_loss: 1.1923 - val_bounding_box_accuracy: 0.5302 -
val_class_label_accuracy: 0.5988
Epoch 36/50
62/62 [==============================] - 5s 79ms/step - loss: 1.2452 -
bounding_box_loss: 0.0239 - class_label_loss: 1.2213 -
bounding_box_accuracy: 0.7211 - class_label_accuracy: 0.5280 -
val_loss: 1.2805 - val_bounding_box_loss: 0.0651 -
val_class_label_loss: 1.2153 - val_bounding_box_accuracy: 0.4617 -
val_class_label_accuracy: 0.6109
Epoch 37/50
62/62 [==============================] - 5s 76ms/step - loss: 1.1452 -
bounding_box_loss: 0.0237 - class_label_loss: 1.1215 -
bounding_box_accuracy: 0.7463 - class_label_accuracy: 0.5638 -
val_loss: 1.2707 - val_bounding_box_loss: 0.0673 -
val_class_label_loss: 1.2034 - val_bounding_box_accuracy: 0.5081 -
val_class_label_accuracy: 0.5645
Epoch 38/50
62/62 [==============================] - 4s 67ms/step - loss: 1.1639 -
bounding_box_loss: 0.0239 - class_label_loss: 1.1401 -
```

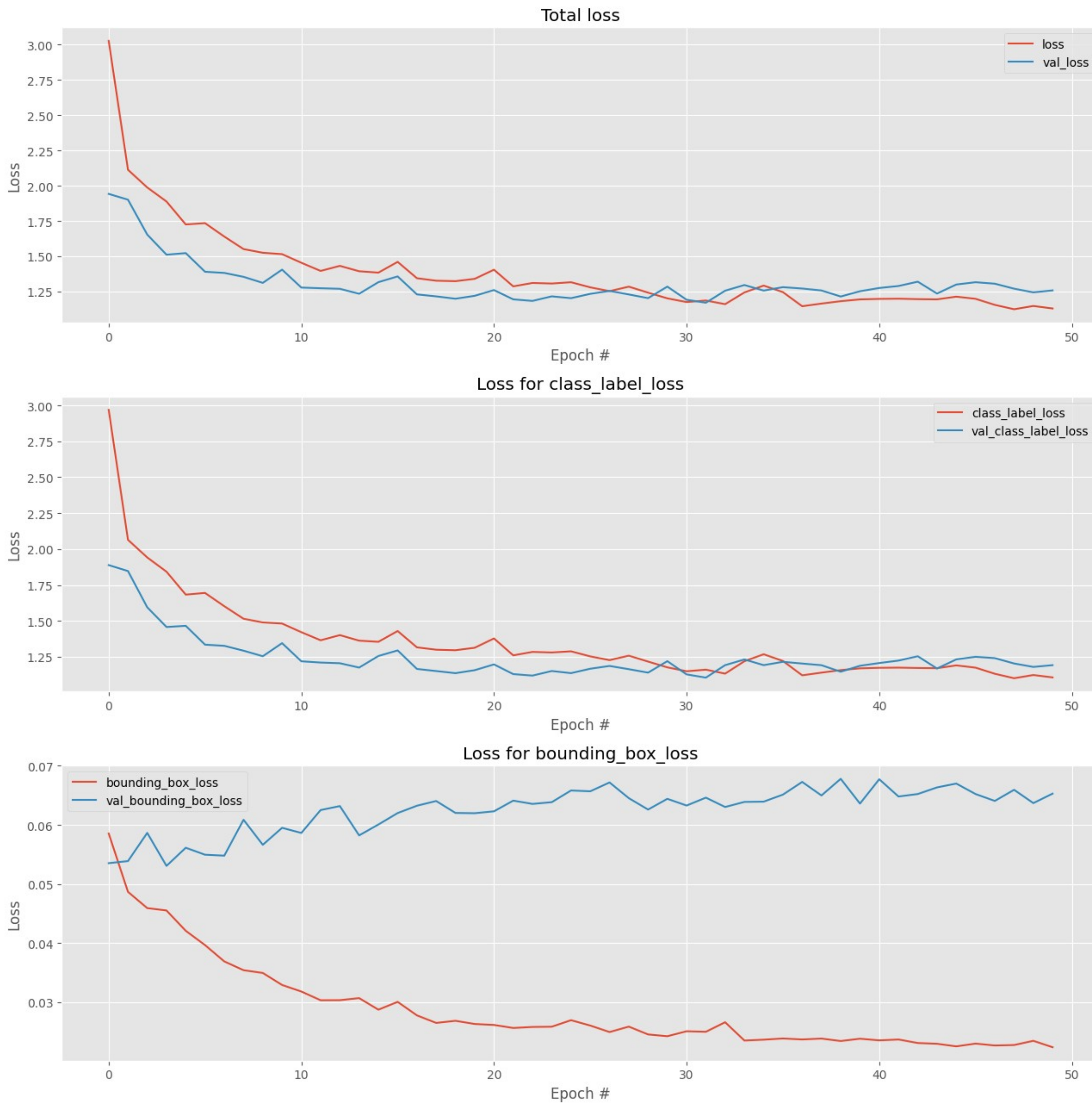
```
bounding_box_accuracy: 0.7514 - class_label_accuracy: 0.5618 -
val_loss: 1.2569 - val_bounding_box_loss: 0.0650 -
val_class_label_loss: 1.1919 - val_bounding_box_accuracy: 0.5302 -
val_class_label_accuracy: 0.6492
Epoch 39/50
62/62 [==============================] - 5s 80ms/step - loss: 1.1810 -
bounding_box_loss: 0.0235 - class_label_loss: 1.1575 -
bounding_box_accuracy: 0.7297 - class_label_accuracy: 0.5628 -
val_loss: 1.2141 - val_bounding_box_loss: 0.0678 -
val_class_label_loss: 1.1463 - val_bounding_box_accuracy: 0.5202 -
val_class_label_accuracy: 0.5968
Epoch 40/50
62/62 [==============================] - 5s 75ms/step - loss: 1.1938 -
bounding_box_loss: 0.0238 - class_label_loss: 1.1700 -
bounding_box_accuracy: 0.7327 - class_label_accuracy: 0.5456 -
val_loss: 1.2514 - val_bounding_box_loss: 0.0636 -
val_class_label_loss: 1.1878 - val_bounding_box_accuracy: 0.4899 -
val_class_label_accuracy: 0.6169
Epoch 41/50
62/62 [==============================] - 5s 75ms/step - loss: 1.1973 -
bounding_box_loss: 0.0236 - class_label_loss: 1.1737 -
bounding_box_accuracy: 0.7201 - class_label_accuracy: 0.5466 -
val_loss: 1.2746 - val_bounding_box_loss: 0.0677 -
val_class_label_loss: 1.2069 - val_bounding_box_accuracy: 0.5544 -
val_class_label_accuracy: 0.5887
Epoch 42/50
62/62 [==============================] - 5s 79ms/step - loss: 1.1986 -
bounding_box_loss: 0.0237 - class_label_loss: 1.1749 -
bounding_box_accuracy: 0.7302 - class_label_accuracy: 0.5517 -
val_loss: 1.2887 - val_bounding_box_loss: 0.0648 -
val_class_label_loss: 1.2239 - val_bounding_box_accuracy: 0.5141 -
val_class_label_accuracy: 0.5948
Epoch 43/50
62/62 [==============================] - 4s 67ms/step - loss: 1.1955 -
bounding_box_loss: 0.0231 - class_label_loss: 1.1724 -
bounding_box_accuracy: 0.7458 - class_label_accuracy: 0.5557 -
val_loss: 1.3193 - val_bounding_box_loss: 0.0652 -
val_class_label_loss: 1.2541 - val_bounding_box_accuracy: 0.4980 -
val_class_label_accuracy: 0.6089
Epoch 44/50
62/62 [==============================] - 5s 75ms/step - loss: 1.1940 -
bounding_box_loss: 0.0230 - class_label_loss: 1.1710 -
bounding_box_accuracy: 0.7458 - class_label_accuracy: 0.5547 -
val_loss: 1.2351 - val_bounding_box_loss: 0.0663 -
val_class_label_loss: 1.1687 - val_bounding_box_accuracy: 0.5343 -
val_class_label_accuracy: 0.6129
Epoch 45/50
62/62 [==============================] - 4s 70ms/step - loss: 1.2131 -
bounding_box_loss: 0.0225 - class_label_loss: 1.1906 -
```

```
bounding_box_accuracy: 0.7312 - class_label_accuracy: 0.5456 -
val_loss: 1.2993 - val_bounding_box_loss: 0.0670 -
val_class_label_loss: 1.2323 - val_bounding_box_accuracy: 0.4798 -
val_class_label_accuracy: 0.6290
Epoch 46/50
62/62 [==============================] - 5s 76ms/step - loss: 1.1978 -
bounding_box_loss: 0.0230 - class_label_loss: 1.1748 -
bounding_box_accuracy: 0.7393 - class_label_accuracy: 0.5547 -
val_loss: 1.3155 - val_bounding_box_loss: 0.0652 -
val_class_label_loss: 1.2503 - val_bounding_box_accuracy: 0.5020 -
val_class_label_accuracy: 0.5685
Epoch 47/50
62/62 [==============================] - 4s 68ms/step - loss: 1.1548 -
bounding_box_loss: 0.0227 - class_label_loss: 1.1321 -
bounding_box_accuracy: 0.7438 - class_label_accuracy: 0.5688 -
val_loss: 1.3051 - val_bounding_box_loss: 0.0640 -
val_class_label_loss: 1.2410 - val_bounding_box_accuracy: 0.5060 -
val_class_label_accuracy: 0.6048
Epoch 48/50
62/62 [==============================] - 5s 81ms/step - loss: 1.1239 -
bounding_box_loss: 0.0228 - class_label_loss: 1.1011 -
bounding_box_accuracy: 0.7292 - class_label_accuracy: 0.5875 -
val_loss: 1.2697 - val_bounding_box_loss: 0.0659 -
val_class_label_loss: 1.2038 - val_bounding_box_accuracy: 0.4919 -
val_class_label_accuracy: 0.6310
Epoch 49/50
62/62 [==============================] - 4s 67ms/step - loss: 1.1470 -
bounding_box_loss: 0.0235 - class_label_loss: 1.1235 -
bounding_box_accuracy: 0.7211 - class_label_accuracy: 0.5769 -
val_loss: 1.2435 - val_bounding_box_loss: 0.0637 -
val_class_label_loss: 1.1799 - val_bounding_box_accuracy: 0.4516 -
val_class_label_accuracy: 0.6190
Epoch 50/50
62/62 [==============================] - 4s 66ms/step - loss: 1.1293 -
bounding_box_loss: 0.0224 - class_label_loss: 1.1069 -
bounding_box_accuracy: 0.7156 - class_label_accuracy: 0.5749 -
val_loss: 1.2575 - val_bounding_box_loss: 0.0653 -
val_class_label_loss: 1.1922 - val_bounding_box_accuracy: 0.5262 -
val_class_label_accuracy: 0.5968
```

Visualizes our three loss components: the class label loss, bounding box loss, and total loss

```
# plot the total loss, label loss, and bounding box loss
epochs=50
lossNames = ["loss", "class_label_loss", "bounding_box_loss"]
N = np.arange(0, epochs)
plt.style.use("ggplot")
(fig, ax) = plt.subplots(3, 1, figsize=(13, 13))
```

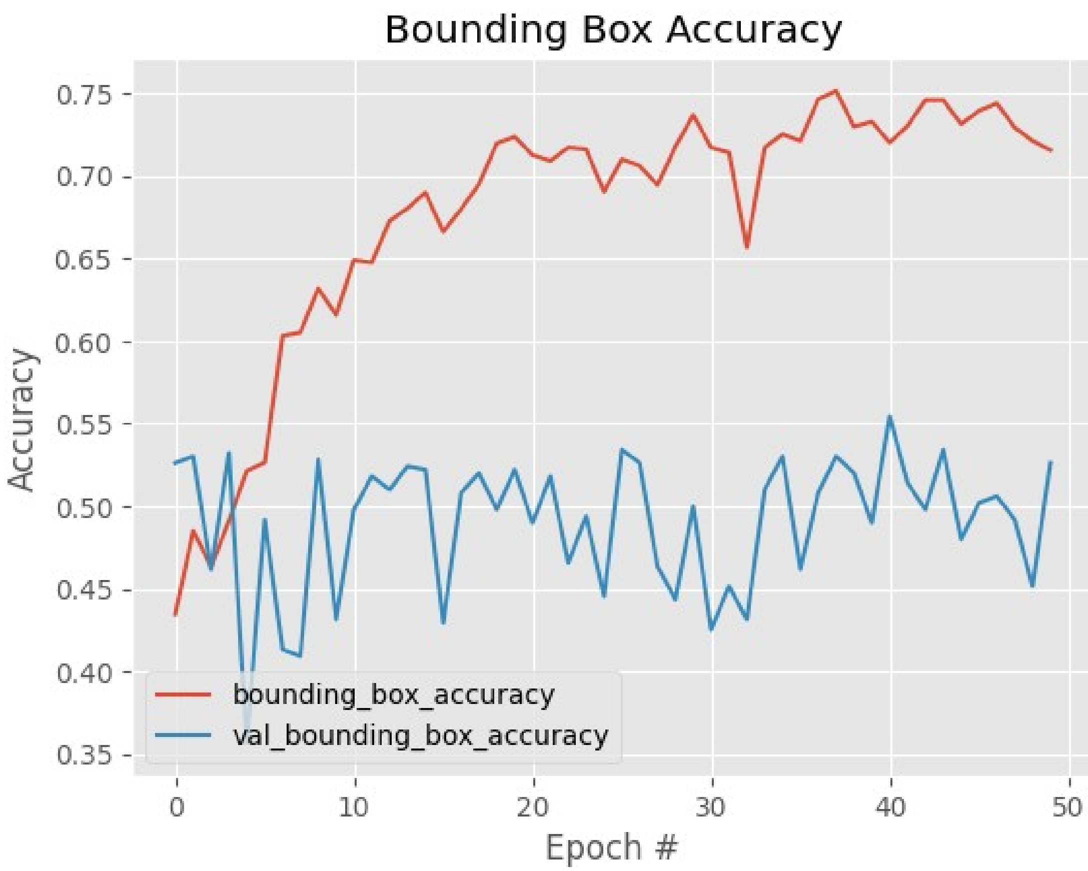
```
# loop over the loss names
for (i, l) in enumerate(lossNames):
    # plot the loss for both the training and validation data
    title = "Loss for {}".format(l) if l != "loss" else "Total loss"
    ax[i].set_title(title)
    ax[i].set_xlabel("Epoch #")
    ax[i].set_ylabel("Loss")
    ax[i].plot(N, H.history[l], label=l)
    ax[i].plot(N, H.history["val_" + l], label="val_" + l)
    ax[i].legend()
# save the losses figure and create a new figure for the accuracies
plt.tight_layout()
```



Visualizes two accuracy components: bounding box loss, class label loss

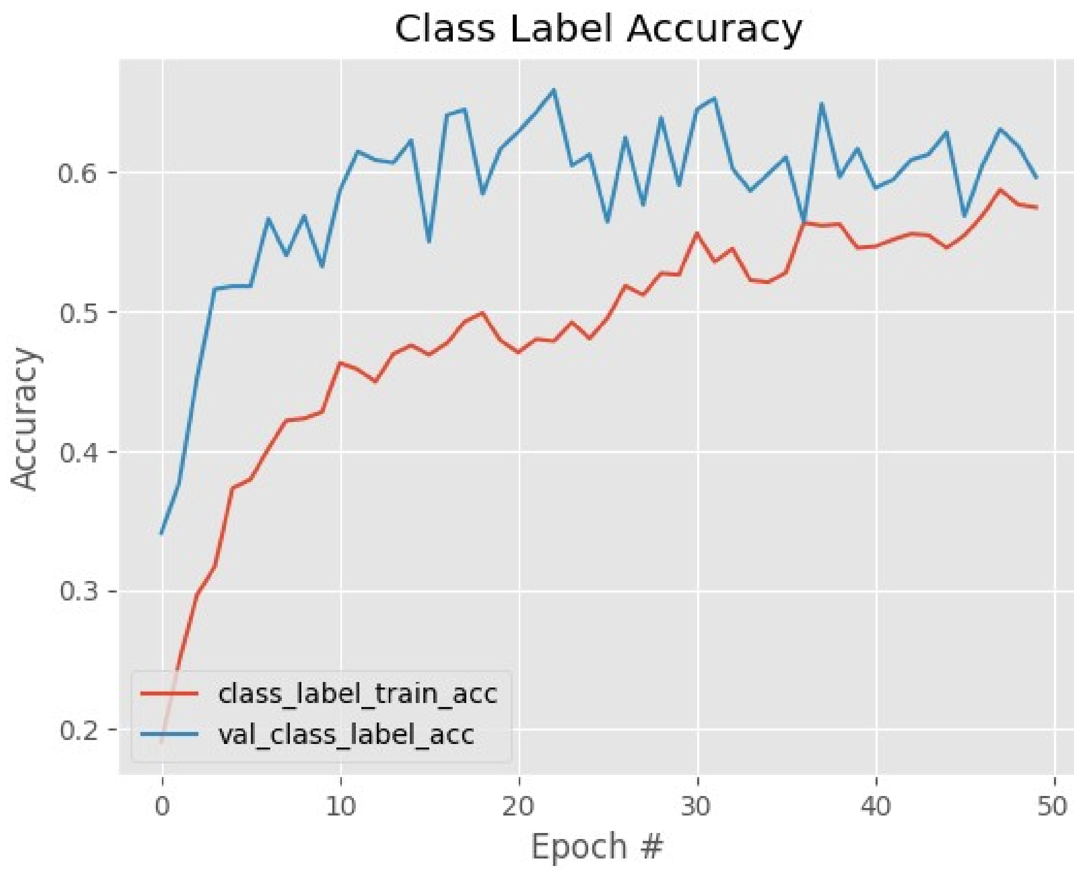
```
# create a new figure for the accuracies
plt.style.use("ggplot")
plt.figure()
plt.plot(N, H.history["bounding_box_accuracy"],
      label="bounding_box_accuracy")
plt.plot(N, H.history["val_bounding_box_accuracy"],
      label="val_bounding_box_accuracy")
plt.title("Bounding Box Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Accuracy")
plt.legend(loc="lower left")
```

```
<matplotlib.legend.Legend at 0x7fcf08075b70>
```




```
# create a new figure for the accuracies
plt.style.use("ggplot")
plt.figure()
plt.plot(N, H.history["class_label_accuracy"],
      label="class_label_train_acc")
plt.plot(N, H.history["val_class_label_accuracy"],
      label="val_class_label_acc")
```

```
plt.title("Class Label Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Accuracy")
plt.legend(loc="lower left")

<matplotlib.legend.Legend at 0x7fcf080d26b0>
```



Predict multi-class objects

```
img =
'/content/crop-disease-ghana/input/Corn/Corn__Cercospora_Leaf_Spot/
images/20230524_104642.jpg'
#img =
'/content/crop-disease-ghana/input/Tomato/Tomato__Septoria/images/
2N8A0600.JPG'

# loop over the images that we'll be testing using our bounding box
# regression model
#for imagePath in imagePaths:
	# load the input image (in Keras format) from disk and preprocess
	# it, scaling the pixel intensities to the range [0, 1]

image = load_img(img, target_size=(224, 224))
```

```
image = img_to_array(image) / 255.0
image = np.expand_dims(image, axis=0)
# predict the bounding box of the object along with the class
# label
(boxPreds, labelPreds) = modell.predict(image)
(startX, startY, endX, endY) = boxPreds[0]
# determine the class label with the largest predicted
# probability
i = np.argmax(labelPreds, axis=1)
label = label_binarizer.classes_[i][0]
```

```
1/1 [==============================] - 0s 487ms/step
```

```
print(startX, startY, endX, endY)
```

```
0.54288334 0.51715934 0.6258746 0.61109596
```

```
print(label)
```

```
Corn Common Rust
```

```
# load the input image (in OpenCV format), resize it such that it
# fits on our screen, and grab its dimensions
from imutils import paths

image = cv2.imread(img)
image = image.copy()
image = cv2.resize(image, (400, 600))
#image = imutils.resize(image, width=600)
(h, w) = image.shape[:2]
# scale the predicted bounding box coordinates based on the image
# dimensions
startX = int(startX * w)
startY = int(startY * h)
endX = int(endX * w)
endY = int(endY * h)
print(startX, startY, endX, endY)
# draw the predicted bounding box and class label on the image
y = startY - 10 if startY - 10 > 10 else startY + 10
cv2.putText(image, label, (startX, y), cv2.FONT_HERSHEY_SIMPLEX,0.65,
(0, 255, 0), 2)
cv2.rectangle(image, (startX, startY), (endX, endY), (0, 255, 0), 2)
# show the output image
cv2_imshow(image)
cv2.waitKey(0)
```

```
217 310 250 366
```


```
-1
```

Model Prediction and Matrix

```
scores = modell.evaluate(testImages, testTargets)
print(f"Test Bounding Box Accuracy: {scores[3]*100}")
print(f"Test Class Label Accuracy: {scores[4]*100}")
```

```
16/16 [==============================] - 1s 48ms/step - loss: 1.2575 -
bounding_box_loss: 0.0653 - class_label_loss: 1.1922 -
bounding_box_accuracy: 0.5262 - class_label_accuracy: 0.5968
Test Bounding Box Accuracy: 52.620965242385864
Test Class Label Accuracy: 59.67742204666138
```

```
pred_test=modell.predict(testImages)
```

```
16/16 [==============================] - 1s 42ms/step
```

```
# Reshape to remove the redundant dimension
converted_coordinates = testBBoxes.reshape((testBBoxes.shape[0],
testBBoxes.shape[1]))

print(converted_coordinates)
```

```
[[0.45542297 0.66766346 0.5261052  0.70759094]
 [0.4472397  0.45805028 0.5366876  0.5310316 ]
 [0.5735199  0.22531866 0.67679214 0.2906433 ]
 ...
 [0.441478   0.43594    0.4965056  0.5346279 ]
 [0.6053255  0.32573956 0.64561933 0.36646754]
 [0.30718216 0.3675907  0.39954984 0.44447142]]
```

```
from sklearn.metrics import mean_squared_error

mse_bbox = mean_squared_error(converted_coordinates, pred_test[0])
```

MSE of bounding box predictions

```
print(f"Test Bounding Box Mean Square Error: {mse_bbox*100}")
```

```
Test Bounding Box Mean Square Error: 6.52831494808197
```

```
binary_predictions = np.argmax(pred_test[1] , axis=1).astype(int)

# threshold = 0.5
# binary_predictions = (pred_test[1] > threshold).astype(int)

testLabelsNonBinary=testLabels.argmax(axis=1)
```

F1 Score, Accuracy, Precision and Recall of class label prediction

```
# accuracy: (tp + tn) / (p + n)
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
```

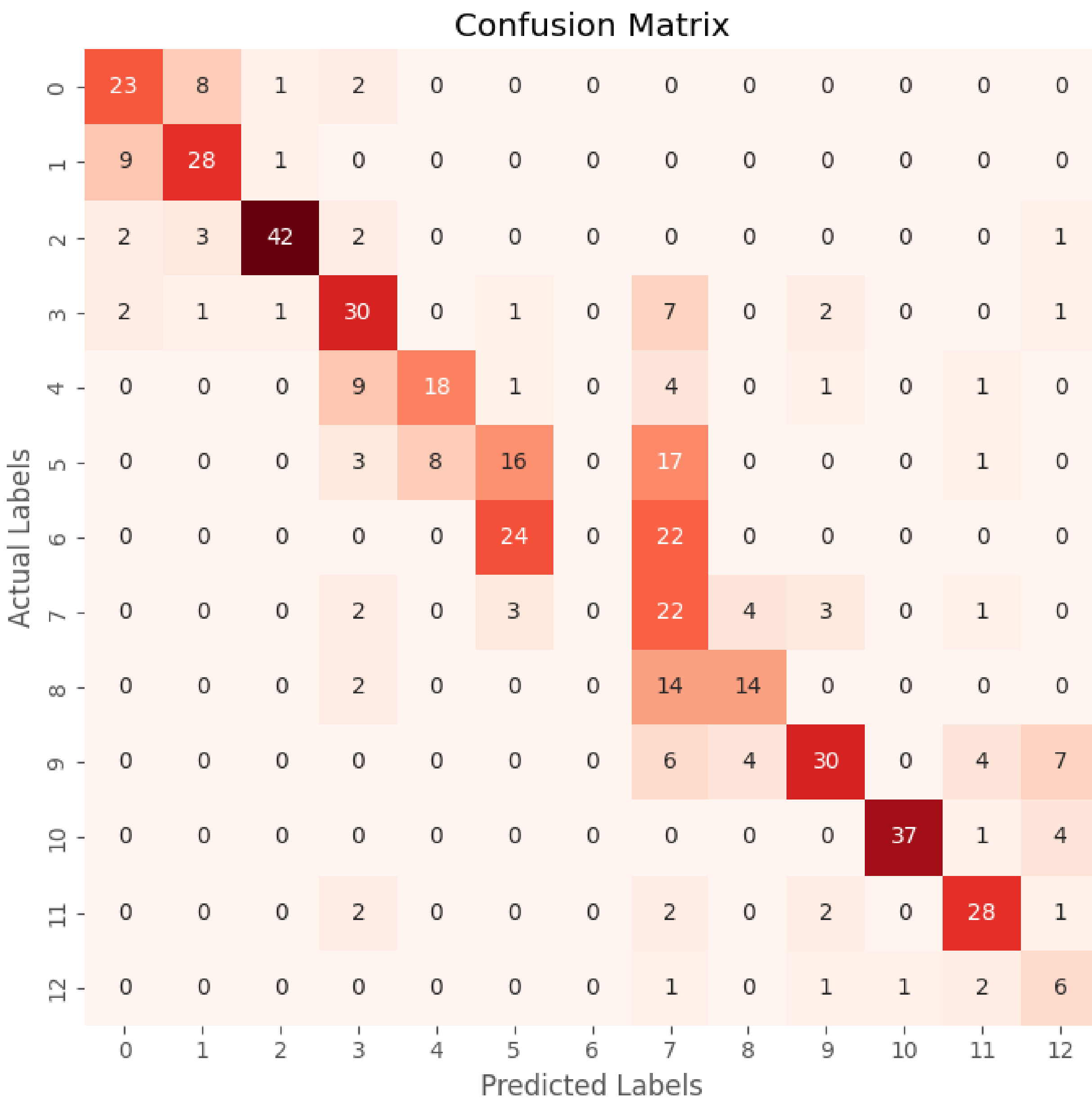
```python
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

f1_test = f1_score(testLabelsNonBinary, binary_predictions,
average='weighted')
print(f"Test Classifications F1 score: {f1_test*100}")
accuracy = accuracy_score(testLabelsNonBinary, binary_predictions)
print(f"Test Classifications accracy: {accuracy*100}")
# precision tp / (tp + fp)
precision = precision_score(testLabelsNonBinary, binary_predictions,
average='weighted')
print(f"Test Classifications precision: {precision*100}")
# recall: tp / (tp + fn)
recall = recall_score(testLabelsNonBinary, binary_predictions,
average='weighted')
print(f"Test Classifications recall: {recall*100}")
```

```
Test Classifications F1 score: 59.705838466327286
Test Classifications accracy: 59.67741935483871
Test Classifications precision: 63.84565384949366
Test Classifications recall: 59.67741935483871
```

```python
def evaluating_model(y_true, y_pred):
    conf_matrix = confusion_matrix(y_true=y_true, y_pred=y_pred)
    plt.figure(figsize=(7, 7))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cbar=False,
cmap='Reds');
    plt.title('Confusion Matrix');
    plt.xlabel('Predicted Labels');
    plt.ylabel('Actual Labels');
    plt.tight_layout();

    print(classification_report(y_true, y_pred))

from sklearn.metrics import classification_report, confusion_matrix
evaluating_model(testLabelsNonBinary, binary_predictions)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1344: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
```

```
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

              precision    recall  f1-score   support

           0       0.64      0.68      0.66        34
           1       0.70      0.74      0.72        38
           2       0.93      0.84      0.88        50
           3       0.58      0.67      0.62        45
           4       0.69      0.53      0.60        34
           5       0.36      0.36      0.36        45
           6       0.00      0.00      0.00        46
           7       0.23      0.63      0.34        35
           8       0.64      0.47      0.54        30
           9       0.77      0.59      0.67        51
          10       0.97      0.88      0.93        42
          11       0.74      0.80      0.77        35
          12       0.30      0.55      0.39        11

    accuracy                           0.59       496
   macro avg       0.58      0.59      0.57       496
weighted avg       0.60      0.59      0.58       496
```


Confusion Matrix
Actual Labels
Predicted Labels
0 1 2 3 4 5 6 7 8 9 10 11 12
23 8 1 2 0 0 0 0 0 0 0 0 0
9 28 1 0 0 0 0 0 0 0 0 0 0
2 3 42 2 0 0 0 0 0 0 0 0 1
2 1 1 30 0 1 0 7 0 2 0 0 1
0 0 0 9 18 1 0 4 0 1 0 1 0
0 0 0 3 8 16 0 17 0 0 0 1 0
0 0 0 0 0 24 0 22 0 0 0 0 0
0 0 0 2 0 3 0 22 4 3 0 1 0
0 0 0 2 0 0 0 14 14 0 0 0 0
0 0 0 0 0 0 0 6 4 30 0 4 7
0 0 0 0 0 0 0 0 0 0 37 1 4
0 0 0 2 0 0 0 2 0 2 0 28 1
0 0 0 0 0 0 0 1 0 1 1 2 6