Introduction

This kernel is a simple example of fruit classification with a simple CNN implemented with Keras model and tools. Click the blue "Edit Notebook" or "Fork Notebook" button at the top of this kernel to begin editing.

```
from google.colab import drive

drive.mount('/content/drive')
```

```
    Drive already mounted at /content/drive; to attempt to forcibly remount, call driv
```

General Libs

```
# General Libs
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, BatchNormalization,
from tensorflow.keras.optimizers import Adam
import numpy as np
import random
import matplotlib.pyplot as plt
%matplotlib inline
```

Exploratory Analysis

Let's view some dataset samples.

This example uses keras ImageDataGenerator. This lib turns easier to read and use image classes from a subdirectoty structure.

Reading the dataset

```
im_shape = (250,250)

TRAINING_DIR = '../content/drive/MyDrive/ds_frutas_am/train'
TEST_DIR = '../content/drive/MyDrive/ds_frutas_am/test'

seed = 10

BATCH_SIZE = 16
```

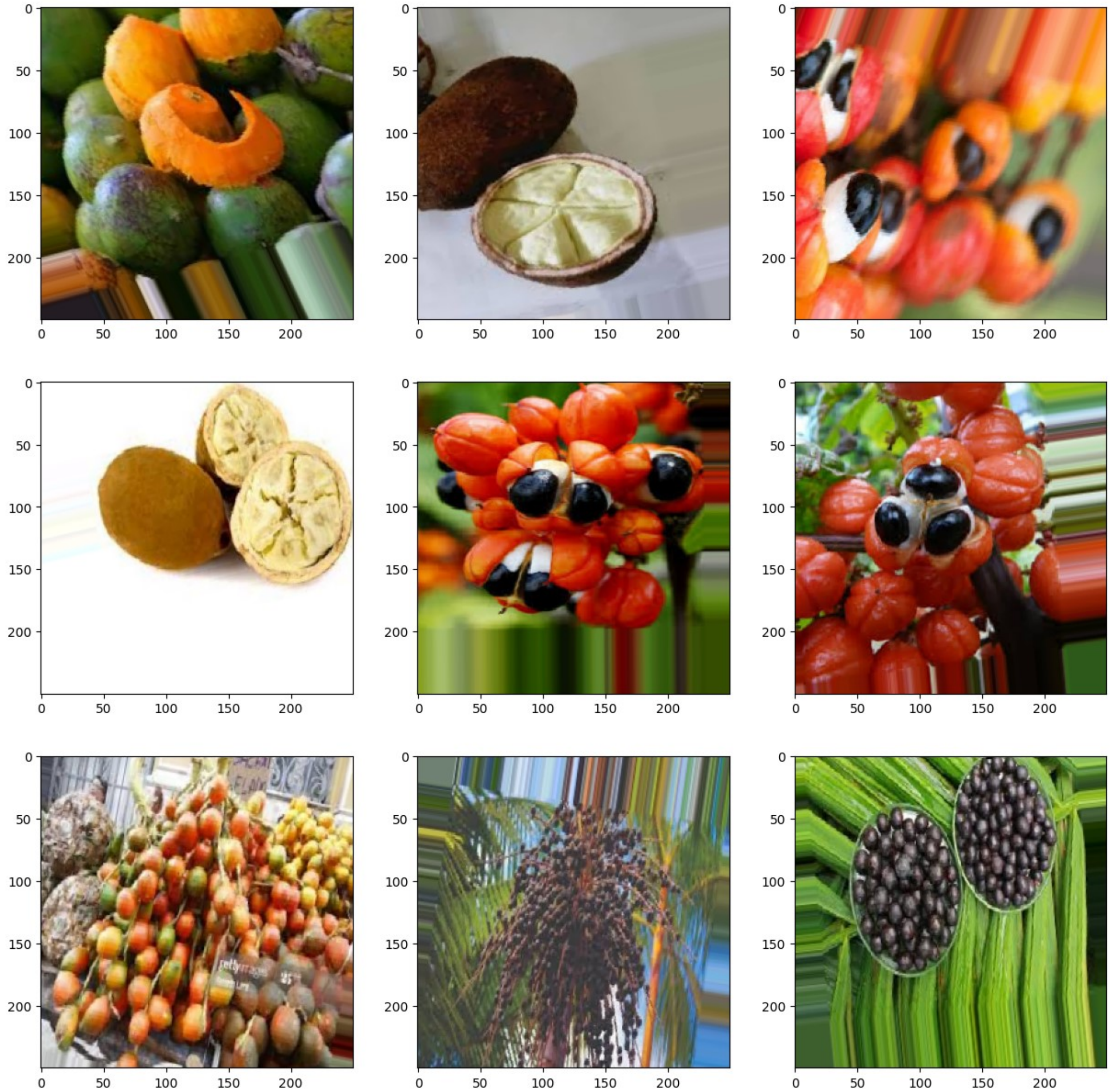
```
#Using keras ImageGenerator and flow_from_directoty

# Subdivision in test/validation
data_generator = ImageDataGenerator(rescale=1./255, validation_split=0.2)
val_data_generator = ImageDataGenerator(rescale=1./255, validation_split=0.2)


# If you want data augmentation, uncomment and run this cell
data_generator = ImageDataGenerator(
        validation_split=0.2,
        rotation_range=20,
        width_shift_range=0.2,
        height_shift_range=0.2,
        rescale=1./255,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True,
        fill_mode='nearest')

val_data_generator = ImageDataGenerator(rescale=1./255, validation_split=0.2)


# Generator para parte train
train_generator = data_generator.flow_from_directory(TRAINING_DIR, target_size=im_shape
                                                     class_mode='categorical', batch_si
# Generator para parte validação
validation_generator = val_data_generator.flow_from_directory(TRAINING_DIR, target_size
                                                     class_mode='categorical', batch_si

# Generator para dataset de teste
test_generator = ImageDataGenerator(rescale=1./255)
test_generator = test_generator.flow_from_directory(TEST_DIR, target_size=im_shape, shu
                                                     class_mode='categorical', batch_si

nb_train_samples = train_generator.samples
nb_validation_samples = validation_generator.samples
nb_test_samples = test_generator.samples
classes = list(train_generator.class_indices.keys())
print('Classes: '+str(classes))
num_classes  = len(classes)
```

```
Found 72 images belonging to 6 classes.
Found 18 images belonging to 6 classes.
Found 30 images belonging to 6 classes.
Classes: ['acai', 'cupuacu', 'graviola', 'guarana', 'pupunha', 'tucuma']
```

Showing some examples

```
# Visualizing some examples
plt.figure(figsize=(15,15))
for i in range(9):
```

```
    #gera subfigures
    plt.subplot(330 + 1 + i)
    batch = train_generator.next()[0]*255
    image = batch[0].astype('uint8')
    plt.imshow(image)
plt.show()
```



Creating a simple CNN Model

Creating a simple CNN Model

```
model = Sequential()
model.add(Conv2D(20, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=(im_shape[0],im_shape[1],3)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(40, kernel_size=(3,3), activation='relu'))
model.add(Flatten())
model.add(Dense(100, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(num_classes, activation='softmax'))
model.summary()

# Compila o modelo
model.compile(loss='categorical_crossentropy',
              optimizer=Adam(),
              metrics=['accuracy'])
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 248, 248, 20)      560

 max_pooling2d (MaxPooling2  (None, 124, 124, 20)      0
 D)

 conv2d_1 (Conv2D)           (None, 122, 122, 40)      7240

 flatten (Flatten)           (None, 595360)            0

 dense (Dense)               (None, 100)               59536100

 dropout (Dropout)           (None, 100)               0

 dense_1 (Dense)             (None, 6)                 606

=================================================================
Total params: 59544506 (227.14 MB)
Trainable params: 59544506 (227.14 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

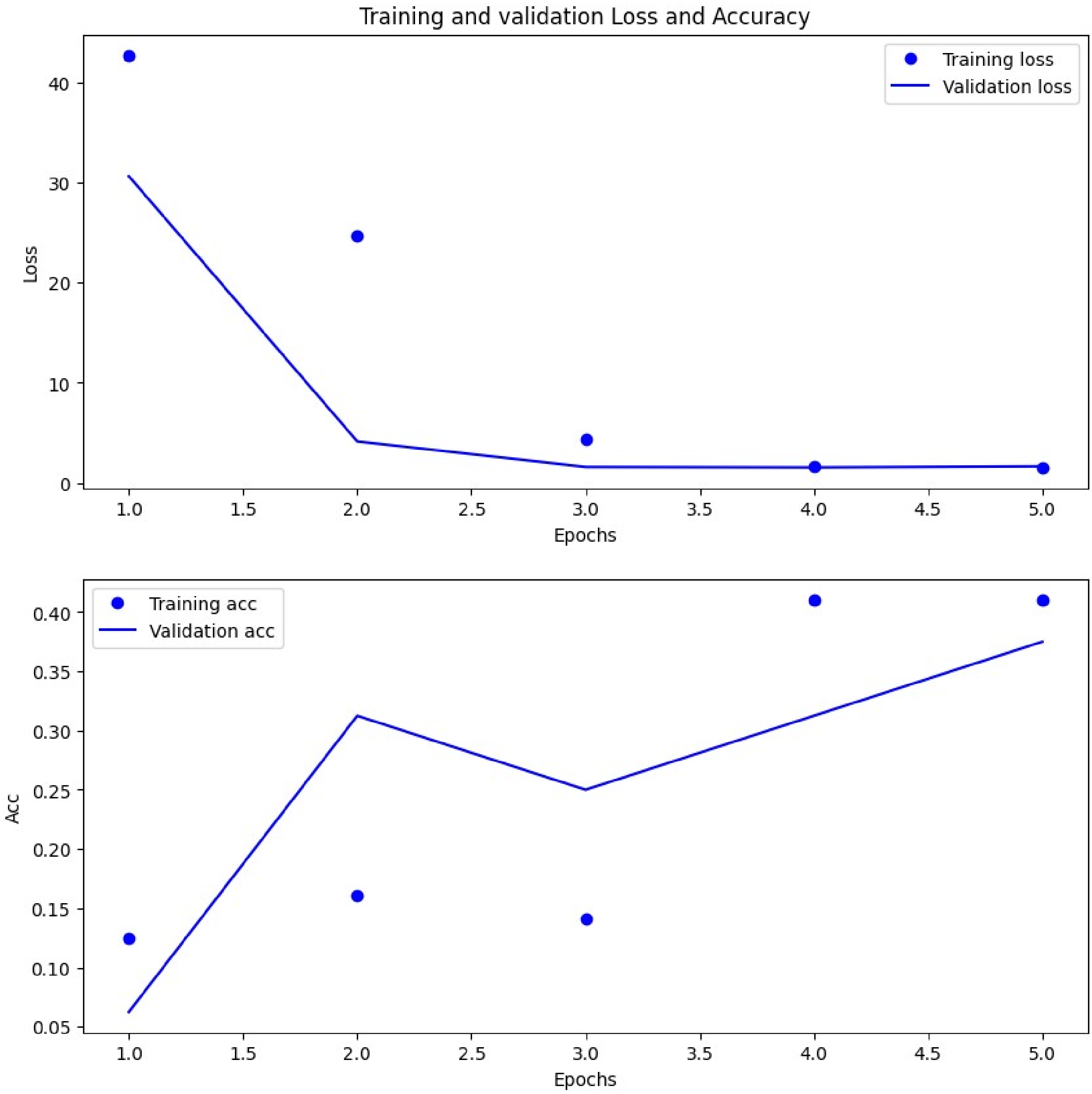
```
epochs = 5

#Callback to save the best model
callbacks_list = [
    keras.callbacks.ModelCheckpoint(
        filepath='model.h5',
        monitor='val_loss', save_best_only=True, verbose=1),
    keras.callbacks.EarlyStopping(monitor='val_loss', patience=10,verbose=1)
]
```

```
#Training
history = model.fit(
        train_generator,
        steps_per_epoch=nb_train_samples // BATCH_SIZE,
        epochs=epochs,
        callbacks = callbacks_list,
        validation_data=validation_generator,
        verbose = 1,
        validation_steps=nb_validation_samples // BATCH_SIZE)
```

```
Epoch 1/5
4/4 [==============================] - ETA: 0s - loss: 42.7706 - accuracy: 0.1250
Epoch 1: val_loss improved from inf to 30.65786, saving model to model.h5
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3000: UserWar
  saving_api.save_model(
4/4 [==============================] - 13s 3s/step - loss: 42.7706 - accuracy: 0.1
Epoch 2/5
4/4 [==============================] - ETA: 0s - loss: 24.7431 - accuracy: 0.1607
Epoch 2: val_loss improved from 30.65786 to 4.14188, saving model to model.h5
4/4 [==============================] - 13s 4s/step - loss: 24.7431 - accuracy: 0.1
Epoch 3/5
4/4 [==============================] - ETA: 0s - loss: 4.3579 - accuracy: 0.1406
Epoch 3: val_loss improved from 4.14188 to 1.59791, saving model to model.h5
4/4 [==============================] - 15s 4s/step - loss: 4.3579 - accuracy: 0.14
Epoch 4/5
4/4 [==============================] - ETA: 0s - loss: 1.5971 - accuracy: 0.4107
Epoch 4: val_loss improved from 1.59791 to 1.55511, saving model to model.h5
4/4 [==============================] - 12s 3s/step - loss: 1.5971 - accuracy: 0.41
Epoch 5/5
4/4 [==============================] - ETA: 0s - loss: 1.5341 - accuracy: 0.4107
Epoch 5: val_loss did not improve from 1.55511
4/4 [==============================] - 9s 2s/step - loss: 1.5341 - accuracy: 0.41
```

```
# Training curves
import matplotlib.pyplot as plt

history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs_x = range(1, len(loss_values) + 1)
plt.figure(figsize=(10,10))
plt.subplot(2,1,1)
plt.plot(epochs_x, loss_values, 'bo', label='Training loss')
plt.plot(epochs_x, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation Loss and Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.subplot(2,1,2)
acc_values = history_dict['accuracy']
val_acc_values = history_dict['val_accuracy']
plt.plot(epochs_x, acc_values, 'bo', label='Training acc')
plt.plot(epochs_x, val_acc_values, 'b', label='Validation acc')
#plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
```

```
plt.xlabel('Epochs')
plt.ylabel('Acc')
plt.legend()
plt.show()
```



Evaluating the model

```
# Load the best saved model
from tensorflow.keras.models import load_model

model = load_model('model.h5')
```

```
# Using the validation dataset
score = model.evaluate_generator(validation_generator)
print('Val loss:', score[0])
print('Val accuracy:', score[1])
```

```
<ipython-input-13-0b1386c018fa>:2: UserWarning: `Model.evaluate_generator` is depr
  score = model.evaluate_generator(validation_generator)
Val loss: 1.57163667678833
Val accuracy: 0.2777777910232544
```

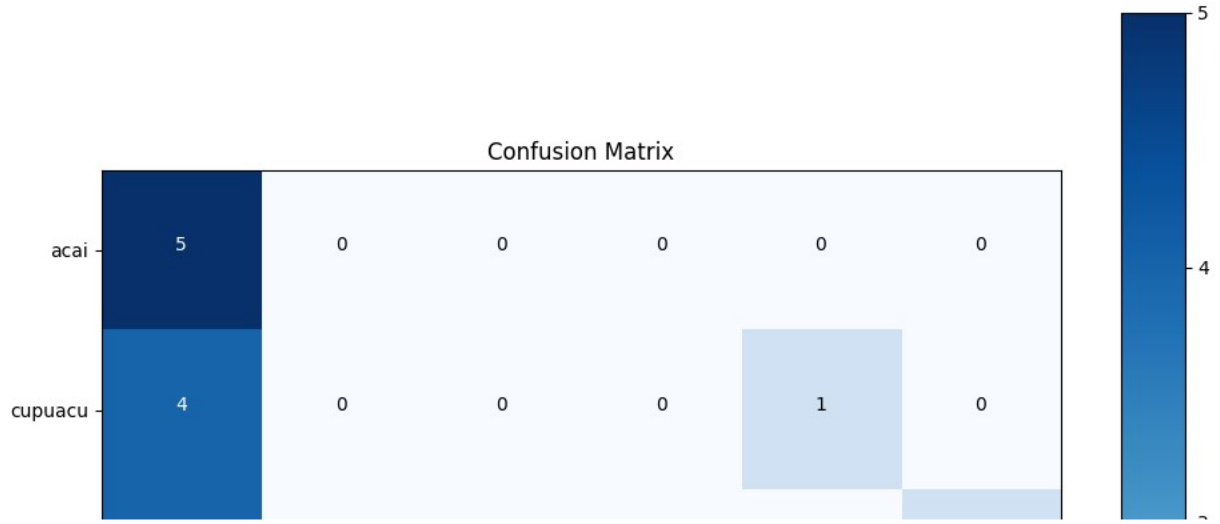
```
# Using the test dataset
score = model.evaluate_generator(test_generator)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

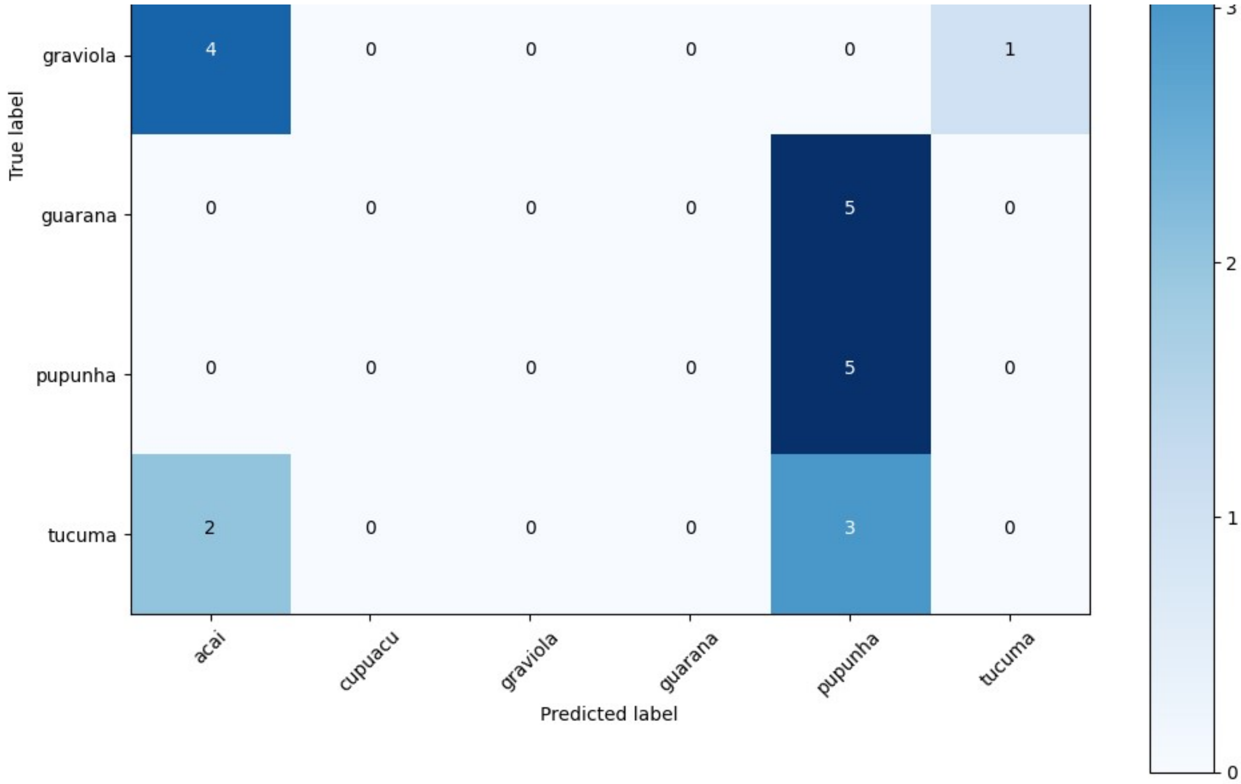
```
<ipython-input-14-8baddd65724c>:2: UserWarning: `Model.evaluate_generator` is depr
  score = model.evaluate_generator(test_generator)
Test loss: 1.487316608428955
Test accuracy: 0.3333333432674408
```

```
import itertools

#Plot the confusion matrix. Set Normalize = True/False
def plot_confusion_matrix(cm, classes, normalize=True, title='Confusion matrix', cmap=p
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.figure(figsize=(10,10))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        cm = np.around(cm, decimals=2)
        cm[np.isnan(cm)] = 0.0
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

```
# Some reports
from sklearn.metrics import classification_report, confusion_matrix
import numpy as np

#On test dataset
Y_pred = model.predict_generator(test_generator)
y_pred = np.argmax(Y_pred, axis=1)
target_names = classes

#Confution Matrix
cm = confusion_matrix(test_generator.classes, y_pred)
plot_confusion_matrix(cm, target_names, normalize=False, title='Confusion Matrix')

#Classification Report
print('Classification Report')
print(classification_report(test_generator.classes, y_pred, target_names=target_names))
```

```
<ipython-input-16-4a63cf876f11>:6: UserWarning: `Model.predict_generator` is depre
  Y_pred = model.predict_generator(test_generator)
Classification Report
              precision    recall  f1-score   support

        acai       0.33      1.00      0.50         5
     cupuacu       0.00      0.00      0.00         5
    graviola       0.00      0.00      0.00         5
     guarana       0.00      0.00      0.00         5
     pupunha       0.36      1.00      0.53         5
      tucuma       0.00      0.00      0.00         5

    accuracy                           0.33        30
   macro avg       0.12      0.33      0.17        30
weighted avg       0.12      0.33      0.17        30

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
  _warn_prf(average, modifier, msg_start, len(result))
```





graviola
guarana
pupunha
tucuma
True label
4
0
1
5
2
3
acai
cupuacu
graviola
guarana
pupunha
tucuma
Predicted label