

projectml-2024

November 17, 2024

```
[1]: import numpy as np
      from sklearn.metrics import classification_report, confusion_matrix
      import seaborn as sns
      import tensorflow as tf
      from tensorflow import keras
      from tensorflow.keras import layers
      from tensorflow.keras.models import Sequential
      import PIL
      import matplotlib.pyplot as plt
```

```
[2]: IMAGE_SHAPE = (250, 250)
      batch_size = 30
      image_generator = tf.keras.preprocessing.image.ImageDataGenerator(rescale=1/255)
      train_d = 'train'
      training_image_data = image_generator.flow_from_directory(train_d,
      ↪target_size=IMAGE_SHAPE)

      test_d = 'test'
      testing_image_data = image_generator.flow_from_directory(test_d,
      ↪target_size=IMAGE_SHAPE)
```

Found 1156 images belonging to 9 classes.

Found 502 images belonging to 9 classes.

```
[3]: train_ds = tf.keras.utils.image_dataset_from_directory(
      train_d,
      image_size=IMAGE_SHAPE,
      batch_size=batch_size
      )

      test_ds = tf.keras.utils.image_dataset_from_directory(
      test_d,
      image_size=IMAGE_SHAPE,
      batch_size=batch_size
      )
```

Found 1156 files belonging to 9 classes.

Found 502 files belonging to 9 classes.

```

[4]: class_names = train_ds.class_names
print("Class Names:", class_names)

images_per_class = {}
for images, labels in train_ds:
    for image, label in zip(images, labels):
        class_name = class_names[label.numpy()]
        if class_name not in images_per_class:
            images_per_class[class_name] = image

        if len(images_per_class) == len(class_names):
            break
if len(images_per_class) == len(class_names):
    break

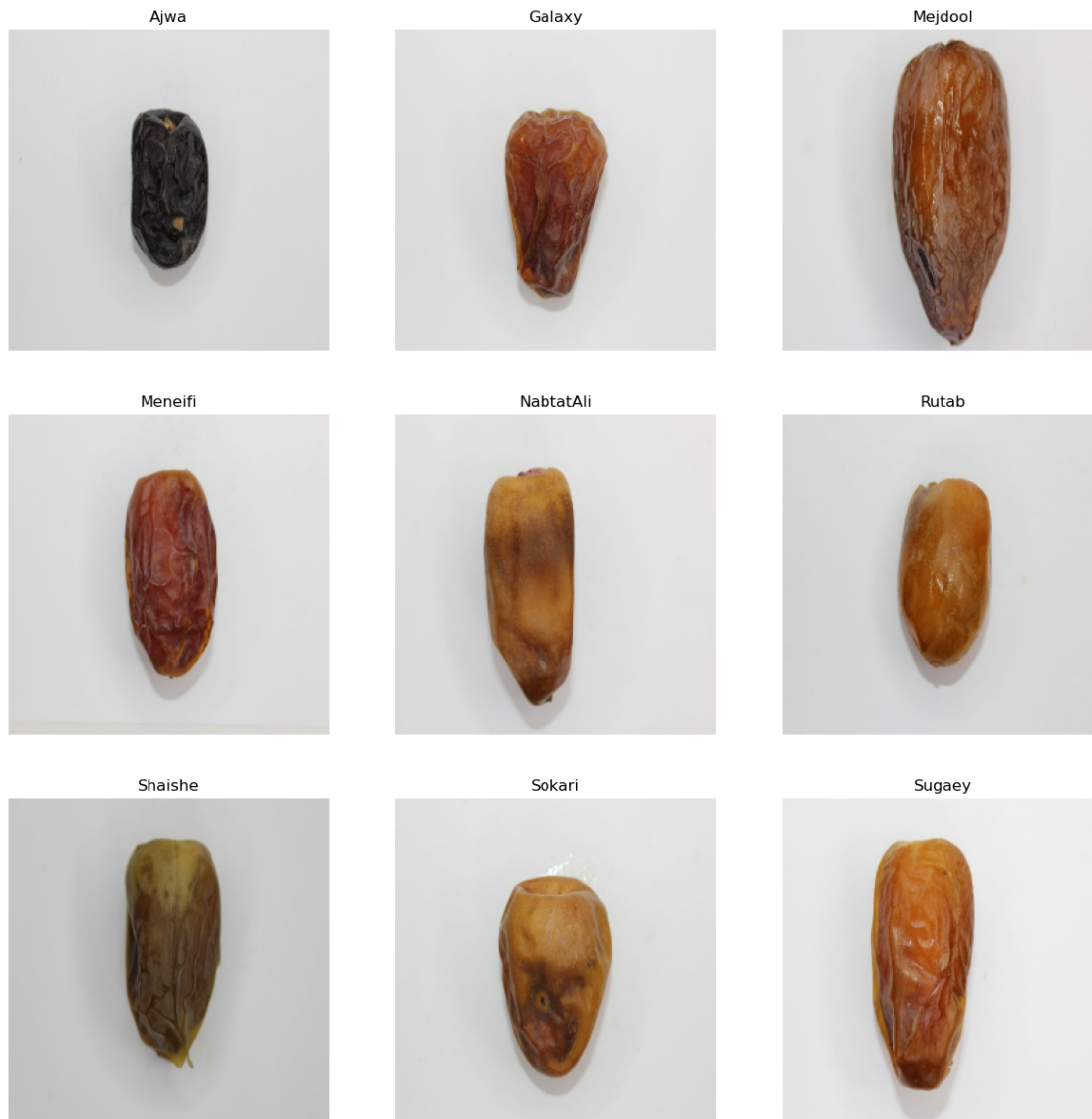
plt.figure(figsize=(15, 15))
for i, class_name in enumerate(class_names):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(images_per_class[class_name].numpy().astype("uint8"))
    plt.title(class_name)
    plt.axis("off")

plt.show()

AUTOTUNE = tf.data.AUTOTUNE

```

Class Names: ['Ajwa', 'Galaxy', 'Mejdool', 'Meneifi', 'NabtatAli', 'Rutab', 'Shaishe', 'Sokari', 'Sugaey']



```
[5]: train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
      val_ds = test_ds.cache().prefetch(buffer_size=AUTOTUNE)

      normalization_layer = layers.Rescaling(1./255)

      normalized_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
      image_batch, labels_batch = next(iter(normalized_ds))
      first_image = image_batch[0]
```

```
[6]: num_classes = len(class_names)

      model = Sequential([
```

```

layers.Rescaling(1./255, input_shape=(IMAGE_SHAPE[0], IMAGE_SHAPE[1], 3)),
layers.Conv2D(16, 3, padding='same', activation='relu'),
layers.MaxPooling2D(),
layers.Conv2D(32, 3, padding='same', activation='relu'),
layers.MaxPooling2D(),
layers.Conv2D(64, 3, padding='same', activation='relu'),
layers.MaxPooling2D(),
layers.Flatten(),
layers.Dense(128, activation='relu'),
layers.Dense(num_classes)
])

model.compile(optimizer='adam', loss=tf.keras.losses.
    SparseCategoricalCrossentropy(from_logits=True),
    metrics=['accuracy'])

model.summary()

```

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|--------------------------------|----------------------|---------|
| rescaling_1 (Rescaling) | (None, 250, 250, 3) | 0 |
| conv2d (Conv2D) | (None, 250, 250, 16) | 448 |
| max_pooling2d (MaxPooling2D) | (None, 125, 125, 16) | 0 |
| conv2d_1 (Conv2D) | (None, 125, 125, 32) | 4640 |
| max_pooling2d_1 (MaxPooling2D) | (None, 62, 62, 32) | 0 |
| conv2d_2 (Conv2D) | (None, 62, 62, 64) | 18496 |
| max_pooling2d_2 (MaxPooling2D) | (None, 31, 31, 64) | 0 |
| flatten (Flatten) | (None, 61504) | 0 |
| dense (Dense) | (None, 128) | 7872640 |
| dense_1 (Dense) | (None, 9) | 1161 |

```
=====
Total params: 7,897,385
Trainable params: 7,897,385
Non-trainable params: 0
-----
```

```
[7]: epochs = 17
      history = model.fit(
          train_ds,
          validation_data=val_ds,
          epochs=epochs
      )
```

```
Epoch 1/17
39/39 [=====] - 51s 1s/step - loss: 1.9212 - accuracy:
0.3322 - val_loss: 1.3392 - val_accuracy: 0.5558
Epoch 2/17
39/39 [=====] - 92s 2s/step - loss: 0.8878 - accuracy:
0.6877 - val_loss: 0.7521 - val_accuracy: 0.7191
Epoch 3/17
39/39 [=====] - 90s 2s/step - loss: 0.5083 - accuracy:
0.8452 - val_loss: 0.4704 - val_accuracy: 0.8247
Epoch 4/17
39/39 [=====] - 83s 2s/step - loss: 0.3452 - accuracy:
0.8884 - val_loss: 0.4857 - val_accuracy: 0.8207
Epoch 5/17
39/39 [=====] - 85s 2s/step - loss: 0.3853 - accuracy:
0.8668 - val_loss: 0.4051 - val_accuracy: 0.8586
Epoch 6/17
39/39 [=====] - 86s 2s/step - loss: 0.2918 - accuracy:
0.9005 - val_loss: 0.4147 - val_accuracy: 0.8486
Epoch 7/17
39/39 [=====] - 90s 2s/step - loss: 0.2960 - accuracy:
0.9005 - val_loss: 0.4009 - val_accuracy: 0.8526
Epoch 8/17
39/39 [=====] - 86s 2s/step - loss: 0.1881 - accuracy:
0.9412 - val_loss: 0.3418 - val_accuracy: 0.8785
Epoch 9/17
39/39 [=====] - 88s 2s/step - loss: 0.1121 - accuracy:
0.9732 - val_loss: 0.4792 - val_accuracy: 0.8586
Epoch 10/17
39/39 [=====] - 91s 2s/step - loss: 0.1447 - accuracy:
0.9542 - val_loss: 0.2771 - val_accuracy: 0.8944
Epoch 11/17
39/39 [=====] - 93s 2s/step - loss: 0.0807 - accuracy:
0.9766 - val_loss: 0.3104 - val_accuracy: 0.8944
Epoch 12/17
39/39 [=====] - 87s 2s/step - loss: 0.1016 - accuracy:
```

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0.9654 - val_loss: 0.3241 - val_accuracy: 0.8725
Epoch 13/17
39/39 [=====] - 89s 2s/step - loss: 0.1455 - accuracy:
0.9507 - val_loss: 0.3909 - val_accuracy: 0.8765
Epoch 14/17
39/39 [=====] - 91s 2s/step - loss: 0.0814 - accuracy:
0.9740 - val_loss: 0.4560 - val_accuracy: 0.8645
Epoch 15/17
39/39 [=====] - 92s 2s/step - loss: 0.0799 - accuracy:
0.9766 - val_loss: 0.3732 - val_accuracy: 0.8785
Epoch 16/17
39/39 [=====] - 86s 2s/step - loss: 0.0354 - accuracy:
0.9922 - val_loss: 0.3454 - val_accuracy: 0.9084
Epoch 17/17
39/39 [=====] - 87s 2s/step - loss: 0.0236 - accuracy:
0.9939 - val_loss: 0.3289 - val_accuracy: 0.9064

```

```

[8]: acc = history.history['accuracy']
     val_acc = history.history['val_accuracy']

     loss = history.history['loss']
     val_loss = history.history['val_loss']

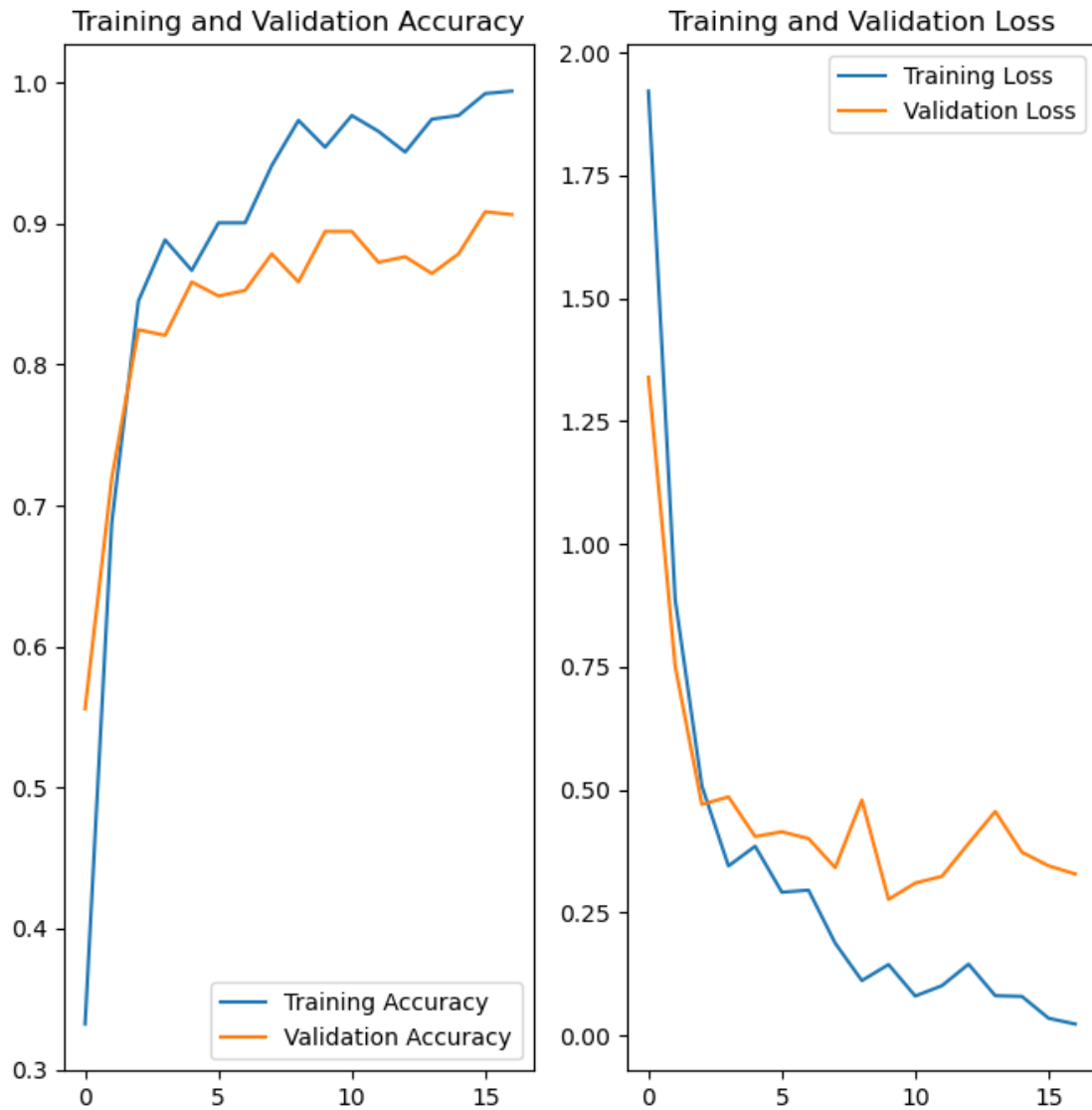
     epochs_range = range(epochs)

```

```

[9]: plt.figure(figsize=(8, 8))
     plt.subplot(1, 2, 1)
     plt.plot(epochs_range, acc, label='Training Accuracy')
     plt.plot(epochs_range, val_acc, label='Validation Accuracy')
     plt.legend(loc='lower right')
     plt.title('Training and Validation Accuracy')
     plt.subplot(1, 2, 2)
     plt.plot(epochs_range, loss, label='Training Loss')
     plt.plot(epochs_range, val_loss, label='Validation Loss')
     plt.legend(loc='upper right')
     plt.title('Training and Validation Loss')
     plt.show()

```



```
[10]: test_images, test_labels = [], []
      for images, labels in test_ds:
          test_images.extend(images.numpy())
          test_labels.extend(labels.numpy())
```

```
[11]: test_images = np.array(test_images)
      test_labels = np.array(test_labels)
```

```
[12]: predictions = model.predict(test_images)
      predicted_labels = np.argmax(predictions, axis=1)
```

16/16 [=====] - 7s 439ms/step

```
[13]: print("Classification Report:")
print(classification_report(test_labels, predicted_labels,
    ↳target_names=class_names))

print("Confusion Matrix:")
cm = confusion_matrix(test_labels, predicted_labels)
print(cm)
```

Classification Report:

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Ajwa | 0.98 | 1.00 | 0.99 | 53 |
| Galaxy | 0.89 | 0.88 | 0.88 | 57 |
| Mejdool | 0.95 | 0.93 | 0.94 | 41 |
| Meneifi | 0.84 | 0.87 | 0.85 | 70 |
| NabtatAli | 0.92 | 0.83 | 0.87 | 54 |
| Rutab | 0.98 | 0.93 | 0.95 | 44 |
| Shaishe | 0.96 | 0.98 | 0.97 | 52 |
| Sokari | 0.93 | 0.88 | 0.90 | 80 |
| Sugaey | 0.77 | 0.90 | 0.83 | 51 |
| accuracy | | | 0.91 | 502 |
| macro avg | 0.91 | 0.91 | 0.91 | 502 |
| weighted avg | 0.91 | 0.91 | 0.91 | 502 |

Confusion Matrix:

```
[[53  0  0  0  0  0  0  0  0]
 [ 0 50  0  5  0  0  1  1  0]
 [ 0  0 38  2  0  0  0  0  1]
 [ 1  1  1 61  0  1  0  1  4]
 [ 0  0  0  0 45  0  0  3  6]
 [ 0  0  0  0  0 41  0  0  3]
 [ 0  0  0  1  0  0 51  0  0]
 [ 0  5  0  2  2  0  1 70  0]
 [ 0  0  1  2  2  0  0  0 46]]
```

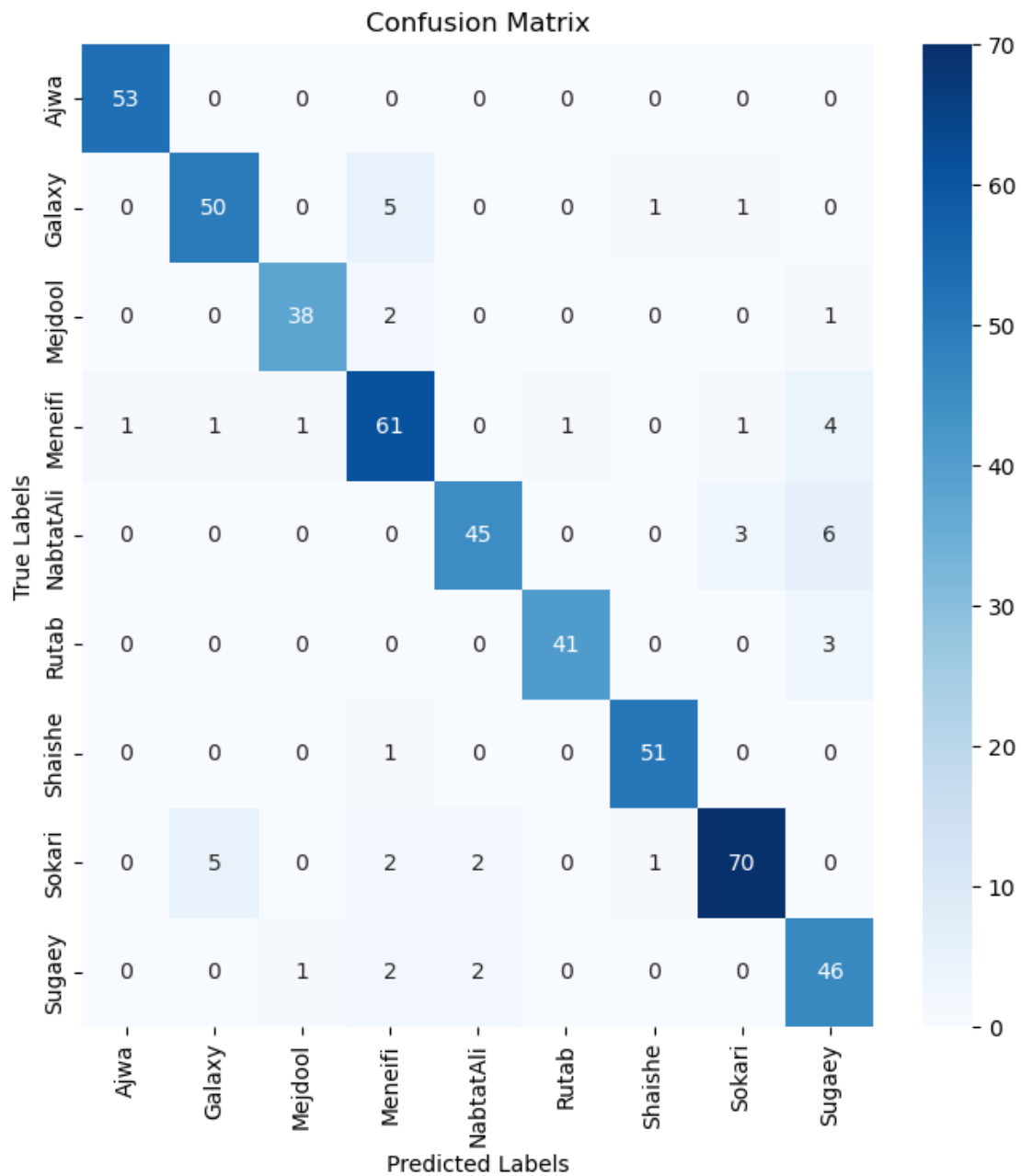
```
[14]: accuracy = np.sum(test_labels == predicted_labels) / len(test_labels)
print("Accuracy:", accuracy)
```

Accuracy: 0.9063745019920318

```
[15]: plt.figure(figsize=(8, 8))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=class_names,
    ↳yticklabels=class_names)
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
```



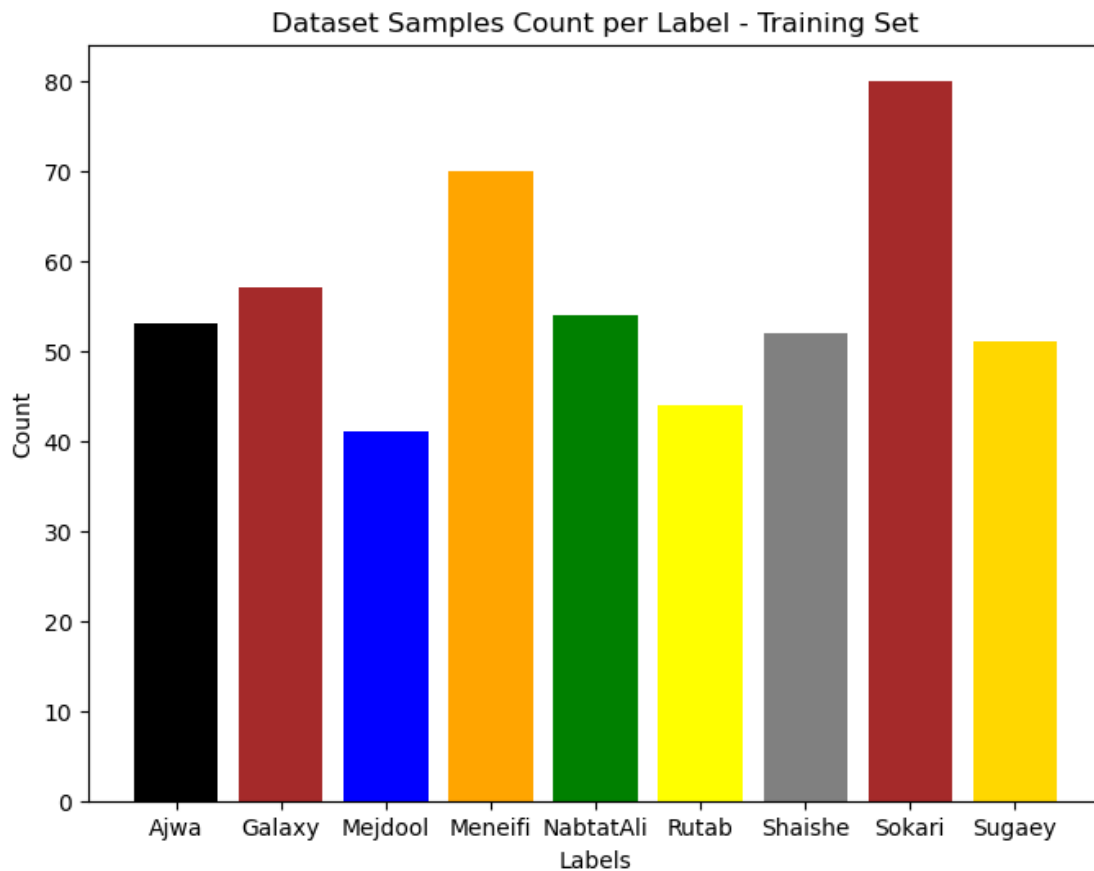
```
plt.show()
```



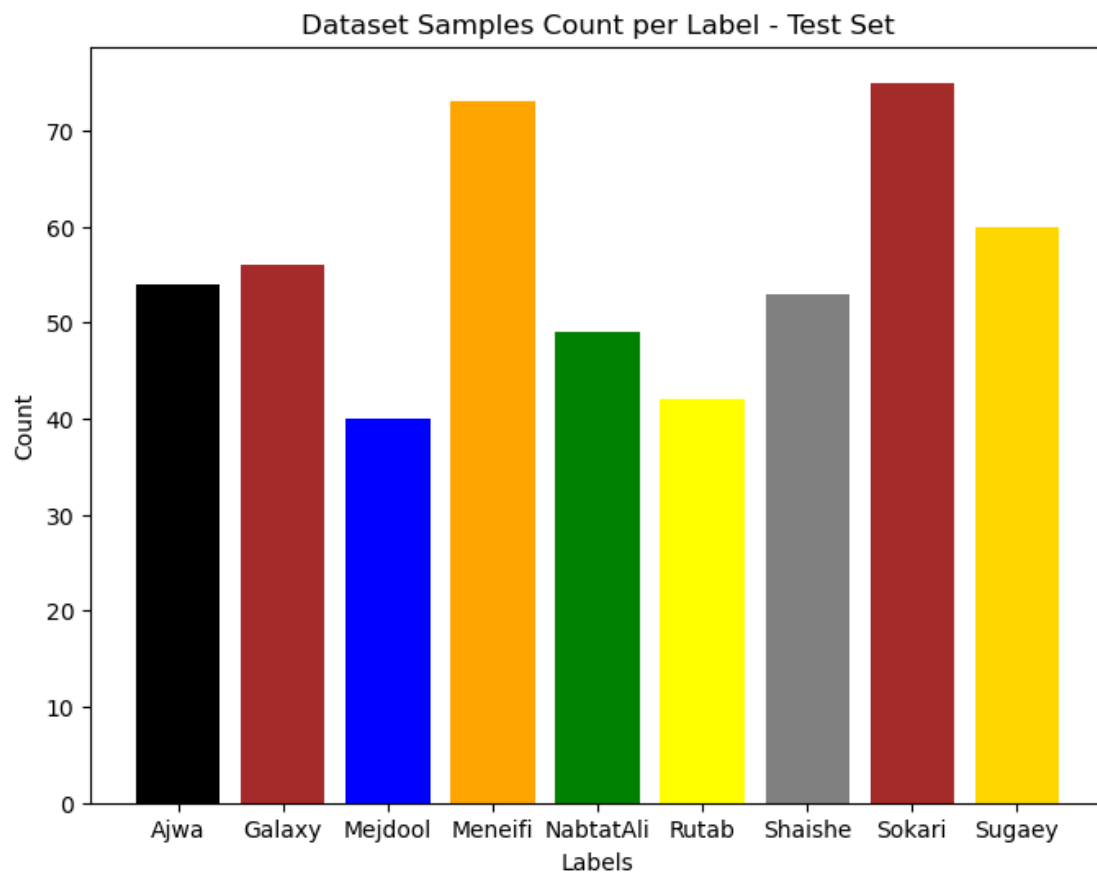
```
[16]: c = ['black', 'brown', 'blue', 'orange', 'green', 'yellow', 'grey', 'brown', 'gold']

plt.figure(figsize=(8, 6))
train_labels_count = [len(np.where(test_labels == i)[0]) for i in range(num_classes)]
```

```
plt.bar(class_names, train_labels_count, color = c)
plt.title("Dataset Samples Count per Label - Training Set")
plt.xlabel("Labels")
plt.ylabel("Count")
plt.show()
```



```
[17]: plt.figure(figsize=(8, 6))
test_labels_count = [len(np.where(predicted_labels == i)[0]) for i in
    range(num_classes)]
plt.bar(class_names, test_labels_count, color = c)
plt.title("Dataset Samples Count per Label - Test Set")
plt.xlabel("Labels")
plt.ylabel("Count")
plt.show()
```



[]:

[]: