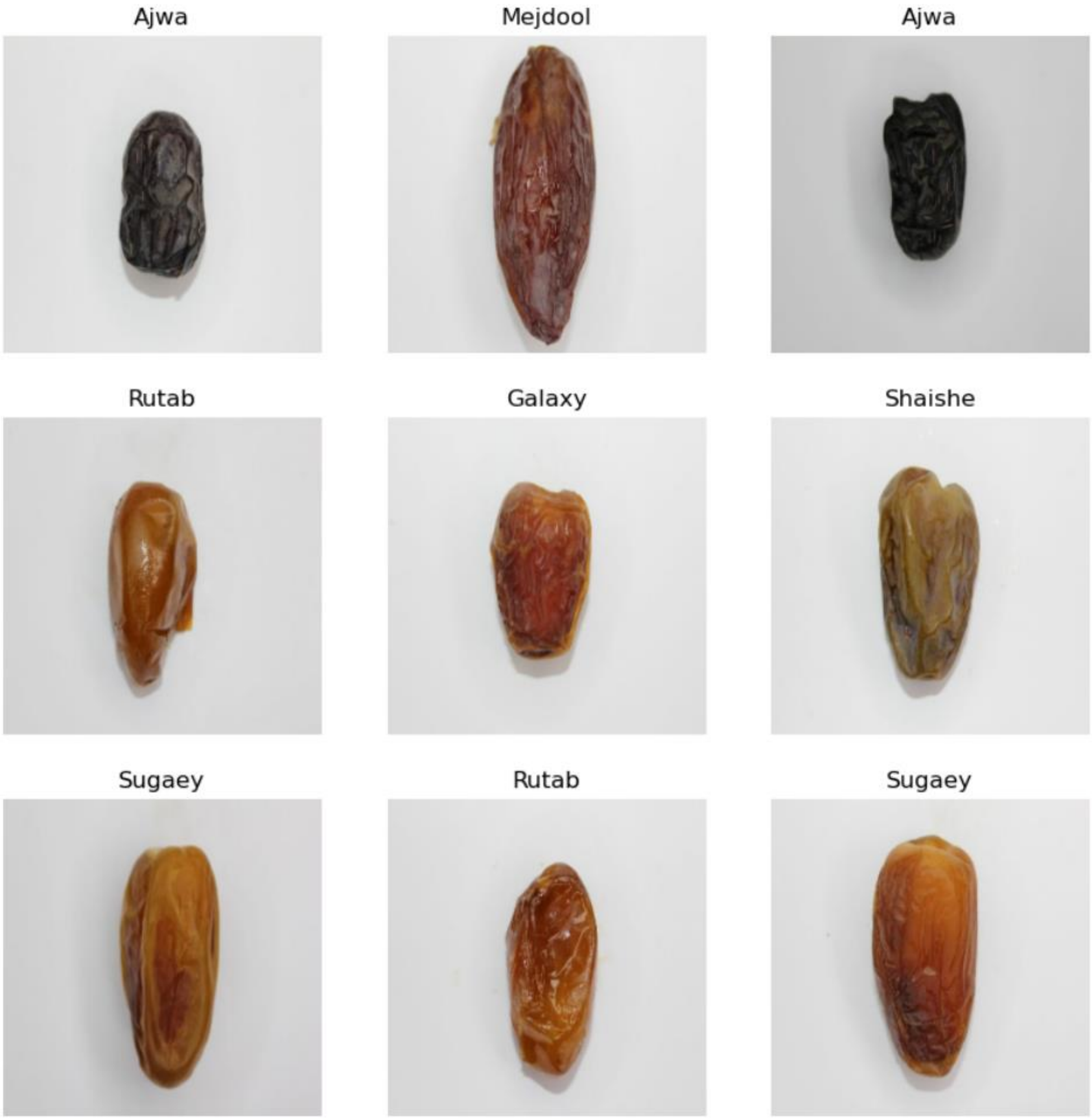
جامعة الملك سعود
King Saud University

Course Project: Date Fruit Image Classification



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Problem Description

We are implementing a machine learning model that will be able to accurately identify the type of the date fruit.

Importance

This model can enhance the quality of agricultural and retail processes, it can be used also for education purposes.

Roles

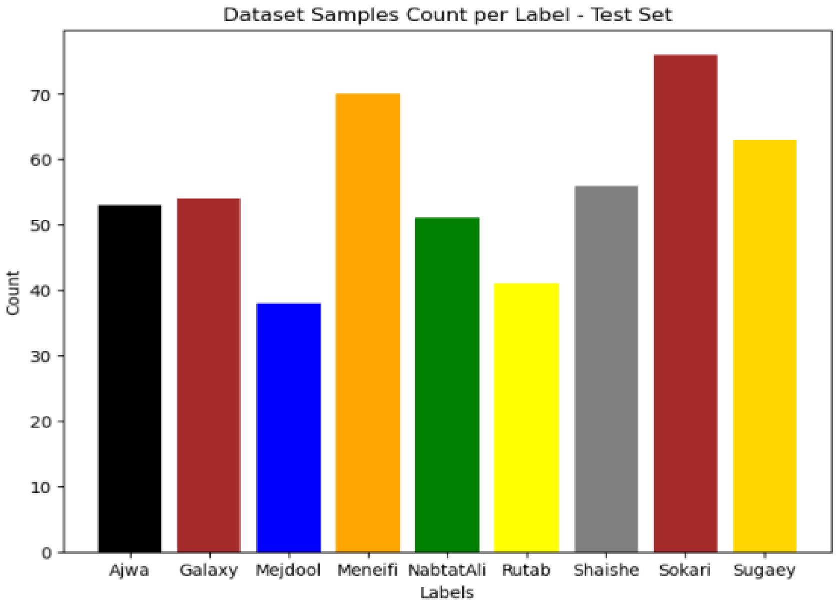
Abdulrahman: Building the model.

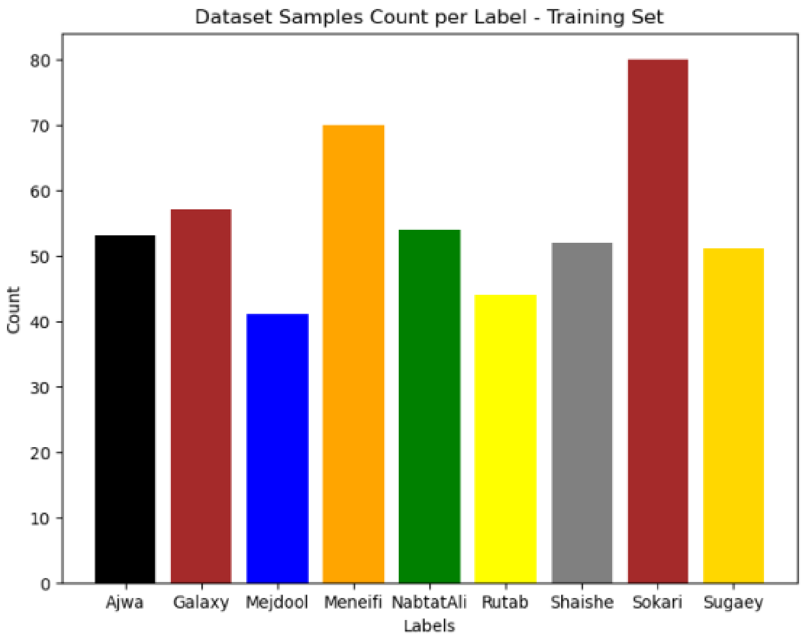
Khaled: Observing the process and writing the report and presentation.

Platform

Jupyter Notebook & Google Colab

Dataset Samples Count Per Label Charts





Data Preprocessing

Rescaling: Pixel values are scaled to the range of 0 to 1 using layers.Rescaling(1./255). This normalization helps to standardize the input data and improve model training.

CNN Architecture

The model was built sequentially with the following layers:

Input Layer: Receives input images of size 250x250x3.

Convolutional Layers:

- Conv2D Layer 1: Applies 16 filters of size 3x3 with ReLU activation and same padding.
- MaxPooling2D Layer 1: Downsamples the feature maps by a factor of 2.
- Conv2D Layer 2: Applies 32 filters of size 3x3 with ReLU activation and same padding.
- MaxPooling2D Layer 2: Downsamples the feature maps by a factor of 2.
- Conv2D Layer 3: Applies 64 filters of size 3x3 with ReLU activation and same padding.
- MaxPooling2D Layer 3: Downsamples the feature maps by a factor of 2.

Flatten Layer: Flattens the output of the convolutional layers into a 1D vector.

Dense Layers:

- Dense Layer 1: Fully connected layer with 128 units and ReLU activation.
- Output Layer: Fully connected layer with the number of units equal to the number of classes, using softmax activation for multi-class classification.

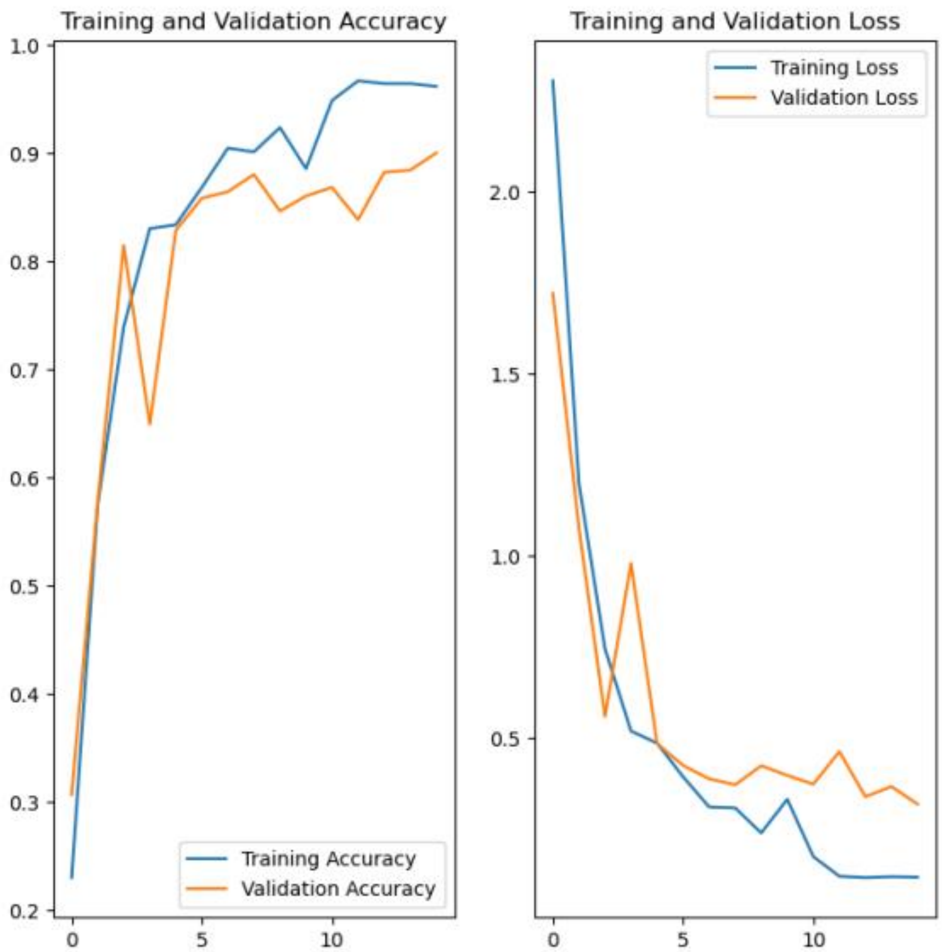
Its a combination of multiple CNN architecture found online.

Optimizer

Used Adam optimizer with the default hyperparameters.

Epochs

15 epochs.



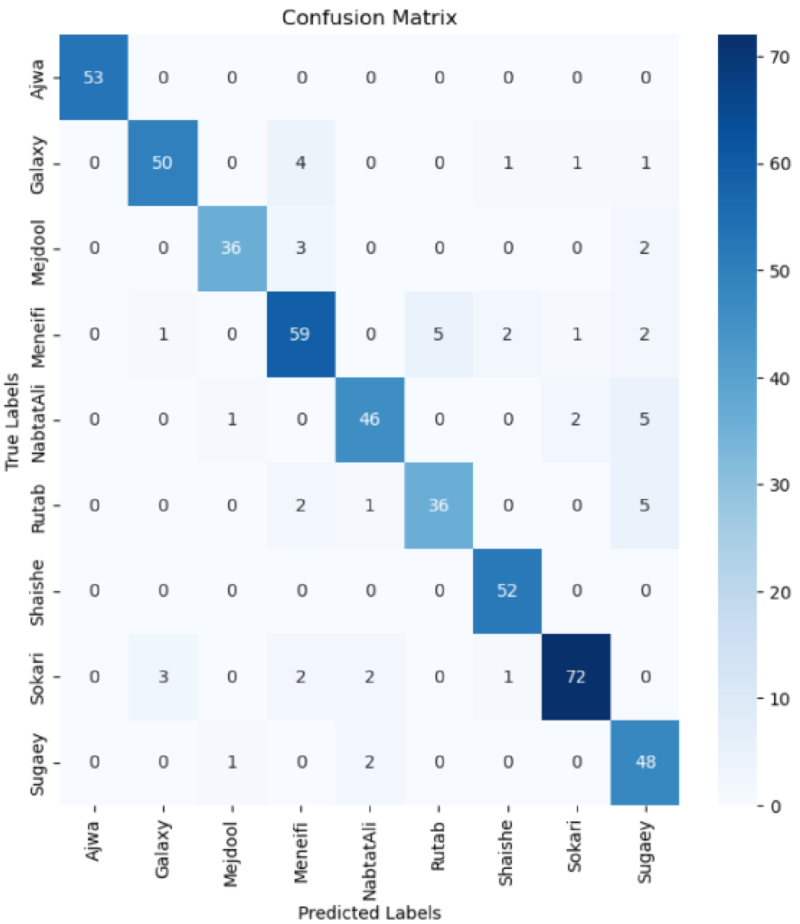
Classification Report

```
Classification Report:
              precision    recall  f1-score   support

        Ajwa       1.00      1.00      1.00        53
      Galaxy       0.93      0.88      0.90        57
     Mejdool       0.95      0.88      0.91        41
     Meneifi       0.84      0.84      0.84        70
   NabtatAli       0.90      0.85      0.88        54
       Rutab       0.88      0.82      0.85        44
     Shaishe       0.93      1.00      0.96        52
      Sokari       0.95      0.90      0.92        80
      Sugaey       0.76      0.94      0.84        51

    accuracy                           0.90       502
   macro avg       0.90      0.90      0.90       502
weighted avg       0.90      0.90      0.90       502
```

Confusion Matrix



Code

```
[ ]:
import numpy as np

import tensorflow as tf
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
import PIL
import matplotlib.pyplot as plt
```

```
[ ]:
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)
```

```
[ ]:
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
)
```

[ ]:
```
class_names = train_ds.class_names
print(class_names)

plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")

AUTOTUNE = tf.data.AUTOTUNE
```

[ ]:
```

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]
```

[ ]:
```

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()
```

[ ]:
```
epochs = 15
history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=epochs
)
```

[ ]:
```

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

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

epochs_range = range(epochs)
```

[ ]:

```
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()
```

[ ]:

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

[ ]:

```
test_images = np.array(test_images)
test_labels = np.array(test_labels)
```

[ ]:

```
predictions = model.predict(test_images)
predicted_labels = np.argmax(predictions, axis=1)
```

[ ]:

```
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)
```

[ ]:

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

[ ]:

```
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()
```

[ ]:

```
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()
```

[ ]:

```
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()
```