Mounting drive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import matplotlib.pyplot as plt
import numpy as np
import os
import PIL
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
```

```
import pathlib
dataset_url = '/content/drive/MyDrive/Colab Notebooks/dataset/'
data_dir = pathlib.Path(dataset_url)
```

```
image_count = len(list(data_dir.glob('**/*.jpg')))
print(image_count)
```

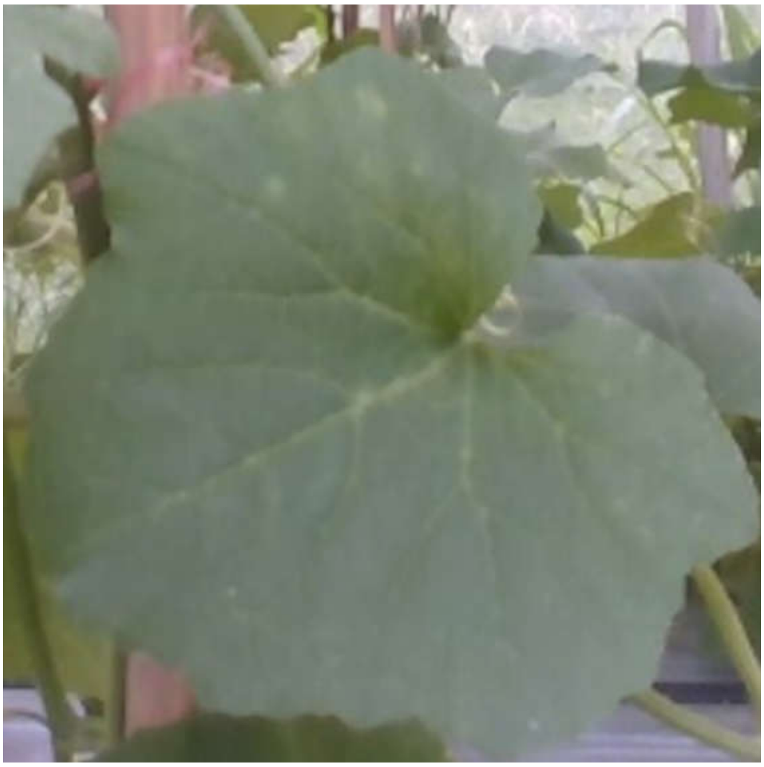
```
101
```

```
buah = list(data_dir.glob('**/buah/*'))
PIL.Image.open(str(buah[0]))
```

```
PIL.Image.open(str(buah[1]))
```

```
daun = list(data_dir.glob('**/daun/*'))
PIL.Image.open(str(daun[0]))
```

```
PIL.Image.open(str(daun[1]))
```



```
batch_size = 32
img_height = 180
img_width = 180
```

```
train_ds = tf.keras.utils.image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset="training",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

```
    Found 101 files belonging to 3 classes.
    Using 81 files for training.
```

```
val_ds = tf.keras.utils.image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset="validation",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

```
    Found 101 files belonging to 3 classes.
    Using 20 files for validation.
```

```
class_names = train_ds.class_names
print(class_names)
```

```
    ['buah', 'daun', 'testing']
```

```
import matplotlib.pyplot as plt
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")
```


```
for image_batch, labels_batch in train_ds:
  print(image_batch.shape)
  print(labels_batch.shape)
  break
```

```
(32, 180, 180, 3)
(32,)
```

```
AUTOTUNE = tf.data.AUTOTUNE
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_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]

# Notice the pixel values are now in `[0,1]`.
print(np.min(first_image), np.max(first_image))
```

```
0.0 0.8547599
```

```
num_classes = len(class_names)
model = Sequential([
  layers.Rescaling(1./255, input_shape=(img_height, img_width, 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, 180, 180, 3)       0         
                                                                 
 conv2d (Conv2D)             (None, 180, 180, 16)      448       
                                                                 
 max_pooling2d (MaxPooling2D  (None, 90, 90, 16)       0         
 )                                                               
                                                                 
 conv2d_1 (Conv2D)           (None, 90, 90, 32)        4640      
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 45, 45, 32)       0         
 2D)                                                             
                                                                 
 conv2d_2 (Conv2D)           (None, 45, 45, 64)        18496     
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 22, 22, 64)       0         
 2D)                                                             
                                                                 
 flatten (Flatten)           (None, 30976)             0         
                                                                 
 dense (Dense)               (None, 128)               3965056   
                                                                 
 dense_1 (Dense)             (None, 3)                 387       
                                                                 
=================================================================
Total params: 3,989,027
Trainable params: 3,989,027
Non-trainable params: 0
_________________________________________________________________
```

```
epochs=180
history = model.fit(
train_ds,
validation_data=val_ds,
epochs=epochs
)
```

```
Epoch 1/180
3/3 [==============================] - 10s 3s/step - loss: 1.1035 - accuracy: 0.5185 - val_loss: 0.6255 - val_accuracy: 0.6500
Epoch 2/180
3/3 [==============================] - 3s 1s/step - loss: 0.8423 - accuracy: 0.4691 - val_loss: 0.8067 - val_accuracy: 0.3500
Epoch 3/180
3/3 [==============================] - 5s 2s/step - loss: 0.7487 - accuracy: 0.5926 - val_loss: 0.7424 - val_accuracy: 0.5500
Epoch 4/180
3/3 [==============================] - 3s 935ms/step - loss: 0.6632 - accuracy: 0.7778 - val_loss: 0.5086 - val_accuracy: 0.8000
Epoch 5/180
3/3 [==============================] - 3s 961ms/step - loss: 0.5411 - accuracy: 0.8765 - val_loss: 0.4208 - val_accuracy: 0.8000
Epoch 6/180
3/3 [==============================] - 5s 2s/step - loss: 0.4495 - accuracy: 0.8889 - val_loss: 0.3666 - val_accuracy: 0.8500
Epoch 7/180
3/3 [==============================] - 4s 1s/step - loss: 0.3994 - accuracy: 0.9012 - val_loss: 0.4395 - val_accuracy: 0.7000
Epoch 8/180
3/3 [==============================] - 3s 1s/step - loss: 0.3240 - accuracy: 0.9136 - val_loss: 0.3150 - val_accuracy: 0.8500
Epoch 9/180
3/3 [==============================] - 3s 991ms/step - loss: 0.2689 - accuracy: 0.9383 - val_loss: 0.3186 - val_accuracy: 0.8000
Epoch 10/180
3/3 [==============================] - 6s 2s/step - loss: 0.1860 - accuracy: 0.9630 - val_loss: 0.3764 - val_accuracy: 0.8000
Epoch 11/180
3/3 [==============================] - 3s 957ms/step - loss: 0.1336 - accuracy: 0.9630 - val_loss: 0.3143 - val_accuracy: 0.8000
Epoch 12/180
3/3 [==============================] - 5s 2s/step - loss: 0.0789 - accuracy: 0.9877 - val_loss: 0.4299 - val_accuracy: 0.8000
Epoch 13/180
3/3 [==============================] - 3s 955ms/step - loss: 0.0504 - accuracy: 0.9877 - val_loss: 0.3013 - val_accuracy: 0.8500
Epoch 14/180
3/3 [==============================] - 3s 1s/step - loss: 0.0328 - accuracy: 1.0000 - val_loss: 0.7301 - val_accuracy: 0.8000
Epoch 15/180
3/3 [==============================] - 5s 2s/step - loss: 0.0160 - accuracy: 1.0000 - val_loss: 0.3902 - val_accuracy: 0.9000
Epoch 16/180
3/3 [==============================] - 3s 998ms/step - loss: 0.0205 - accuracy: 1.0000 - val_loss: 0.5683 - val_accuracy: 0.8000
Epoch 17/180
3/3 [==============================] - 3s 1s/step - loss: 0.0219 - accuracy: 1.0000 - val_loss: 0.7868 - val_accuracy: 0.8000
Epoch 18/180
3/3 [==============================] - 4s 1s/step - loss: 0.0106 - accuracy: 1.0000 - val_loss: 0.2962 - val_accuracy: 0.9000
Epoch 19/180
3/3 [==============================] - 3s 975ms/step - loss: 0.0069 - accuracy: 1.0000 - val_loss: 0.4110 - val_accuracy: 0.8500
Epoch 20/180
3/3 [==============================] - 3s 1s/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 0.7574 - val_accuracy: 0.8000
Epoch 21/180
3/3 [==============================] - 3s 1s/step - loss: 0.0029 - accuracy: 1.0000 - val_loss: 0.8247 - val_accuracy: 0.8000
Epoch 22/180
3/3 [==============================] - 3s 989ms/step - loss: 0.0014 - accuracy: 1.0000 - val_loss: 0.6453 - val_accuracy: 0.8000
Epoch 23/180
3/3 [==============================] - 3s 949ms/step - loss: 6.3638e-04 - accuracy: 1.0000 - val_loss: 0.5155 - val_accuracy: 0.
Epoch 24/180
3/3 [==============================] - 4s 1s/step - loss: 4.8480e-04 - accuracy: 1.0000 - val_loss: 0.4556 - val_accuracy: 0.850
Epoch 25/180
3/3 [==============================] - 3s 1s/step - loss: 5.3514e-04 - accuracy: 1.0000 - val_loss: 0.4352 - val_accuracy: 0.850
Epoch 26/180
3/3 [==============================] - 3s 990ms/step - loss: 5.3906e-04 - accuracy: 1.0000 - val_loss: 0.4462 - val_accuracy: 0.
Epoch 27/180
3/3 [==============================] - 3s 1s/step - loss: 4.1922e-04 - accuracy: 1.0000 - val_loss: 0.4690 - val_accuracy: 0.850
Epoch 28/180
3/3 [==============================] - 4s 2s/step - loss: 3.1578e-04 - accuracy: 1.0000 - val_loss: 0.5054 - val_accuracy: 0.850
Epoch 29/180
```

```
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()
```


```
sunflower_path = '/content/drive/MyDrive/Colab Notebooks/dataset/testing/bd_1.jpg'

img = tf.keras.utils.load_img(sunflower_path, target_size=(img_height, img_width))

img_array = tf.keras.utils.img_to_array(img)
img_array = tf.expand_dims(img_array, 0) # Create a batch

predictions = model.predict(img_array)
score = tf.nn.softmax(predictions[0])

print(
  "This image most likely belongs to {} with a {:.2f} percent confidence.".format(class_names[np.argmax(score)], 100 * np.max(score))
)
```

```
1/1 [==============================] - 0s 168ms/step
This image most likely belongs to testing with a 99.99 percent confidence.
```

✓ 0s completed at 10:19 AM