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Task: CNN (Flower Classification)

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

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

```
data_path="/content/drive/MyDrive/Flower Classification/Train"
```

```
import matplotlib.pyplot as plt
import numpy as np
import os
import PIL
import tensorflow as tf
from tensorflow.keras.optimizers import Adam
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
# Define hyperparameters
batch_size = 40
img_height = 256
img_width = 256
dropout_rate = 0.2
```

Tasks and Marks Division-CNN

Data Understanding, Analysis, Visualization and Cleaning[5]:

How many total images are in the dataset?

```
# Initialize a variable to store the total number of images
total_images = 0

# Iterate over the directory and its subdirectories
for root, dirs, files in os.walk(data_path):
    # Count the number of files in each directory
    num_files = len(files)
    # Add the number of files to the total_images variable
    total_images += num_files

# Print the total number of images
print("Total number of images:", total_images)
```

```
Total number of images: 4312
```

How many images per class?

```
# Count images per class
classes = os.listdir(data_path)     # List all the classes in the directory
images_per_class = {}             # Create an empty dictionary to store the number of images per class
for class_name in classes:        # Loop over each class and count the number of images
    class_path = os.path.join(data_path, class_name)      # Create a path to the current class directory
    if os.path.isdir(class_path):          # Check if the path is a directory (as opposed to a file)
        images_per_class[class_name] = len(os.listdir(class_path))          # Count the number of images in the directory and store it in the
print("Total number of images per classes:", images_per_class)
```

```
Total number of images per classes: {'sunflower': 732, 'daisy': 763, 'tulip': 983, 'rose': 783, 'dandelion': 1051}
```

How do you split between validation and train set?

```
train_ds = tf.keras.utils.image_dataset_from_directory(
    data_path,                  # Path to the directory containing the image data.
    batch_size=32,              # Number of images to include in each batch of training data.
    image_size=(256, 256),      # Size to resize the input images to.
    shuffle=True,               #  shuffle the order of the images each epoch.
    seed=100,                   # Random seed for shuffling the data.
    validation_split=0.1,        # Fraction of data to use for validation.
    subset="training",          # "training"  subset of the data.

  )
```

```
Found 4312 files belonging to 5 classes.
Using 3881 files for training.
```

```
val_ds = tf.keras.utils.image_dataset_from_directory(

    data_path,                  # Path to the directory containing the image data.
    batch_size=32,              # Number of images to include in each batch of training data.
    image_size=(256, 256),      # Size to resize the input images to.
    shuffle=True,               #   Whether to shuffle the order of the images each epoch.
    seed=100,                   # Random seed for shuffling the data.
    validation_split=0.3,         # Fraction of data to use for validation.
    subset="validation",        # "validation" subset of the data.

  )
```

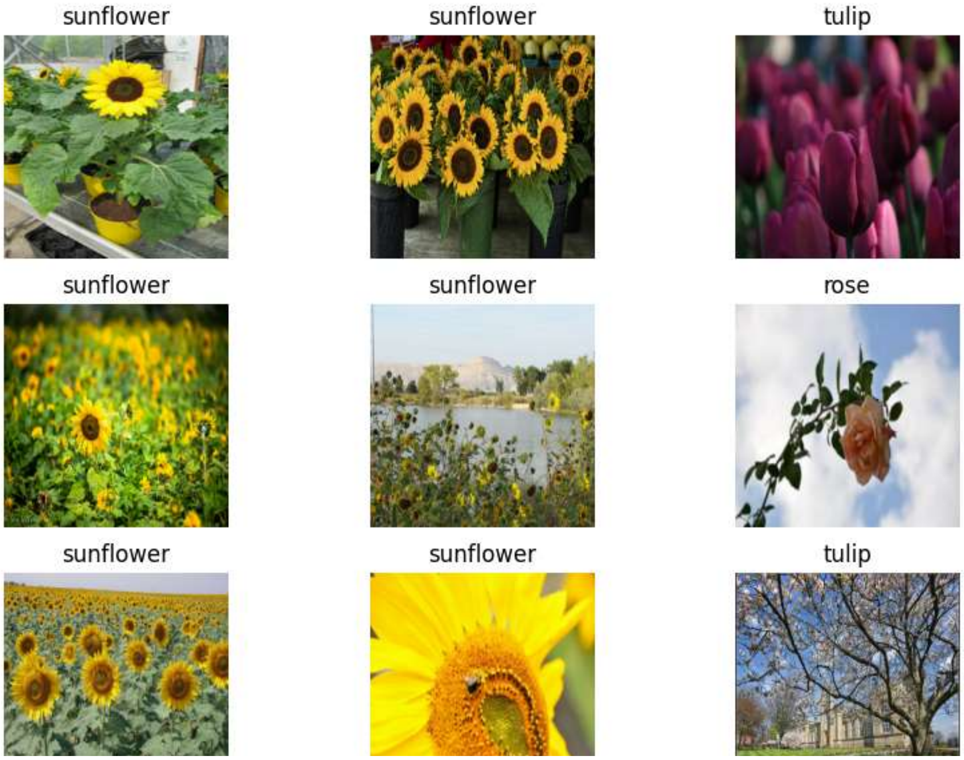
```
Found 4312 files belonging to 5 classes.
Using 1293 files for validation.
```

Visualization

```
# Printing out number of Classes
class_names = train_ds.class_names
print(class_names)
```

```
['daisy', 'dandelion', 'rose', 'sunflower', 'tulip']
```

```
#This code block is using Matplotlib to visualize a sample of 12 images from the train_ds dataset. Here's a brief comment on each line of cod
plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
  for i in range(12):
    ax = plt.subplot(4, 3, i + 1)
    plt.imshow(images[i].numpy().astype("uint8"))
    plt.title(class_names[labels[i]])
    plt.axis("off")
```



Build Model

Based on the size of your input image, design and build your CNN model. You can have as many layers you think is required for your task.

```
# Defining a function to generate a CNN model.
def generate_model(image_height, image_width, nchannels, num_classes):
  # Creating a sequential model.
  model = tf.keras.Sequential([
      # Rescaling and input layer, [For keras the input shape must be(image height, image width, channels)]
      layers.Rescaling(1./255, input_shape=(image_height,image_width, nchannels)),
      # First Block of Convolution and Pooling Operations.
      layers.Conv2D(filters=16, kernel_size=3, padding="same", activation="relu"),
      layers.MaxPooling2D(),
      # Second Block of Convolution and Pooling Operations.
      layers.Conv2D(filters=32, kernel_size=3, padding="same", activation="relu"),
      layers.MaxPooling2D(),

      # Fully connected classifier.
      layers.Flatten(),
      layers.Dense(128, activation="relu"),
      layers.Dropout(0.5),
      layers.BatchNormalization(),
      layers.Dense(num_classes, activation='softmax')
  ])
  return model
```

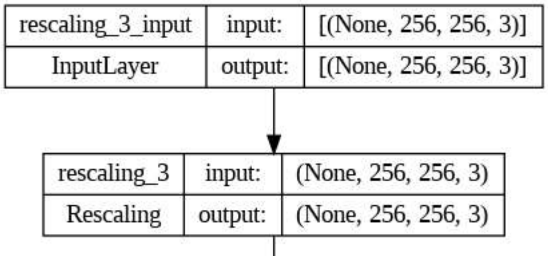
```
# In the given code, num_classes is calculated as the length of a list of class names, and then a model is generated using the generate_model
num_classes = len(class_names)
model = generate_model(img_height, img_width, 3, num_classes)
```

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_3 (Rescaling)     (None, 256, 256, 3)       0

 conv2d_6 (Conv2D)           (None, 256, 256, 16)      448

 max_pooling2d_6 (MaxPooling  (None, 128, 128, 16)     0
```

```
 2D)

 conv2d_7 (Conv2D)           (None, 128, 128, 32)      4640

 max_pooling2d_7 (MaxPooling  (None, 64, 64, 32)       0
 2D)

 flatten_3 (Flatten)         (None, 131072)            0

 dense_5 (Dense)             (None, 128)               16777344

 dropout_2 (Dropout)         (None, 128)               0

 batch_normalization_2 (Batc  (None, 128)              512
 hNormalization)

 dense_6 (Dense)             (None, 5)                 645

=================================================================
Total params: 16,783,589
Trainable params: 16,783,333
Non-trainable params: 256
_________________________________________________________________
```

```
keras.utils.plot_model(model, show_shapes=True)  # Plotting the neural network model.
```



Training of the Model

```
model.compile(loss="sparse_categorical_crossentropy",optimizer="adam",metrics=["accuracy"])    # Compiling the neural network model.
```

```
class Mycallback(tf.keras.callbacks.Callback):        # Defining a custom callback class.
  def on_epoch_end(self, epoch, logs={}):             # Overriding the on_epoch_end method of the Callback class.
    if(logs.get("accuracy")>0.95):                   #·Checking·if·the·accuracy·of·the·current·epoch·is·greater·than·0.95.
      print('\nLoss is low so stop training')
      self.model.stop_training =True
```

```
callbacks=Mycallback()
```

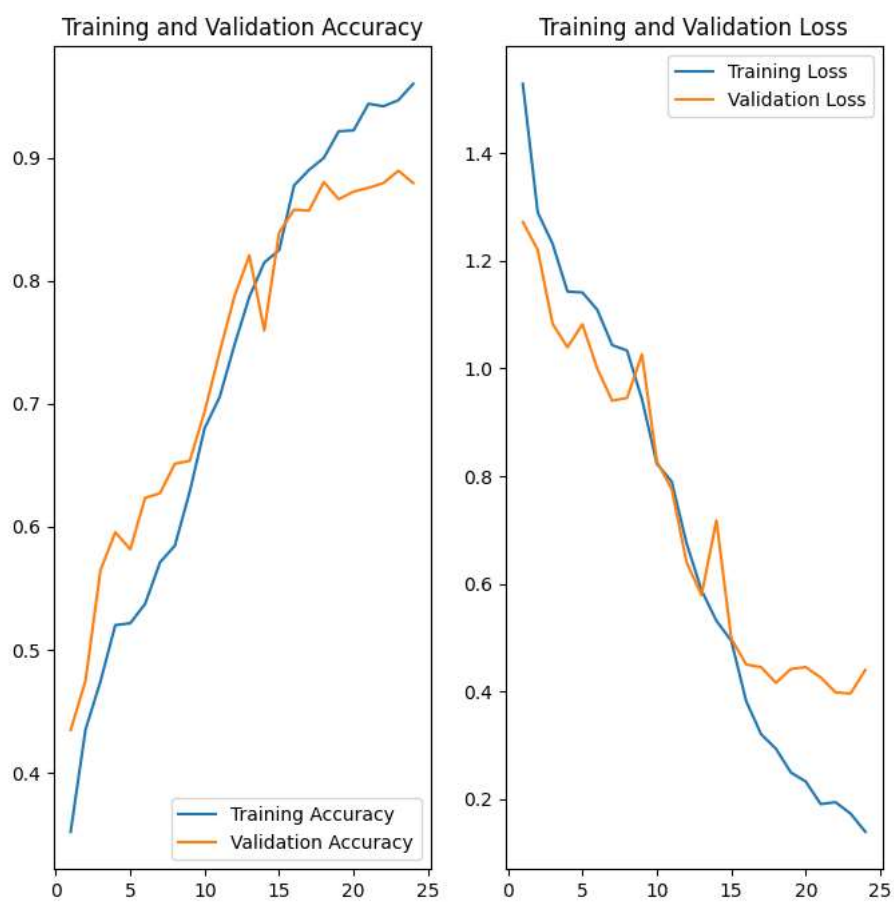
```
# Training the model and storing the history of training in a variable.
epochs = 30
history = model.fit(
  train_ds,              # Training dataset.
  validation_data=val_ds,   #  Validation dataset.
  epochs=epochs,        # Number of epochs to train for.
  callbacks=[callbacks]     # Custom callback to stop training early if accuracy is high enough.
)
```

```
Epoch 1/30
122/122 [==============================] - 28s 192ms/step - loss: 1.5293 - accuracy: 0.3520 - val_loss: 1.2723 - val_accuracy: 0.4346
Epoch 2/30
122/122 [==============================] - 16s 130ms/step - loss: 1.2905 - accuracy: 0.4352 - val_loss: 1.2206 - val_accuracy: 0.4749
Epoch 3/30
122/122 [==============================] - 16s 128ms/step - loss: 1.2318 - accuracy: 0.4741 - val_loss: 1.0832 - val_accuracy: 0.5646
Epoch 4/30
122/122 [==============================] - 19s 148ms/step - loss: 1.1431 - accuracy: 0.5200 - val_loss: 1.0394 - val_accuracy: 0.5955
Epoch 5/30
122/122 [==============================] - 16s 130ms/step - loss: 1.1413 - accuracy: 0.5215 - val_loss: 1.0823 - val_accuracy: 0.5816
Epoch 6/30
122/122 [==============================] - 16s 128ms/step - loss: 1.1093 - accuracy: 0.5372 - val_loss: 1.0000 - val_accuracy: 0.6234
Epoch 7/30
122/122 [==============================] - 16s 129ms/step - loss: 1.0435 - accuracy: 0.5710 - val_loss: 0.9402 - val_accuracy: 0.6272
Epoch 8/30
122/122 [==============================] - 18s 142ms/step - loss: 1.0333 - accuracy: 0.5846 - val_loss: 0.9453 - val_accuracy: 0.6512
Epoch 9/30
122/122 [==============================] - 21s 164ms/step - loss: 0.9431 - accuracy: 0.6287 - val_loss: 1.0263 - val_accuracy: 0.6535
Epoch 10/30
122/122 [==============================] - 18s 144ms/step - loss: 0.8230 - accuracy: 0.6802 - val_loss: 0.8277 - val_accuracy: 0.6937
Epoch 11/30
122/122 [==============================] - 16s 128ms/step - loss: 0.7897 - accuracy: 0.7052 - val_loss: 0.7757 - val_accuracy: 0.7417
Epoch 12/30
122/122 [==============================] - 18s 141ms/step - loss: 0.6746 - accuracy: 0.7477 - val_loss: 0.6396 - val_accuracy: 0.7873
Epoch 13/30
122/122 [==============================] - 17s 132ms/step - loss: 0.5879 - accuracy: 0.7869 - val_loss: 0.5787 - val_accuracy: 0.8206
Epoch 14/30
122/122 [==============================] - 16s 129ms/step - loss: 0.5311 - accuracy: 0.8147 - val_loss: 0.7176 - val_accuracy: 0.7595
Epoch 15/30
122/122 [==============================] - 16s 129ms/step - loss: 0.4939 - accuracy: 0.8248 - val_loss: 0.4979 - val_accuracy: 0.8391
Epoch 16/30
122/122 [==============================] - 16s 129ms/step - loss: 0.3817 - accuracy: 0.8774 - val_loss: 0.4498 - val_accuracy: 0.8577
Epoch 17/30
122/122 [==============================] - 17s 131ms/step - loss: 0.3204 - accuracy: 0.8900 - val_loss: 0.4449 - val_accuracy: 0.8569
Epoch 18/30
122/122 [==============================] - 16s 128ms/step - loss: 0.2931 - accuracy: 0.8998 - val_loss: 0.4158 - val_accuracy: 0.8801
Epoch 19/30
122/122 [==============================] - 16s 129ms/step - loss: 0.2490 - accuracy: 0.9214 - val_loss: 0.4414 - val_accuracy: 0.8662
Epoch 20/30
122/122 [==============================] - 18s 144ms/step - loss: 0.2322 - accuracy: 0.9222 - val_loss: 0.4450 - val_accuracy: 0.8724
Epoch 21/30
```

```
122/122 [==============================] - 16s 128ms/step - loss: 0.1904 - accuracy: 0.9438 - val_loss: 0.4258 - val_accuracy: 0.8755
Epoch 22/30
122/122 [==============================] - 16s 130ms/step - loss: 0.1939 - accuracy: 0.9418 - val_loss: 0.3980 - val_accuracy: 0.8794
Epoch 23/30
122/122 [==============================] - 22s 174ms/step - loss: 0.1729 - accuracy: 0.9467 - val_loss: 0.3959 - val_accuracy: 0.8894
Epoch 24/30
120/122 [============================>.] - ETA: 0s - loss: 0.1391 - accuracy: 0.9599
Loss is low so stop training
122/122 [==============================] - 16s 130ms/step - loss: 0.1389 - accuracy: 0.9601 - val_loss: 0.4397 - val_accuracy: 0.8794
```

Evaluate the model:

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

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

# Adjust the lengths of the arrays to match the actual number of epochs executed
epochs_range = range(1, len(acc) + 1)

# Creating a figure with two subplots to visualize the training and validation accuracy and loss over time.
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()
```



```
#In this code, we are evaluating the performance of our trained model on the test dataset, which we loaded earlier using the val_ds variable.
test_loss, test_accuracy = model.evaluate(val_ds)
print("Test Loss:", test_loss)
print("Test Accuracy:", test_accuracy)
```

```
41/41 [==============================] - 3s 71ms/step - loss: 0.4397 - accuracy: 0.8794
Test Loss: 0.43968042731285095
Test Accuracy: 0.8793503642082214
```

Results and Prediction:

```
# Function to predict input examples and plot the results
def predict_and_plot(model, dataset, class_names):
    plt.figure(figsize=(12, 12))
    for images, labels in dataset.take(1):
        predictions = model.predict(images)
        for i in range(9):
            ax = plt.subplot(3, 3, i + 1)
            plt.imshow(images[i].numpy().astype("uint8"))
            plt.title(class_names[np.argmax(predictions[i])])
            plt.axis("off")

# Create test dataset
test_dir = "/content/drive/MyDrive/Flower Classification/test"
test_ds = tf.keras.utils.image_dataset_from_directory(
    test_dir,
    batch_size=32,
    image_size=(256, 256),
    shuffle=True
)

# Evaluate the model on the test dataset
test_loss, test_accuracy = model.evaluate(test_ds)
print("Test Loss:", test_loss)
print("Test Accuracy:", test_accuracy)

# Predict and plot examples from the test set
predict_and_plot(model, test_ds, class_names)
```

```
Found 50 files belonging to 5 classes.
2/2 [==============================] - 0s 20ms/step - loss: 0.2566 - accuracy: 0.9200
Test Loss: 0.2565712034702301
Test Accuracy: 0.9200000166893005
1/1 [==============================] - 0s 93ms/step
```


```
sunflower_url = "/content/drive/MyDrive/Flower Classification/test/dandelion/13910677675_4900fa3dbf_n.jpg"


#This line loads the image from the given path using tf.keras.utils.load_img method and resizes it to the target size specified by img_height
img = tf.keras.utils.load_img(
    sunflower_url, target_size=(img_height, img_width)
)
img_array = tf.keras.utils.img_to_array(img)      #This line converts the image loaded in the previous step to a numpy array using tf.keras.u
img_array = tf.expand_dims(img_array, 0)

predictions = model.predict(img_array)        #This line uses the loaded trained model to make predictions on the image numpy array 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 18ms/step
This image most likely belongs to dandelion with a 40.25 percent confidence.
```

After conducting an evaluation of the model's accuracy on the validation and test sets, it was found that the model had a test accuracy of 87.94% and a test loss of 0.4397 on the validation set, and a test accuracy of 92% and a test loss of 0.2566 on the test set. These results indicate that the model performs well in predicting the correct class for flower images and has good generalization ability.

To meet the model requirements, we must use the prediction and plot functions to predict the classes and visually inspect the performance of the model on the test set. The evaluate method was used to calculate the overall accuracy and loss of the model on a dataset of 50 images with five different classes of flowers.

In summary, the model's performance on the validation and test sets was satisfactory, and the plot function was used to visually assess the model's performance on the test set. The evaluate method was used to determine the accuracy and loss of the model on a given dataset.

Fine-tuning a pre-trained model(Transfer Learning):

```
#one-hot encoding of the target labels in the train_ds and val_ds datasets.
train_ds = train_ds.map(lambda x, y: (x, tf.one_hot(y, depth=5)))
val_ds = val_ds.map(lambda x, y: (x, tf.one_hot(y, depth=5)))
```

```
#Rsnet 50 model
resnet_model = Sequential()

pretrained_model= tf.keras.applications.ResNet50(include_top=False,
                   input_shape=(256,256,3),
                   pooling='avg',classes=5,
                   weights='imagenet')
for layer in pretrained_model.layers:
        layer.trainable=False

resnet_model.add(pretrained_model)
```

```
resnet_model.add(Flatten())
resnet_model.add(Dense(512, activation='relu'))
resnet_model.add(Dropout(0.5)),
resnet_model.add(BatchNormalization()),
resnet_model.add(Dense(5, activation='softmax'))
```

```
resnet_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 resnet50 (Functional)       (None, 2048)              23587712  
                                                                 
 module_wrapper (ModuleWrapp  (None, 2048)             0         
 er)                                                             
                                                                 
 module_wrapper_1 (ModuleWra  (None, 512)              1049088   
 pper)                                                           
                                                                 
 dropout (Dropout)           (None, 512)               0         
                                                                 
 batch_normalization (BatchN  (None, 512)              2048      
 ormalization)                                                   
                                                                 
 module_wrapper_2 (ModuleWra  (None, 5)                2565      
 pper)                                                           
                                                                 
=================================================================
Total params: 24,641,413
Trainable params: 1,052,677
Non-trainable params: 23,588,736
_________________________________________________________________
```

```
resnet_model.compile(optimizer=Adam(lr=0.001),loss='categorical_crossentropy',metrics=['accuracy'])
```

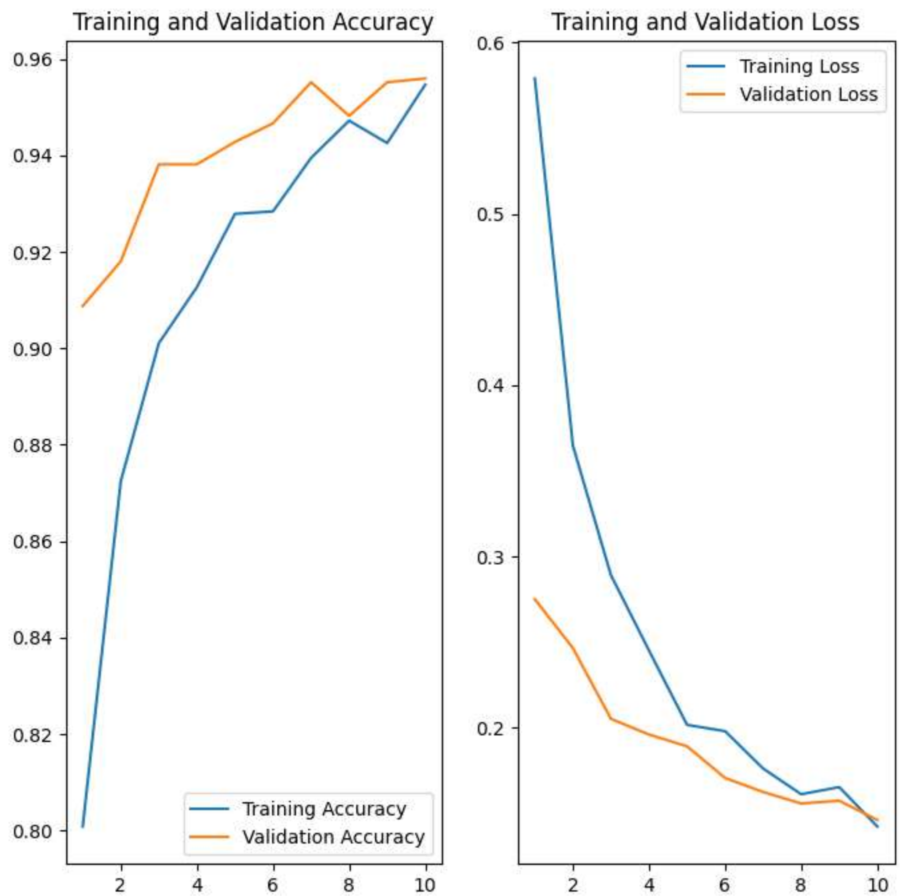
```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer, e.g.,tf.keras.optimizers.leg
```

```
epochs=10
history = resnet_model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/10
122/122 [==============================] - 670s 5s/step - loss: 0.5790 - accuracy: 0.8008 - val_loss: 0.2749 - val_accuracy: 0.9087
Epoch 2/10
122/122 [==============================] - 22s 178ms/step - loss: 0.3647 - accuracy: 0.8725 - val_loss: 0.2464 - val_accuracy: 0.9180
Epoch 3/10
122/122 [==============================] - 23s 187ms/step - loss: 0.2890 - accuracy: 0.9011 - val_loss: 0.2051 - val_accuracy: 0.9381
Epoch 4/10
122/122 [==============================] - 27s 219ms/step - loss: 0.2450 - accuracy: 0.9127 - val_loss: 0.1959 - val_accuracy: 0.9381
Epoch 5/10
122/122 [==============================] - 23s 183ms/step - loss: 0.2016 - accuracy: 0.9279 - val_loss: 0.1890 - val_accuracy: 0.9428
Epoch 6/10
122/122 [==============================] - 28s 217ms/step - loss: 0.1979 - accuracy: 0.9284 - val_loss: 0.1705 - val_accuracy: 0.9466
Epoch 7/10
122/122 [==============================] - 27s 216ms/step - loss: 0.1761 - accuracy: 0.9394 - val_loss: 0.1623 - val_accuracy: 0.9551
Epoch 8/10
122/122 [==============================] - 27s 217ms/step - loss: 0.1610 - accuracy: 0.9472 - val_loss: 0.1556 - val_accuracy: 0.9482
Epoch 9/10
122/122 [==============================] - 27s 216ms/step - loss: 0.1652 - accuracy: 0.9425 - val_loss: 0.1573 - val_accuracy: 0.9551
Epoch 10/10
122/122 [==============================] - 27s 216ms/step - loss: 0.1422 - accuracy: 0.9547 - val_loss: 0.1460 - val_accuracy: 0.9559
```

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

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

# Adjust the lengths of the arrays to match the actual number of epochs executed
epochs_range = range(1, len(acc) + 1)

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_url = "/content/drive/MyDrive/Flower Classification/test/roses/21413573151_e681c6a97a.jpg"


img = tf.keras.utils.load_img(
    sunflower_url, 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 = resnet_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 25ms/step
This image most likely belongs to rose with a 36.34 percent confidence.
```

● ×