Demo python programming

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Setup

Import TensorFlow and other necessary libraries:

```
import matplotlib.pyplot as plt
import numpy as np
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 = "https://storage.googleapis.com/download.tensorflow.org/example_images/flower_photos.tgz"
data_dir = tf.keras.utils.get_file('flower_photos', origin=dataset_url, untar=True)
data_dir = pathlib.Path(data_dir)
```

```
Downloading data from https://storage.googleapis.com/download.tensorflow.org/example_images/flower_photos.tgz
228813984/228813984 [==============================] - 3s 0us/step
```

After downloading, you should now have a copy of the dataset available. There are 3,670 total images:

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

```
3670
```

Here are some roses:

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

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

And some tulips:

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

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

Define some parameters for the loader:

```
[ ]  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 3670 files belonging to 5 classes.
Using 2936 files for training.
```


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```
[ ] 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 3670 files belonging to 5 classes.
Using 734 files for validation.
```

You can find the class names in the `class_names` attribute on these datasets. These correspond to the directory names in alphabetical order.

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

```
['daisy', 'dandelion', 'roses', 'sunflowers', 'tulips']
```


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Visualize the data

Here are the first nine images from the training dataset:

```
[ ] 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")
```

You will pass these datasets to the Keras `Model.fit` method for training later in this tutorial. If you like, you can also manually iterate over the dataset and retrieve batches of images:

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

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

Configure the dataset for performance

Make sure to use buffered prefetching, so you can yield data from disk without having I/O become blocking.

```
AUTOTUNE = tf.data.AUTOTUNE

train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

Standardize the data

The RGB channel values are in the `[0, 255]` range. This is not ideal for a neural network; in general you should seek to make your input values small.

Here, you will standardize values to be in the `[0, 1]` range by using `tf.keras.layers.Rescaling`:

```
[ ]  normalization_layer = layers.Rescaling(1./255)
```

There are two ways to use this layer. You can apply it to the dataset by calling `Dataset.map`:

```
[ ]  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 1.0
```

A basic CNN model

Create the model

```
[ ] 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)
    ])
```


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Compile the model

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

Model summary

View all the layers of the network using the Keras `Model.summary` method:

```
[ ] model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_2 (Rescaling)     (None, 180, 180, 3)       0

 conv2d_3 (Conv2D)           (None, 180, 180, 16)      448

 max_pooling2d_3 (MaxPooling  (None, 90, 90, 16)       0
 2D)

 conv2d_4 (Conv2D)           (None, 90, 90, 32)        4640

 max_pooling2d_4 (MaxPooling  (None, 45, 45, 32)       0
 2D)

 conv2d_5 (Conv2D)           (None, 45, 45, 64)        18496

 max_pooling2d_5 (MaxPooling  (None, 22, 22, 64)       0
 2D)

 flatten_1 (Flatten)         (None, 30976)             0

 dense_2 (Dense)             (None, 128)               3965056

 dense_3 (Dense)             (None, 5)                 645

=================================================================
Total params: 3,989,285
Trainable params: 3,989,285
Non-trainable params: 0
_________________________________________________________________
```

Train the model

Train the model for 10 epochs with the Keras `Model.fit` method:

```
[ ]  epochs=10
     history = model.fit(
       train_ds,
       validation_data=val_ds,
       epochs=epochs
     )
```

```
Epoch 1/10
92/92 [==============================] - 11s 37ms/step - loss: 1.3572 - accuracy: 0.4012 - val_loss: 1.1089 - val_accuracy: 0.5681
Epoch 2/10
92/92 [==============================] - 2s 23ms/step - loss: 1.0010 - accuracy: 0.6046 - val_loss: 0.9536 - val_accuracy: 0.5940
Epoch 3/10
92/92 [==============================] - 2s 23ms/step - loss: 0.8055 - accuracy: 0.7027 - val_loss: 0.9053 - val_accuracy: 0.6594
Epoch 4/10
92/92 [==============================] - 2s 24ms/step - loss: 0.5934 - accuracy: 0.7854 - val_loss: 0.9686 - val_accuracy: 0.6526
Epoch 5/10
92/92 [==============================] - 2s 24ms/step - loss: 0.3918 - accuracy: 0.8658 - val_loss: 1.0422 - val_accuracy: 0.6594
Epoch 6/10
92/92 [==============================] - 2s 25ms/step - loss: 0.2248 - accuracy: 0.9244 - val_loss: 1.1349 - val_accuracy: 0.6594
Epoch 7/10
92/92 [==============================] - 2s 23ms/step - loss: 0.1493 - accuracy: 0.9554 - val_loss: 1.3704 - val_accuracy: 0.6608
Epoch 8/10
92/92 [==============================] - 2s 23ms/step - loss: 0.1043 - accuracy: 0.9687 - val_loss: 1.5848 - val_accuracy: 0.6730
Epoch 9/10
92/92 [==============================] - 2s 23ms/step - loss: 0.0328 - accuracy: 0.9939 - val_loss: 1.9913 - val_accuracy: 0.6485
Epoch 10/10
92/92 [==============================] - 2s 25ms/step - loss: 0.0170 - accuracy: 0.9973 - val_loss: 2.1011 - val_accuracy: 0.6553
```


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Visualize training results

Create plots of the loss and accuracy on the training and validation sets:

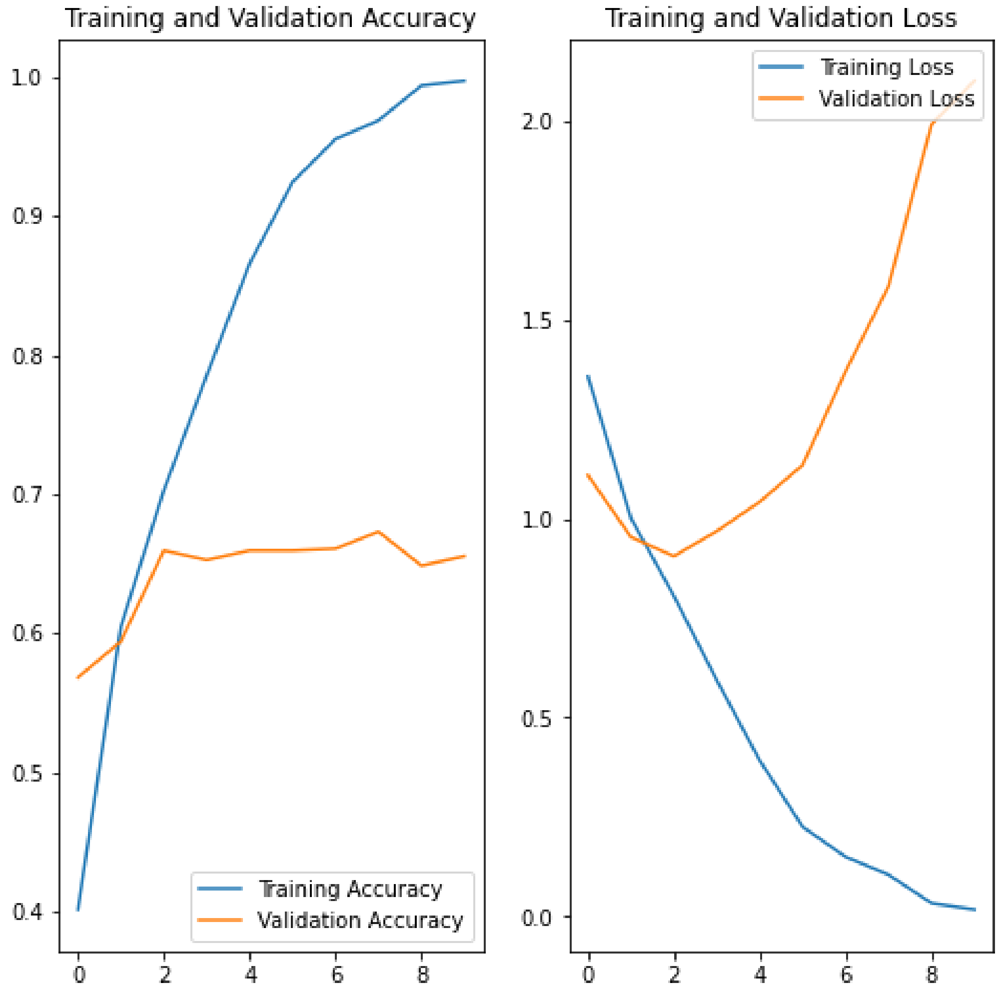
```
[ ] acc = history.history['accuracy']
    val_acc = history.history['val_accuracy']

    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()
```



State of the Art-CNN model Resnet50

```
[ ] from tensorflow.keras.models import Model
    from tensorflow.keras.layers import Conv2D,Flatten,Dense,MaxPool2D,BatchNormalization,GlobalAveragePooling2D
    from tensorflow.keras.applications.resnet50 import preprocess_input,decode_predictions
    from tensorflow.keras.preprocessing.image import ImageDataGenerator,load_img
    from tensorflow.keras.applications.resnet50 import ResNet50
    from tensorflow.keras.preprocessing import image
```

```
base_model = ResNet50(include_top=False,weights= 'imagenet')
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024,activation='relu')(x)
predictions = Dense(5,activation='softmax')(x)
model = Model(inputs=base_model.input,outputs=predictions)

for layer in base_model.layers:
    layer.trainable = False

    model.compile(optimizer='adam',loss='categorical_crossentropy',metrics = ['accuracy'])
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736 [==============================] - 0s 0us/step
```

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

Model summary

View all the layers of the network using the Keras Model.summary method:

```
[ ] model.summary()
```

```
 conv2_block3_1_bn (BatchNormal  (None, None, None,   256        ['conv2_block3_1_conv[0][0]']
 ization)                       64)

 conv2_block3_1_relu (Activatio  (None, None, None,   0          ['conv2_block3_1_bn[0][0]']
 n)                             64)

 conv2_block3_2_conv (Conv2D)   (None, None, None,   36928      ['conv2_block3_1_relu[0][0]']
                                64)

 conv2_block3_2_bn (BatchNormal  (None, None, None,   256        ['conv2_block3_2_conv[0][0]']
 ization)                       64)

 conv2_block3_2_relu (Activatio  (None, None, None,   0          ['conv2_block3_2_bn[0][0]']
 n)                             64)

 conv2_block3_3_conv (Conv2D)   (None, None, None,   16640      ['conv2_block3_2_relu[0][0]']
                                256)

 conv2_block3_3_bn (BatchNormal  (None, None, None,   1024       ['conv2_block3_3_conv[0][0]']
 ization)                       256)

                                  ⋮

 global_average_pooling2d (Glob  (None, 2048)        0           ['conv5_block3_out[0][0]']
 alAveragePooling2D)

 dense_4 (Dense)                (None, 1024)         2098176     ['global_average_pooling2d[0][0]'
                                                                  ]

 dense_5 (Dense)                (None, 5)            5125        ['dense_4[0][0]']

==================================================================================================
Total params: 25,691,013
Trainable params: 2,103,301
Non-trainable params: 23,587,712
__________________________________________________________________________________________________
```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```python
epochs=10
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/10
/usr/local/lib/python3.8/dist-packages/tensorflow/python/util/dispatch.py:1082: UserWarning: "`sparse_categorical_crossentropy` received
  return dispatch_target(*args, **kwargs)
92/92 [==============================] - 14s 110ms/step - loss: 0.7490 - accuracy: 0.7793 - val_loss: 0.3433 - val_accuracy: 0.8828
Epoch 2/10
92/92 [==============================] - 8s 89ms/step - loss: 0.2634 - accuracy: 0.9077 - val_loss: 0.3493 - val_accuracy: 0.8815
Epoch 3/10
92/92 [==============================] - 8s 88ms/step - loss: 0.1460 - accuracy: 0.9482 - val_loss: 0.4676 - val_accuracy: 0.8447
Epoch 4/10
92/92 [==============================] - 8s 89ms/step - loss: 0.0860 - accuracy: 0.9741 - val_loss: 0.4188 - val_accuracy: 0.8719
Epoch 5/10
92/92 [==============================] - 8s 90ms/step - loss: 0.0444 - accuracy: 0.9905 - val_loss: 0.3737 - val_accuracy: 0.8815
Epoch 6/10
92/92 [==============================] - 8s 91ms/step - loss: 0.0207 - accuracy: 0.9966 - val_loss: 0.4846 - val_accuracy: 0.8583
Epoch 7/10
92/92 [==============================] - 9s 102ms/step - loss: 0.0175 - accuracy: 0.9976 - val_loss: 0.3954 - val_accuracy: 0.9005
Epoch 8/10
92/92 [==============================] - 8s 91ms/step - loss: 0.0056 - accuracy: 1.0000 - val_loss: 0.4361 - val_accuracy: 0.8828
Epoch 9/10
92/92 [==============================] - 8s 91ms/step - loss: 0.0034 - accuracy: 1.0000 - val_loss: 0.4233 - val_accuracy: 0.8951
Epoch 10/10
92/92 [==============================] - 8s 91ms/step - loss: 0.0019 - accuracy: 1.0000 - val_loss: 0.4222 - val_accuracy: 0.8910
```


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```
[ ] 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()
```

Thank you

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