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Subject - FCI

Experiment No. 2

Aim - Performing image classification through CNN

This model shows how to classify images of flowers. It creates an image classifier using a `keras.Sequential` model, and loads data using `preprocessing.image_dataset_from_directory`.

Import TensorFlow and other libraries

```
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
```

Download and explore the dataset

This tutorial uses a dataset of about 3,700 photos of flowers. The dataset contains 5 sub-directories, one per class:

```
flower_photo/
  daisy/
  dandelion/
  roses/
  sunflowers/
  tulips/
```

```
import pathlib
dataset_url = "https://storage.googleapis.com/download.tensorflow.org/example_images/flower_p
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_ima
228818944/228813984 [==============================] - 1s 0us/step
```

In the dataset, 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]))
```

Load using keras.preprocessing

Let's load these images off disk using the helpful [image_dataset_from_directory](https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/image_dataset_from_directory) utility. This will take you from a directory of images on disk to a `tf.data.Dataset` in just a couple lines of code.

Create a dataset

Define some parameters for the loader:

```
batch_size = 32
```

```
img_height = 180
img_width = 180
```

Here, we use 80% of the images for training, and 20% for validation.

```
train_ds = tf.keras.preprocessing.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.
```

```
val_ds = tf.keras.preprocessing.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']
```

Visualize the data

Here are the first 9 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.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,)
```

The `image_batch` is a tensor of the shape `(32, 180, 180, 3)`. This is a batch of 32 images of shape `180x180x3` (the last dimension refers to color channels RGB). The `label_batch` is a tensor of the shape `(32,)`, these are corresponding labels to the 32 images.

Configure the dataset for performance

Let's make sure to use buffered prefetching so you can yield data from disk without having I/O become blocking. These are two important methods you should use when loading data.

`Dataset.cache()` keeps the images in memory after they're loaded off disk during the first epoch. This will ensure the dataset does not become a bottleneck while training your model.

`Dataset.prefetch()` overlaps data preprocessing and model execution while training.

```
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 a Rescaling layer.

```
normalization_layer = layers.experimental.preprocessing.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 pixels values are now in `[0,1]`.
print(np.min(first_image), np.max(first_image))
```

```
0.0 1.0
```

Create the model

The model consists of three convolution blocks with a max pool layer in each of them. There's a fully connected layer with 128 units on top of it that is activated by a `relu` activation function.

```
num_classes = 5

model = Sequential([
  layers.experimental.preprocessing.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)
  ])
```

Compile the model

Here, chose the `optimizers.Adam` optimizer and `losses.SparseCategoricalCrossentropy` loss function. To view training and validation accuracy for each training epoch, pass the `metrics` argument.

```
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 model's `summary` method:

```
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 (MaxPooling2 (None, 45, 45, 32)        0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 45, 45, 64)        18496     
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 22, 22, 64)        0         
_________________________________________________________________
flatten (Flatten)            (None, 30976)             0         
_________________________________________________________________
dense (Dense)                (None, 128)               3965056   
_________________________________________________________________
dense_1 (Dense)              (None, 5)                 645       
=================================================================
Total params: 3,989,285
Trainable params: 3,989,285
```

```
Non-trainable params: 0
_________________________________________________________________
```

Train the model

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

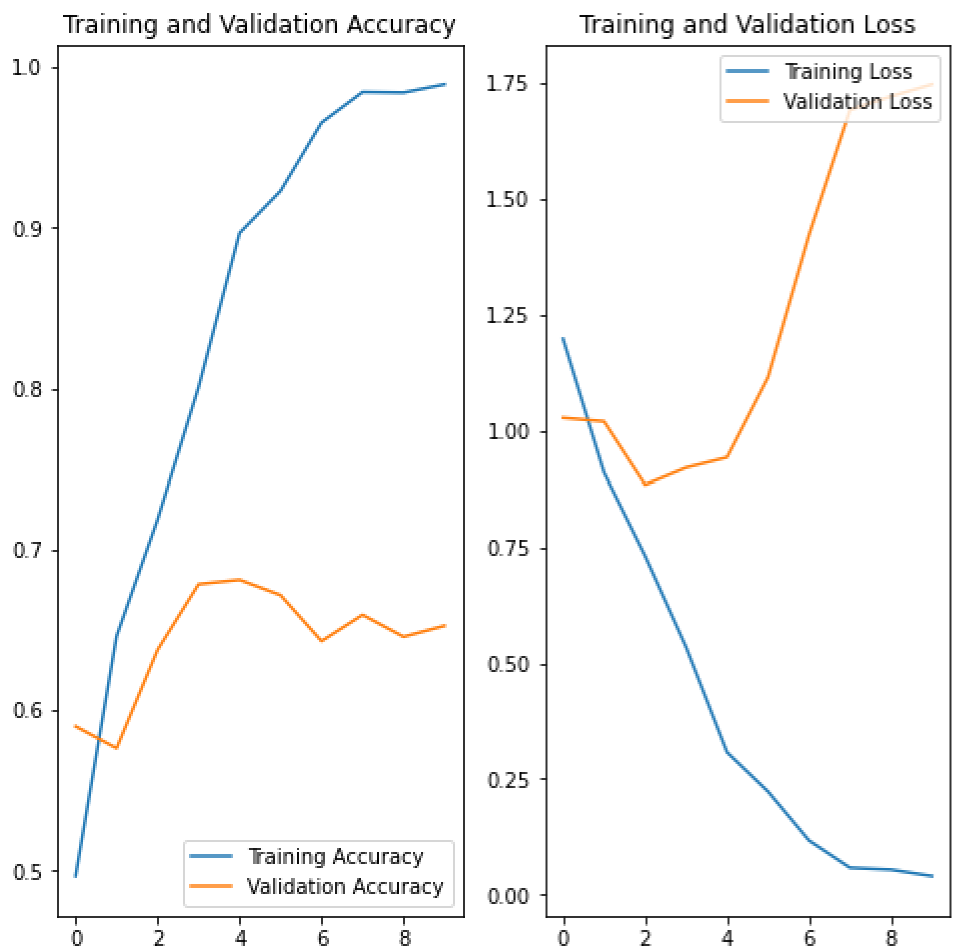
```
Epoch 1/10
92/92 [==============================] - 35s 35ms/step - loss: 1.1978 - accuracy: 0.496(
Epoch 2/10
92/92 [==============================] - 2s 20ms/step - loss: 0.9097 - accuracy: 0.6461
Epoch 3/10
92/92 [==============================] - 2s 20ms/step - loss: 0.7311 - accuracy: 0.7187
Epoch 4/10
92/92 [==============================] - 2s 20ms/step - loss: 0.5344 - accuracy: 0.8007
Epoch 5/10
92/92 [==============================] - 2s 20ms/step - loss: 0.3074 - accuracy: 0.8968
Epoch 6/10
92/92 [==============================] - 2s 20ms/step - loss: 0.2226 - accuracy: 0.9230
Epoch 7/10
92/92 [==============================] - 2s 20ms/step - loss: 0.1168 - accuracy: 0.9656
Epoch 8/10
92/92 [==============================] - 2s 20ms/step - loss: 0.0580 - accuracy: 0.9847
Epoch 9/10
92/92 [==============================] - 2s 20ms/step - loss: 0.0539 - accuracy: 0.9843
Epoch 10/10
92/92 [==============================] - 2s 20ms/step - loss: 0.0401 - accuracy: 0.9894
```

Visualize training results

Create plots of 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()
```



Here, as it is seen, training accuracy and validation accuracy are off by large margin and the model has achieved only around 60% accuracy on the validation set.

Let's look at what went wrong and try to increase the overall performance of the model.

Overfitting

In the plots above, the training accuracy is increasing linearly over time, whereas validation accuracy stalls around 60% in the training process. Also, the difference in accuracy between training and validation accuracy is noticeable—a sign of overfitting.

When there are a small number of training examples, the model sometimes learns from noises or unwanted details from training examples—to an extent that it negatively impacts the performance of the model on new examples. This phenomenon is known as overfitting. It means that the model will have a difficult time generalizing on a new dataset.

There are multiple ways to fight overfitting in the training process. In this tutorial, you'll use *data augmentation* and add *Dropout* to your model.

Data augmentation

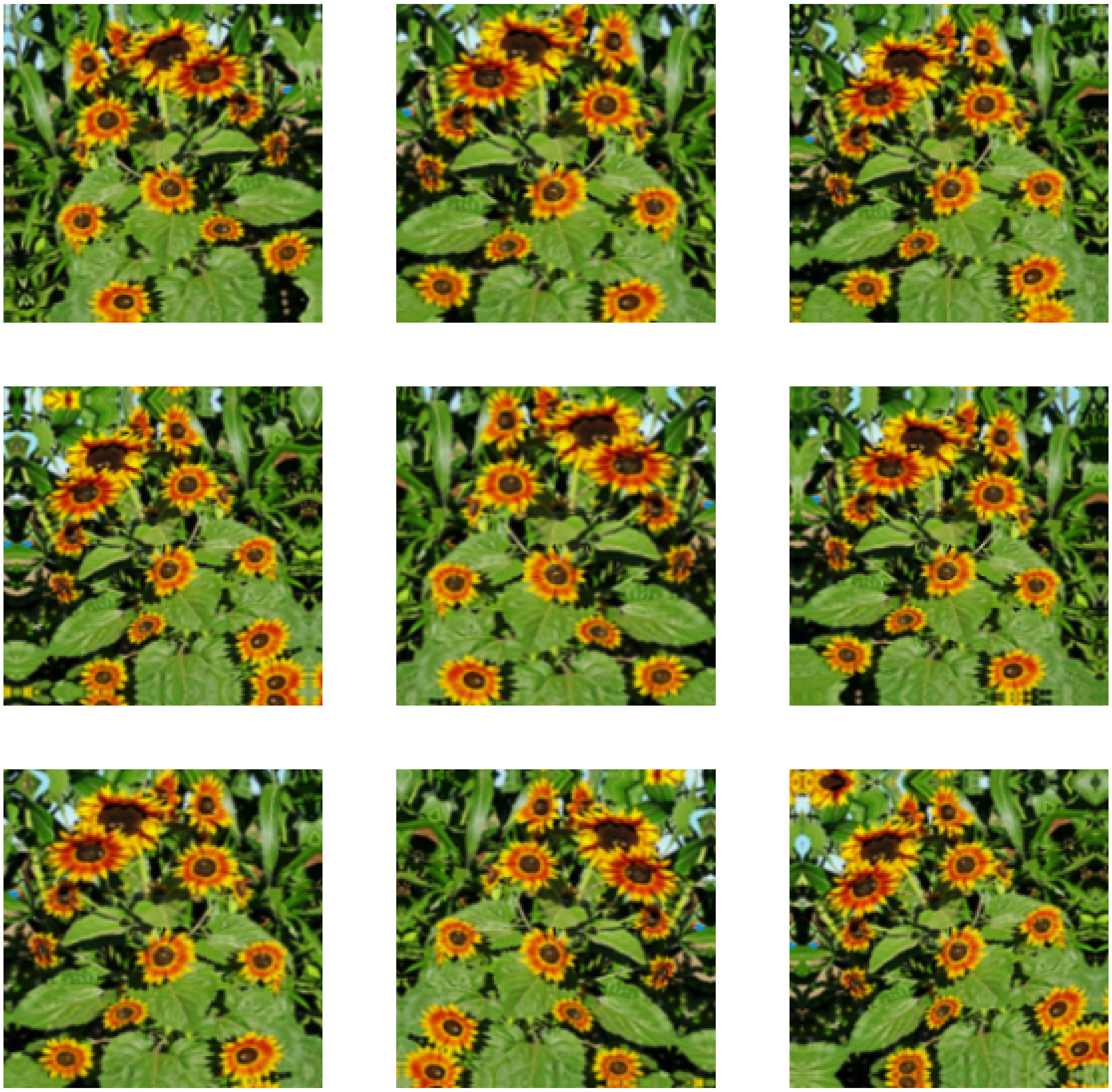
Overfitting generally occurs when there are a small number of training examples. Data augmentation takes the approach of generating additional training data from your existing examples by augmenting them using random transformations that yield believable-looking images. This helps expose the model to more aspects of the data and generalize better.

You will implement data augmentation using the layers from `tf.keras.layers.experimental.preprocessing`. These can be included inside your model like other layers, and run on the GPU.

```
data_augmentation = keras.Sequential(
  [
    layers.experimental.preprocessing.RandomFlip("horizontal",
                                                 input_shape=(img_height,
                                                              img_width,
                                                              3)),
    layers.experimental.preprocessing.RandomRotation(0.1),
    layers.experimental.preprocessing.RandomZoom(0.1),
  ]
)
```

Let's visualize what a few augmented examples look like by applying data augmentation to the same image several times:

```
plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
  for i in range(9):
    augmented_images = data_augmentation(images)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")
```



Dropout

Another technique to reduce overfitting is to introduce Dropout to the network, a form of *regularization*.

When you apply Dropout to a layer it randomly drops out (by setting the activation to zero) a number of output units from the layer during the training process. Dropout takes a fractional number as its input value, in the form such as 0.1, 0.2, 0.4, etc. This means dropping out 10%, 20% or 40% of the output units randomly from the applied layer.

Let's create a new neural network using `layers.Dropout`, then train it using augmented images.

```
model = Sequential([
  data_augmentation,
  layers.experimental.preprocessing.Rescaling(1./255),
  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.Dropout(0.2),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(num_classes)
  ])
```

Compile and train the model

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

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
sequential_1 (Sequential)    (None, 180, 180, 3)       0         
_________________________________________________________________
rescaling_2 (Rescaling)      (None, 180, 180, 3)       0         
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 180, 180, 16)      448       
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 90, 90, 16)        0         
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 90, 90, 32)        4640      
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 45, 45, 32)        0         
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 45, 45, 64)        18496     
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 22, 22, 64)        0         
_________________________________________________________________
dropout (Dropout)            (None, 22, 22, 64)        0         
_________________________________________________________________
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
_________________________________________________________________
```

```
epochs = 15
```

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

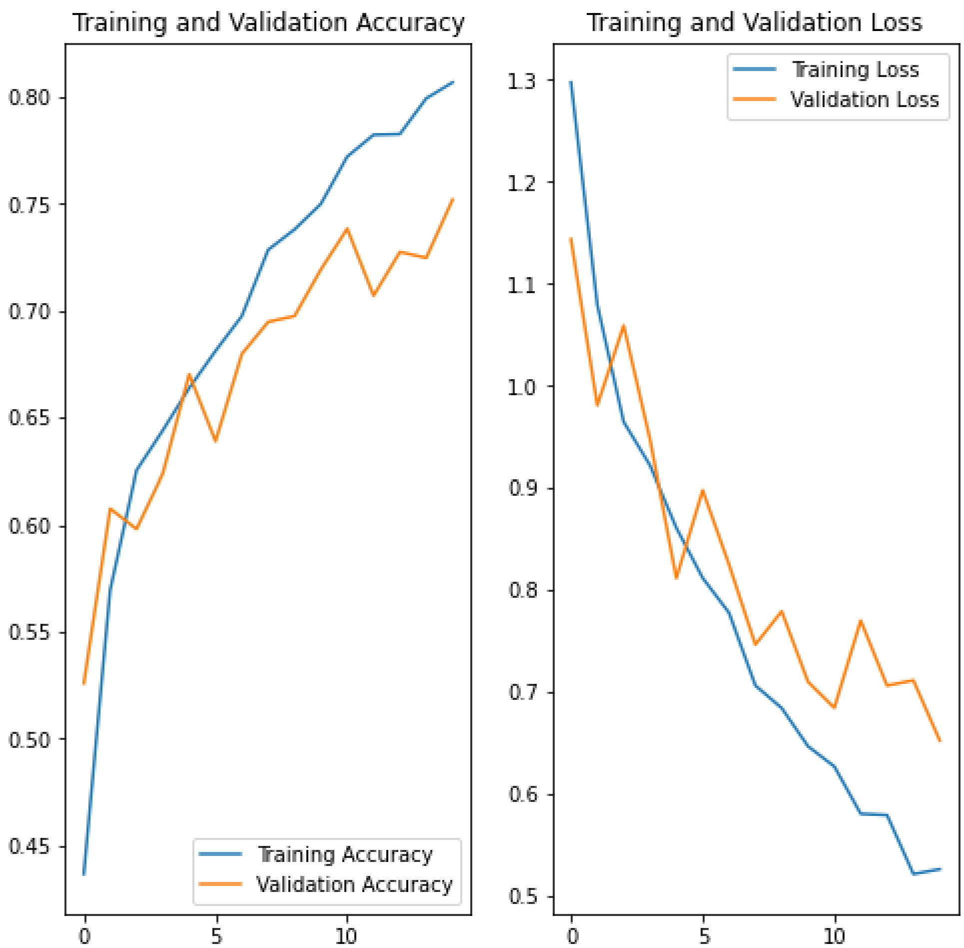
```
Epoch 1/15
92/92 [==============================] - 3s 24ms/step - loss: 1.2975 - accuracy: 0.4366
Epoch 2/15
92/92 [==============================] - 2s 22ms/step - loss: 1.0793 - accuracy: 0.5695
Epoch 3/15
92/92 [==============================] - 2s 22ms/step - loss: 0.9645 - accuracy: 0.6253
Epoch 4/15
92/92 [==============================] - 2s 22ms/step - loss: 0.9219 - accuracy: 0.6441
Epoch 5/15
92/92 [==============================] - 2s 22ms/step - loss: 0.8610 - accuracy: 0.6638
Epoch 6/15
92/92 [==============================] - 2s 22ms/step - loss: 0.8118 - accuracy: 0.6812
Epoch 7/15
92/92 [==============================] - 2s 22ms/step - loss: 0.7777 - accuracy: 0.6975
Epoch 8/15
92/92 [==============================] - 2s 22ms/step - loss: 0.7064 - accuracy: 0.7285
Epoch 9/15
92/92 [==============================] - 2s 22ms/step - loss: 0.6843 - accuracy: 0.7381
Epoch 10/15
92/92 [==============================] - 2s 22ms/step - loss: 0.6468 - accuracy: 0.7500
Epoch 11/15
92/92 [==============================] - 2s 22ms/step - loss: 0.6269 - accuracy: 0.7721
Epoch 12/15
92/92 [==============================] - 2s 22ms/step - loss: 0.5805 - accuracy: 0.7824
Epoch 13/15
92/92 [==============================] - 2s 22ms/step - loss: 0.5793 - accuracy: 0.7827
Epoch 14/15
92/92 [==============================] - 2s 22ms/step - loss: 0.5215 - accuracy: 0.7994
Epoch 15/15
92/92 [==============================] - 2s 22ms/step - loss: 0.5262 - accuracy: 0.8069
```

Visualize training results

After applying data augmentation and Dropout, there is less overfitting than before, and training and validation accuracy are closer aligned.

```
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.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()
```



Predict on new data

Finally, let's use our model to classify an image that wasn't included in the training or validation sets.

Note: Data augmentation and Dropout layers are inactive at inference time.

```
sunflower_url = "https://storage.googleapis.com/download.tensorflow.org/example_images/592px-
```

```
sunflower_path = tf.keras.utils.get_file('Red_sunflower', origin=sunflower_url)

img = keras.preprocessing.image.load_img(
    sunflower_path, target_size=(img_height, img_width)
)
img_array = keras.preprocessing.image.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))
)
```

```
Downloading data from https://storage.googleapis.com/download.tensorflow.org/example_ima
122880/117948 [==============================] - 0s 0us/step
This image most likely belongs to sunflowers with a 89.31 percent confidence.
```

Conclusion:

1. CNN is a type of neural network model which allows us to extract higher representations for the image content. Unlike the classical image recognition where you define the image features yourself, CNN takes the image's raw pixel data, trains the model, then extracts the features automatically for better classification.
2. In this experiment, i tried to implement image classification model using CNN. Here, flower images are classified according to the labels specified. Initially, there was a cosiderable gap between training and validation accuracy.
3. After applying data augmentation and Dropout, there is less overfitting than before, and training and validation accuracy are closer aligned. This model predcited the label of Sunflower image with 89.31% confidence.

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