

assignment9-2

April 15, 2021

```
[14]: !unzip -qq /home/hiraditya/Desktop/HomeWork/SJSU/cs156/jupyter/JupyterBooks/  
      ↪homework9_input_data.zip
```

replace __MACOSX/._flowers? [y]es, [n]o, [A]ll, [N]one, [r]ename: ^C

```
[15]: import tensorflow as tf  
      from tensorflow import keras  
      from tensorflow.keras import layers  
      import os  
      import matplotlib.pyplot as plt  
      import pydot  
      from skimage import io  
      import numpy as np  
      import pandas as pd  
      import seaborn as sb  
      from sklearn.metrics import accuracy_score
```

```
[17]: num_skipped = 0  
      for folder_name in ("daisy", "dandelion", "rose", "sunflower", "tulip"):  
          folder_path = os.path.join("/home/hiraditya/Desktop/HomeWork/SJSU/cs156/  
          ↪jupyter/JupyterBooks/flowers/training/", folder_name)  
          for fname in os.listdir(folder_path):  
              fpath = os.path.join(folder_path, fname)  
              try:  
                  fobj = open(fpath, "rb")  
                  is_jfif = tf.compat.as_bytes("JFIF") in fobj.peek(10)  
              finally:  
                  fobj.close()  
  
              if not is_jfif:  
                  num_skipped += 1  
                  # Delete corrupted image  
                  os.remove(fpath)  
  
      print("Deleted %d images" % num_skipped)
```

Deleted 5 images

```
[18]: num_skipped = 0
for folder_name in ("daisy", "dandelion", "rose", "sunflower", "tulip"):
    folder_path = os.path.join("/home/hiraditya/Desktop/HomeWork/SJSU/cs156/
    ↪jupiter/JupyterBooks/flowers/test/", folder_name)
    for fname in os.listdir(folder_path):
        fpath = os.path.join(folder_path, fname)
        try:
            fobj = open(fpath, "rb")
            is_jfif = tf.compat.as_bytes("JFIF") in fobj.peek(10)
        finally:
            fobj.close()

        if not is_jfif:
            num_skipped += 1
            # Delete corrupted image
            os.remove(fpath)

print("Deleted %d images" % num_skipped)
```

Deleted 0 images

```
[19]: image_size = (180, 180)
batch_size = 32

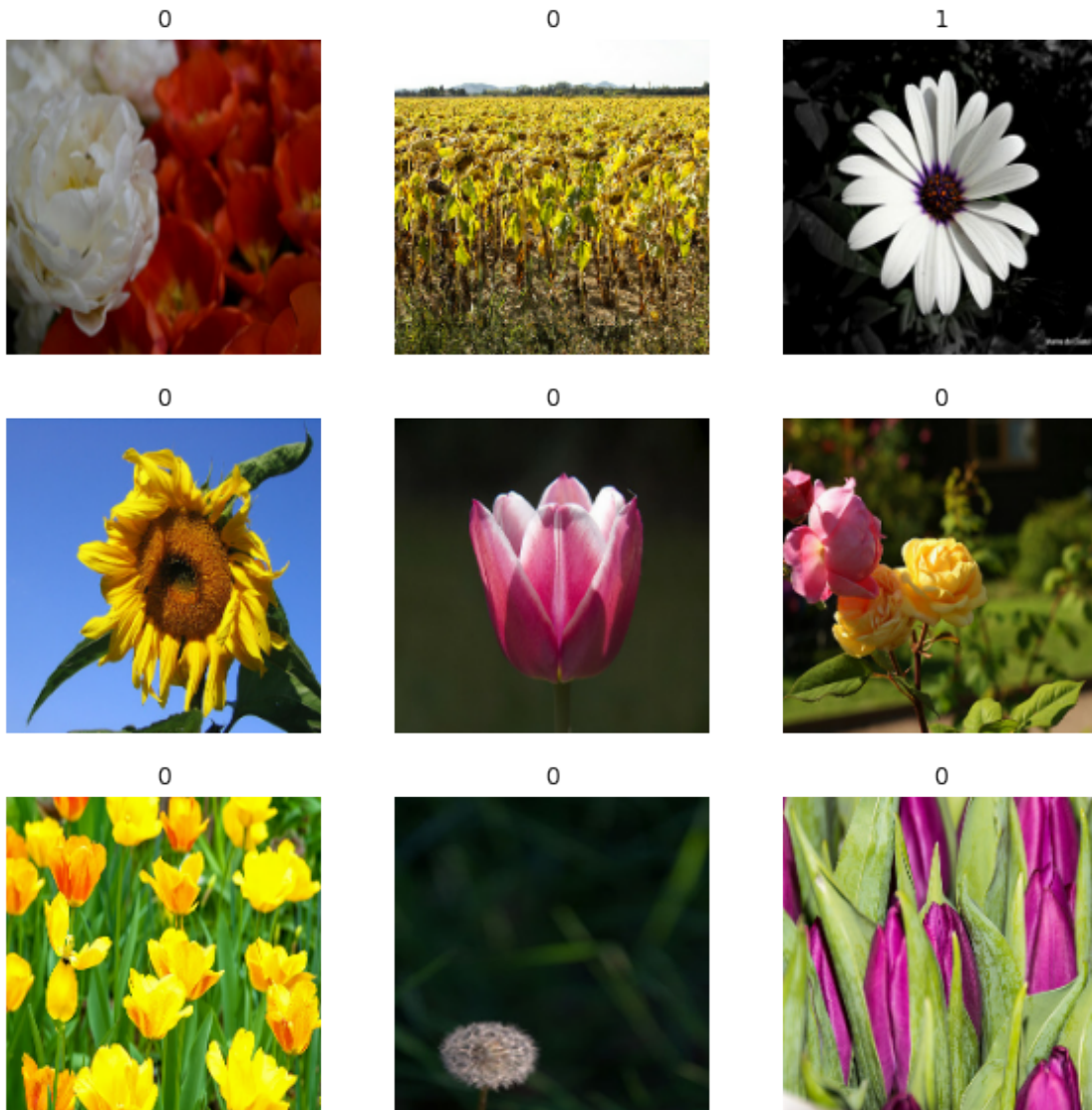
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "/home/hiraditya/Desktop/HomeWork/SJSU/cs156/jupiter/JupyterBooks/flowers/
    ↪training/",
    validation_split=0.2,
    subset="training",
    seed=42,
    image_size=image_size,
    batch_size=batch_size,
    label_mode="categorical",
    labels='inferred'
)
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "/home/hiraditya/Desktop/HomeWork/SJSU/cs156/jupiter/JupyterBooks/flowers/
    ↪training/",
    validation_split=0.2,
    subset="validation",
    seed=42,
    image_size=image_size,
    batch_size=batch_size,
    label_mode="categorical",
    labels='inferred'
)
```

```
test_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "/home/hiraditya/Desktop/HomeWork/SJSU/cs156/jupyter/JupyterBooks/flowers/
↳test/",
    seed=42,
    image_size=image_size,
    batch_size=1,
    label_mode="categorical",
    labels='inferred',
    shuffle=False
)
```

Found 3456 files belonging to 5 classes.
 Using 2765 files for training.
 Found 3456 files belonging to 5 classes.
 Using 691 files for validation.
 Found 861 files belonging to 5 classes.

1 Sample images

```
[20]: 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(int(labels[i][0]))
        plt.axis("off")
```



2 Augmentation

```
[21]: data_augmentation = keras.Sequential(
    [
        layers.experimental.preprocessing.RandomFlip("horizontal"),
        layers.experimental.preprocessing.RandomRotation(0.1),
    ]
)
```

```
[22]: 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")
```



```
[23]: train_ds = train_ds.prefetch(buffer_size=32)
      val_ds = val_ds.prefetch(buffer_size=32)

      def make_model(input_shape, num_classes):
          inputs = keras.Input(shape=input_shape)
```

```

# Image augmentation block
x = data_augmentation(inputs)

# Entry block
x = layers.experimental.preprocessing.Rescaling(1.0 / 255)(x)
x = layers.Conv2D(32, 3, strides=2, padding="same")(x)
x = layers.BatchNormalization()(x)
x = layers.Activation("relu")(x)

x = layers.Conv2D(64, 3, padding="same")(x)
x = layers.BatchNormalization()(x)
x = layers.Activation("relu")(x)

previous_block_activation = x # Set aside residual

for size in [128, 256, 512, 728]:
    x = layers.Activation("relu")(x)
    x = layers.SeparableConv2D(size, 3, padding="same")(x)
    x = layers.BatchNormalization()(x)

    x = layers.Activation("relu")(x)
    x = layers.SeparableConv2D(size, 3, padding="same")(x)
    x = layers.BatchNormalization()(x)

    x = layers.MaxPooling2D(3, strides=2, padding="same")(x)

    # Project residual
    residual = layers.Conv2D(size, 1, strides=2, padding="same")(
        previous_block_activation
    )
    x = layers.add([x, residual]) # Add back residual
    previous_block_activation = x # Set aside next residual

x = layers.SeparableConv2D(1024, 3, padding="same")(x)
x = layers.BatchNormalization()(x)
x = layers.Activation("relu")(x)

x = layers.GlobalAveragePooling2D()(x)

activation = "softmax"
units = num_classes

x = layers.Dropout(0.5)(x)
outputs = layers.Dense(units, activation=activation)(x)
return keras.Model(inputs, outputs)

```



```

model = make_model(input_shape=image_size + (3,), num_classes=5)
#keras.utils.plot_model(model, show_shapes=True)
model.summary()

```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 180, 180, 3)]	0	
sequential (Sequential)	(None, 180, 180, 3)	0	input_1[0][0]
rescaling (Rescaling)	(None, 180, 180, 3)	0	sequential[0][0]
conv2d (Conv2D)	(None, 90, 90, 32)	896	rescaling[0][0]
batch_normalization (BatchNormal	(None, 90, 90, 32)	128	conv2d[0][0]
activation (Activation)	(None, 90, 90, 32)	0	batch_normalization[0][0]
conv2d_1 (Conv2D)	(None, 90, 90, 64)	18496	activation[0][0]
batch_normalization_1 (BatchNor	(None, 90, 90, 64)	256	conv2d_1[0][0]
activation_1 (Activation)	(None, 90, 90, 64)	0	batch_normalization_1[0][0]
activation_2 (Activation)	(None, 90, 90, 64)	0	activation_1[0][0]
separable_conv2d (SeparableConv	(None, 90, 90, 128)	8896	activation_2[0][0]

```

-----
batch_normalization_2 (BatchNor (None, 90, 90, 128) 512
separable_conv2d[0][0]
-----
activation_3 (Activation) (None, 90, 90, 128) 0
batch_normalization_2[0][0]
-----
separable_conv2d_1 (SeparableCo (None, 90, 90, 128) 17664
activation_3[0][0]
-----
batch_normalization_3 (BatchNor (None, 90, 90, 128) 512
separable_conv2d_1[0][0]
-----
max_pooling2d (MaxPooling2D) (None, 45, 45, 128) 0
batch_normalization_3[0][0]
-----
conv2d_2 (Conv2D) (None, 45, 45, 128) 8320
activation_1[0][0]
-----
add (Add) (None, 45, 45, 128) 0
max_pooling2d[0][0]
conv2d_2[0][0]
-----
activation_4 (Activation) (None, 45, 45, 128) 0
add[0][0]
-----
separable_conv2d_2 (SeparableCo (None, 45, 45, 256) 34176
activation_4[0][0]
-----
batch_normalization_4 (BatchNor (None, 45, 45, 256) 1024
separable_conv2d_2[0][0]
-----
activation_5 (Activation) (None, 45, 45, 256) 0
batch_normalization_4[0][0]
-----
separable_conv2d_3 (SeparableCo (None, 45, 45, 256) 68096
activation_5[0][0]

```



```

-----
-----
batch_normalization_5 (BatchNor (None, 45, 45, 256) 1024
separable_conv2d_3[0] [0]
-----
-----
max_pooling2d_1 (MaxPooling2D) (None, 23, 23, 256) 0
batch_normalization_5[0] [0]
-----
-----
conv2d_3 (Conv2D) (None, 23, 23, 256) 33024 add[0] [0]
-----
-----
add_1 (Add) (None, 23, 23, 256) 0
max_pooling2d_1[0] [0]
conv2d_3[0] [0]
-----
-----
activation_6 (Activation) (None, 23, 23, 256) 0 add_1[0] [0]
-----
-----
separable_conv2d_4 (SeparableCo (None, 23, 23, 512) 133888
activation_6[0] [0]
-----
-----
batch_normalization_6 (BatchNor (None, 23, 23, 512) 2048
separable_conv2d_4[0] [0]
-----
-----
activation_7 (Activation) (None, 23, 23, 512) 0
batch_normalization_6[0] [0]
-----
-----
separable_conv2d_5 (SeparableCo (None, 23, 23, 512) 267264
activation_7[0] [0]
-----
-----
batch_normalization_7 (BatchNor (None, 23, 23, 512) 2048
separable_conv2d_5[0] [0]
-----
-----
max_pooling2d_2 (MaxPooling2D) (None, 12, 12, 512) 0
batch_normalization_7[0] [0]
-----
-----
conv2d_4 (Conv2D) (None, 12, 12, 512) 131584 add_1[0] [0]
-----
-----

```

add_2 (Add)	(None, 12, 12, 512)	0	
max_pooling2d_2[0][0]			conv2d_4[0][0]

activation_8 (Activation)	(None, 12, 12, 512)	0	add_2[0][0]

separable_conv2d_6 (SeparableCo	(None, 12, 12, 728)	378072	
activation_8[0][0]			

batch_normalization_8 (BatchNor	(None, 12, 12, 728)	2912	
separable_conv2d_6[0][0]			

activation_9 (Activation)	(None, 12, 12, 728)	0	
batch_normalization_8[0][0]			

separable_conv2d_7 (SeparableCo	(None, 12, 12, 728)	537264	
activation_9[0][0]			

batch_normalization_9 (BatchNor	(None, 12, 12, 728)	2912	
separable_conv2d_7[0][0]			

max_pooling2d_3 (MaxPooling2D)	(None, 6, 6, 728)	0	
batch_normalization_9[0][0]			

conv2d_5 (Conv2D)	(None, 6, 6, 728)	373464	add_2[0][0]

add_3 (Add)	(None, 6, 6, 728)	0	
max_pooling2d_3[0][0]			conv2d_5[0][0]

separable_conv2d_8 (SeparableCo	(None, 6, 6, 1024)	753048	add_3[0][0]

batch_normalization_10 (BatchNo	(None, 6, 6, 1024)	4096	
separable_conv2d_8[0][0]			

activation_10 (Activation)	(None, 6, 6, 1024)	0	

```

batch_normalization_10[0][0]
-----
-----
global_average_pooling2d (GlobalAveragePooling2D) (None, 1024) 0
activation_10[0][0]
-----
-----
dropout (Dropout) (None, 1024) 0
global_average_pooling2d[0][0]
-----
-----
dense (Dense) (None, 5) 5125 dropout[0][0]
=====
=====
Total params: 2,786,749
Trainable params: 2,778,013
Non-trainable params: 8,736
-----
-----

```

3 Training

```

[24]: epochs = 50

callbacks = [
    keras.callbacks.ModelCheckpoint("save_at_{epoch}.h5"),
]
model.compile(
    optimizer=keras.optimizers.Adam(1e-3),
    loss="categorical_crossentropy",
    metrics=["accuracy"],
)
model.fit(
    train_ds, epochs=epochs, callbacks=callbacks, validation_data=val_ds,
)

```

```

Epoch 1/50
87/87 [=====] - 224s 3s/step - loss: 1.3465 - accuracy:
0.4832 - val_loss: 1.7483 - val_accuracy: 0.2590
Epoch 2/50
87/87 [=====] - 218s 3s/step - loss: 1.0236 - accuracy:
0.6029 - val_loss: 2.1732 - val_accuracy: 0.2590
Epoch 3/50
87/87 [=====] - 219s 3s/step - loss: 0.9266 - accuracy:
0.6574 - val_loss: 3.0028 - val_accuracy: 0.2590
Epoch 4/50

```

87/87 [=====] - 232s 3s/step - loss: 0.8780 - accuracy: 0.6635 - val_loss: 3.1405 - val_accuracy: 0.2590
Epoch 5/50
87/87 [=====] - 218s 3s/step - loss: 0.8106 - accuracy: 0.6918 - val_loss: 3.3701 - val_accuracy: 0.2590
Epoch 6/50
87/87 [=====] - 218s 3s/step - loss: 0.7251 - accuracy: 0.7340 - val_loss: 1.7965 - val_accuracy: 0.4182
Epoch 7/50
87/87 [=====] - 218s 3s/step - loss: 0.6986 - accuracy: 0.7460 - val_loss: 1.3393 - val_accuracy: 0.5427
Epoch 8/50
87/87 [=====] - 220s 3s/step - loss: 0.6548 - accuracy: 0.7494 - val_loss: 0.7131 - val_accuracy: 0.7308
Epoch 9/50
87/87 [=====] - 217s 2s/step - loss: 0.6536 - accuracy: 0.7660 - val_loss: 1.2157 - val_accuracy: 0.6078
Epoch 10/50
87/87 [=====] - 223s 3s/step - loss: 0.6052 - accuracy: 0.7608 - val_loss: 1.0400 - val_accuracy: 0.6816
Epoch 11/50
87/87 [=====] - 218s 3s/step - loss: 0.5760 - accuracy: 0.7839 - val_loss: 0.7353 - val_accuracy: 0.7352
Epoch 12/50
87/87 [=====] - 218s 3s/step - loss: 0.5531 - accuracy: 0.7971 - val_loss: 0.8489 - val_accuracy: 0.7265
Epoch 13/50
87/87 [=====] - 218s 3s/step - loss: 0.5359 - accuracy: 0.8015 - val_loss: 0.7992 - val_accuracy: 0.7511
Epoch 14/50
87/87 [=====] - 218s 2s/step - loss: 0.4897 - accuracy: 0.8097 - val_loss: 0.5440 - val_accuracy: 0.8177
Epoch 15/50
87/87 [=====] - 218s 2s/step - loss: 0.5172 - accuracy: 0.8010 - val_loss: 0.8306 - val_accuracy: 0.7337
Epoch 16/50
87/87 [=====] - 218s 3s/step - loss: 0.4708 - accuracy: 0.8260 - val_loss: 0.8424 - val_accuracy: 0.7192
Epoch 17/50
87/87 [=====] - 218s 3s/step - loss: 0.4718 - accuracy: 0.8249 - val_loss: 1.3616 - val_accuracy: 0.6107
Epoch 18/50
87/87 [=====] - 218s 3s/step - loss: 0.4373 - accuracy: 0.8307 - val_loss: 0.6515 - val_accuracy: 0.8003
Epoch 19/50
87/87 [=====] - 218s 3s/step - loss: 0.4367 - accuracy: 0.8436 - val_loss: 0.9319 - val_accuracy: 0.7308
Epoch 20/50

87/87 [=====] - 220s 3s/step - loss: 0.4311 - accuracy:
 0.8426 - val_loss: 0.9469 - val_accuracy: 0.7236
 Epoch 21/50
 87/87 [=====] - 218s 2s/step - loss: 0.3968 - accuracy:
 0.8579 - val_loss: 0.6814 - val_accuracy: 0.8017
 Epoch 22/50
 87/87 [=====] - 217s 2s/step - loss: 0.4027 - accuracy:
 0.8565 - val_loss: 0.8472 - val_accuracy: 0.7641
 Epoch 23/50
 87/87 [=====] - 217s 2s/step - loss: 0.3894 - accuracy:
 0.8553 - val_loss: 0.6170 - val_accuracy: 0.7931
 Epoch 24/50
 87/87 [=====] - 218s 2s/step - loss: 0.3799 - accuracy:
 0.8643 - val_loss: 0.6488 - val_accuracy: 0.7945
 Epoch 25/50
 87/87 [=====] - 218s 3s/step - loss: 0.3280 - accuracy:
 0.8767 - val_loss: 0.6389 - val_accuracy: 0.8017
 Epoch 26/50
 87/87 [=====] - 218s 2s/step - loss: 0.2978 - accuracy:
 0.8911 - val_loss: 0.5093 - val_accuracy: 0.8379
 Epoch 27/50
 87/87 [=====] - 218s 2s/step - loss: 0.3449 - accuracy:
 0.8744 - val_loss: 0.8083 - val_accuracy: 0.7482
 Epoch 28/50
 87/87 [=====] - 217s 2s/step - loss: 0.3190 - accuracy:
 0.8877 - val_loss: 0.8514 - val_accuracy: 0.7742
 Epoch 29/50
 87/87 [=====] - 217s 2s/step - loss: 0.2916 - accuracy:
 0.8945 - val_loss: 1.6230 - val_accuracy: 0.6556
 Epoch 30/50
 87/87 [=====] - 217s 2s/step - loss: 0.3687 - accuracy:
 0.8657 - val_loss: 0.8991 - val_accuracy: 0.7337
 Epoch 31/50
 87/87 [=====] - 217s 2s/step - loss: 0.2846 - accuracy:
 0.8947 - val_loss: 0.5686 - val_accuracy: 0.8278
 Epoch 32/50
 87/87 [=====] - 216s 2s/step - loss: 0.2900 - accuracy:
 0.8974 - val_loss: 0.9521 - val_accuracy: 0.7424
 Epoch 33/50
 87/87 [=====] - 218s 2s/step - loss: 0.2620 - accuracy:
 0.8994 - val_loss: 0.5064 - val_accuracy: 0.8321
 Epoch 34/50
 87/87 [=====] - 217s 2s/step - loss: 0.2526 - accuracy:
 0.9118 - val_loss: 0.8188 - val_accuracy: 0.7685
 Epoch 35/50
 87/87 [=====] - 217s 2s/step - loss: 0.2766 - accuracy:
 0.8994 - val_loss: 0.8129 - val_accuracy: 0.8046
 Epoch 36/50

```

87/87 [=====] - 217s 2s/step - loss: 0.3141 - accuracy:
0.8859 - val_loss: 1.4699 - val_accuracy: 0.7004
Epoch 37/50
87/87 [=====] - 217s 2s/step - loss: 0.2486 - accuracy:
0.9156 - val_loss: 0.9625 - val_accuracy: 0.7236
Epoch 38/50
87/87 [=====] - 217s 2s/step - loss: 0.2417 - accuracy:
0.9134 - val_loss: 1.0098 - val_accuracy: 0.7858
Epoch 39/50
87/87 [=====] - 217s 2s/step - loss: 0.2034 - accuracy:
0.9259 - val_loss: 0.7311 - val_accuracy: 0.7959
Epoch 40/50
87/87 [=====] - 216s 2s/step - loss: 0.2134 - accuracy:
0.9180 - val_loss: 0.8256 - val_accuracy: 0.7844
Epoch 41/50
87/87 [=====] - 216s 2s/step - loss: 0.2087 - accuracy:
0.9213 - val_loss: 0.6728 - val_accuracy: 0.8104
Epoch 42/50
87/87 [=====] - 217s 2s/step - loss: 0.2069 - accuracy:
0.9267 - val_loss: 0.8395 - val_accuracy: 0.8061
Epoch 43/50
87/87 [=====] - 216s 2s/step - loss: 0.2601 - accuracy:
0.9008 - val_loss: 0.5315 - val_accuracy: 0.8524
Epoch 44/50
87/87 [=====] - 216s 2s/step - loss: 0.2084 - accuracy:
0.9260 - val_loss: 0.5010 - val_accuracy: 0.8365
Epoch 45/50
87/87 [=====] - 217s 2s/step - loss: 0.2366 - accuracy:
0.9242 - val_loss: 0.4863 - val_accuracy: 0.8611
Epoch 46/50
87/87 [=====] - 216s 2s/step - loss: 0.1859 - accuracy:
0.9299 - val_loss: 0.6040 - val_accuracy: 0.8350
Epoch 47/50
87/87 [=====] - 216s 2s/step - loss: 0.2127 - accuracy:
0.9180 - val_loss: 0.6580 - val_accuracy: 0.8336
Epoch 48/50
87/87 [=====] - 216s 2s/step - loss: 0.1856 - accuracy:
0.9303 - val_loss: 0.6543 - val_accuracy: 0.8191
Epoch 49/50
87/87 [=====] - 215s 2s/step - loss: 0.1757 - accuracy:
0.9379 - val_loss: 0.8392 - val_accuracy: 0.7742
Epoch 50/50
87/87 [=====] - 217s 2s/step - loss: 0.1891 - accuracy:
0.9300 - val_loss: 0.5563 - val_accuracy: 0.8292

```

[24]: <tensorflow.python.keras.callbacks.History at 0x7f7dbabc12e0>

4 Evaluation

```
[25]: model.evaluate(test_ds)
```

```
861/861 [=====] - 19s 22ms/step - loss: 1.1448 -  
accuracy: 0.7480
```

```
[25]: [1.1448140144348145, 0.7479674816131592]
```

Extracting true labels and the images from test_ds

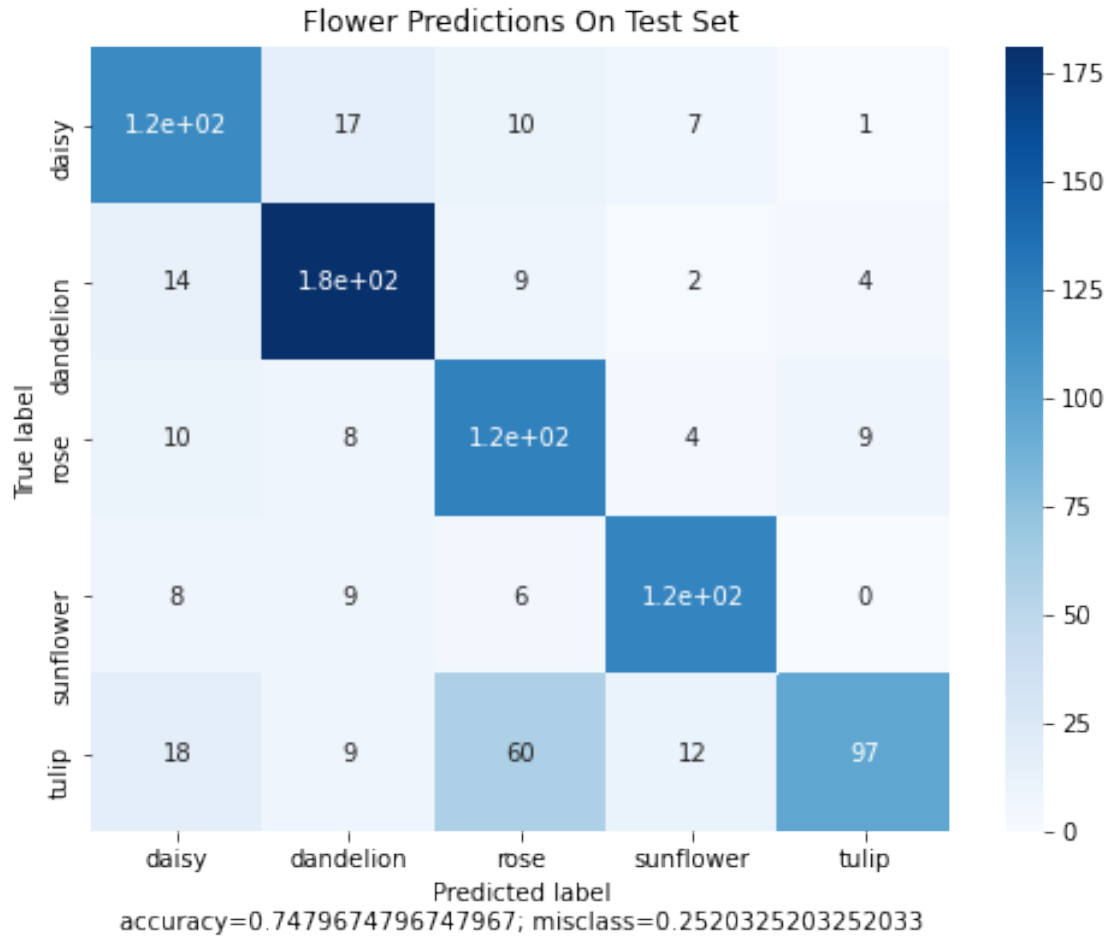
```
[26]: # Test Labels  
true = np.concatenate([y for x, y in test_ds], axis=0)  
true = np.argmax(true, axis=1)  
# Test Images  
test_images = np.concatenate([x for x, y in test_ds], axis=0).astype('int')
```

5 Making Predictions

```
[27]: probas = model.predict(test_ds)  
predicted = np.argmax(probas, axis=-1)
```

6 Confusion Matrix

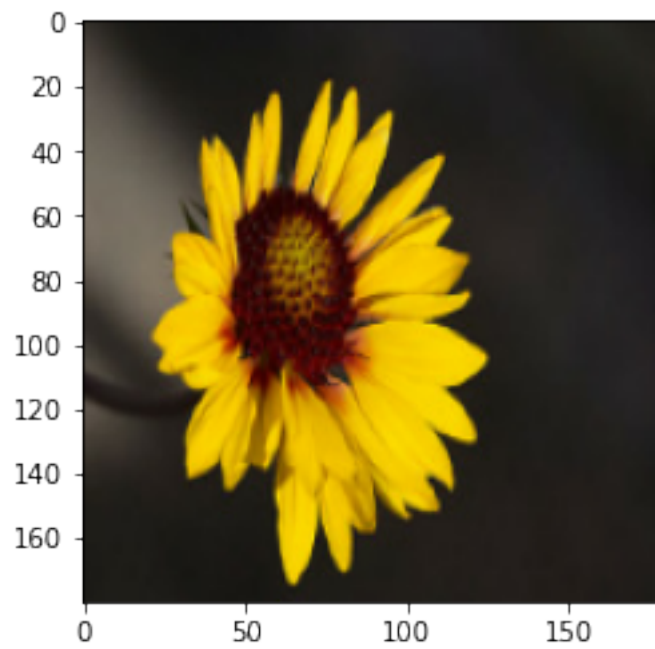
```
[28]: cm = tf.math.confusion_matrix(labels=true, predictions=predicted).numpy()  
cm_df = pd.DataFrame(cm, index = ['daisy', 'dandelion', 'rose', 'sunflower',  
    ↳ 'tulip'], columns = ['daisy', 'dandelion', 'rose', 'sunflower', 'tulip'])  
  
plt.figure(figsize=(8, 6))  
sb.heatmap(cm_df, annot=True, cmap=plt.cm.Blues)  
plt.title('Flower Predictions On Test Set')  
plt.ylabel('True label')  
plt.xlabel('Predicted label\naccuracy={}; misclass={}'.  
    ↳ format(accuracy_score(true, predicted), 1 - accuracy_score(true, predicted)))  
plt.show()
```

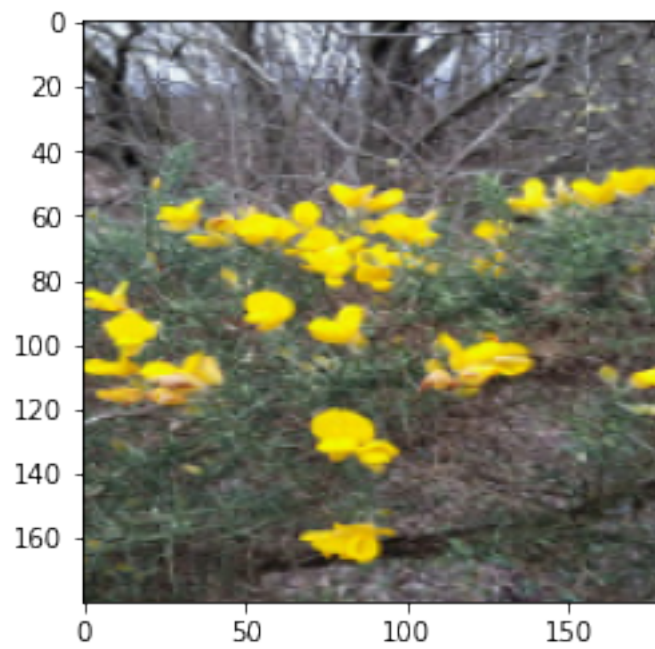
7 3 images that were misclassified

```
[29]: counter = 0
class_names = ['daisy', 'dandelion', 'rose', 'sunflower', 'tulip']
for i in range(100, len(true)):
    if true[i] != predicted[i]:
        if counter < 3:
            print(class_names[true[i]], "predicted as",
↪class_names[predicted[i]], "\n")
            plt.imshow(test_images[i])
            plt.show()
            print("\n\n\n\n")
            counter += 1
```

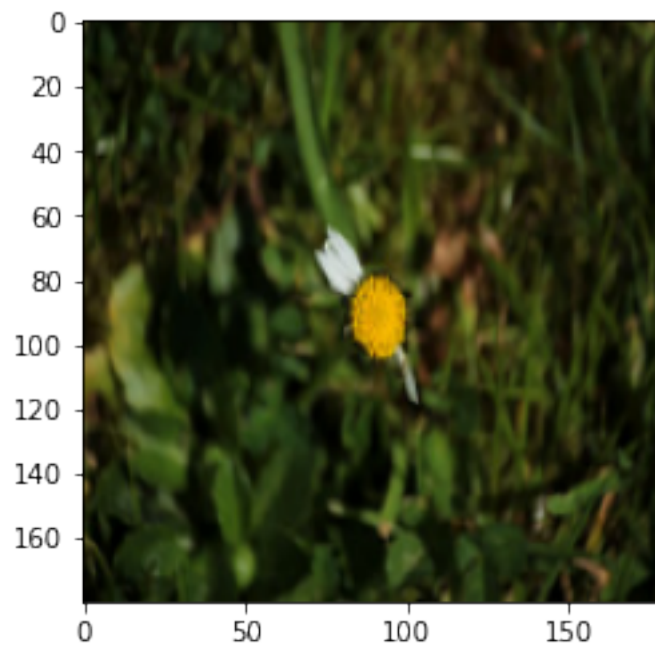
daisy predicted as sunflower



daisy predicted as dandelion



daisy predicted as dandelion



[]: