

## ▼ CS156 (Introduction to AI), Fall 2022

### Homework 8 submission

Roster Name: Preet LNU

Student ID: 014755741

Email address: [preet.lnu@sjsu.edu](mailto:preet.lnu@sjsu.edu)

### ▼ References and sources

List all your references and sources here. This includes all sites/discussion boards/blogs/posts/etc. where you grabbed some code examples.

### ▼ Solution

#### ▼ Load libraries and set random number generator seed

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import os
import matplotlib.pyplot as plt
from skimage import io
import numpy as np
```

```
from zipfile import ZipFile
```

```
np.random.seed(42)
```

#### ▼ Code the solution

```
with ZipFile('/content/homework8_input_data.zip', 'r') as zipObj:
    zipObj.extractall('/content')
```

```

image_size = (180, 180)
batch_size = 32

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "/content/flowers/training",
    validation_split=0.2,
    subset="training",
    seed=42,

    labels='inferred',
    label_mode='categorical',

    image_size=image_size,
    batch_size=batch_size,
)
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "/content/flowers/training",
    validation_split=0.2,
    subset="validation",
    seed=42,

    labels='inferred',
    label_mode='categorical',

    image_size=image_size,
    batch_size=batch_size,
)
test_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "/content/flowers/test",
    seed=42,

    labels='inferred',
    label_mode='categorical',

    image_size=image_size,
    batch_size=1,
)

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.

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

```

```
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")
```



```
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)
if num_classes == 2:
    activation = "sigmoid"
    units = 1
else:
    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()

separable_conv2d_5 (SeparableC (None, 23, 23, 512) 267264 ['activation_7[
onv2D)

```

batch_normalization_7 (Batch Normalization)	(None, 23, 23, 512)	2048	['separable_conv2d_5[0][0][0]']
max_pooling2d_2 (MaxPooling2D)	(None, 12, 12, 512)	0	['batch_normalization_7[0][0][0]']
conv2d_4 (Conv2D)	(None, 12, 12, 512)	131584	['add_1[0][0][0]']
add_2 (Add)	(None, 12, 12, 512)	0	['max_pooling2d_2[0][0][0]']
activation_8 (Activation)	(None, 12, 12, 512)	0	['add_2[0][0][0]']
separable_conv2d_6 (SeparableConv2D)	(None, 12, 12, 728)	378072	['activation_8[0][0][0]']
batch_normalization_8 (Batch Normalization)	(None, 12, 12, 728)	2912	['separable_conv2d_6[0][0][0]']
activation_9 (Activation)	(None, 12, 12, 728)	0	['batch_normalization_8[0][0][0]']
separable_conv2d_7 (SeparableConv2D)	(None, 12, 12, 728)	537264	['activation_9[0][0][0]']
batch_normalization_9 (Batch Normalization)	(None, 12, 12, 728)	2912	['separable_conv2d_7[0][0][0]']
max_pooling2d_3 (MaxPooling2D)	(None, 6, 6, 728)	0	['batch_normalization_9[0][0][0]']
conv2d_5 (Conv2D)	(None, 6, 6, 728)	373464	['add_2[0][0][0]']
add_3 (Add)	(None, 6, 6, 728)	0	['max_pooling2d_3[0][0][0]']
separable_conv2d_8 (SeparableConv2D)	(None, 6, 6, 1024)	753048	['add_3[0][0][0]']
batch_normalization_10 (Batch Normalization)	(None, 6, 6, 1024)	4096	['separable_conv2d_8[0][0][0]']
activation_10 (Activation)	(None, 6, 6, 1024)	0	['batch_normalization_10[0][0][0]']
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1024)	0	['activation_10[0][0][0]']
dropout (Dropout)	(None, 1024)	0	['global_average_pooling2d[0][0][0]']
dense (Dense)	(None, 5)	5125	['dropout[0][0][0]']

```

=====
Total params: 2,786,749
Trainable params: 2,778,013
Non-trainable params: 8,736

```

```
epochs = 20
```

```
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 1/20
87/87 [=====] - 818s 9s/step - loss: 1.2242 - accuracy:
Epoch 2/20
87/87 [=====] - 806s 9s/step - loss: 1.0021 - accuracy:
Epoch 3/20
87/87 [=====] - 808s 9s/step - loss: 0.8992 - accuracy:
Epoch 4/20
87/87 [=====] - 811s 9s/step - loss: 0.8134 - accuracy:
Epoch 5/20
87/87 [=====] - 809s 9s/step - loss: 0.7778 - accuracy:
Epoch 6/20
87/87 [=====] - 821s 9s/step - loss: 0.7100 - accuracy:
Epoch 7/20
87/87 [=====] - 818s 9s/step - loss: 0.6534 - accuracy:
Epoch 8/20
87/87 [=====] - 811s 9s/step - loss: 0.6602 - accuracy:
Epoch 9/20
87/87 [=====] - 811s 9s/step - loss: 0.6017 - accuracy:
Epoch 10/20
87/87 [=====] - 813s 9s/step - loss: 0.5778 - accuracy:
Epoch 11/20
87/87 [=====] - 811s 9s/step - loss: 0.5652 - accuracy:
Epoch 12/20
87/87 [=====] - 811s 9s/step - loss: 0.5201 - accuracy:
Epoch 13/20
87/87 [=====] - 810s 9s/step - loss: 0.5102 - accuracy:
Epoch 14/20
87/87 [=====] - 797s 9s/step - loss: 0.4841 - accuracy:
Epoch 15/20
87/87 [=====] - 774s 9s/step - loss: 0.4753 - accuracy:
Epoch 16/20
87/87 [=====] - 807s 9s/step - loss: 0.4548 - accuracy:
Epoch 17/20
87/87 [=====] - 807s 9s/step - loss: 0.4222 - accuracy:
Epoch 18/20
87/87 [=====] - 808s 9s/step - loss: 0.4424 - accuracy:
Epoch 19/20
87/87 [=====] - 817s 9s/step - loss: 0.4041 - accuracy:
Epoch 20/20
87/87 [=====] - 808s 9s/step - loss: 0.4102 - accuracy:
<keras.callbacks.History at 0x7f6021cf4810>
```

```

true_labels = []
predicted_labels = []
#x = image, y = label
for x, y in test_ds:
    pred = model.predict(x)
    true_labels.append(np.where(y == 1.)[1][0])
    predicted_labels.append(np.where(pred == np.amax(pred))[1][0])

```

```

1/1 [=====] - 1s 600ms/step
1/1 [=====] - 0s 93ms/step
1/1 [=====] - 0s 84ms/step
1/1 [=====] - 0s 91ms/step
1/1 [=====] - 0s 85ms/step
1/1 [=====] - 0s 87ms/step
1/1 [=====] - 0s 92ms/step
1/1 [=====] - 0s 83ms/step
1/1 [=====] - 0s 88ms/step
1/1 [=====] - 0s 89ms/step
1/1 [=====] - 0s 86ms/step
1/1 [=====] - 0s 100ms/step
1/1 [=====] - 0s 89ms/step
1/1 [=====] - 0s 93ms/step
1/1 [=====] - 0s 84ms/step
1/1 [=====] - 0s 88ms/step
1/1 [=====] - 0s 83ms/step
1/1 [=====] - 0s 89ms/step
1/1 [=====] - 0s 99ms/step
1/1 [=====] - 0s 88ms/step
1/1 [=====] - 0s 87ms/step
1/1 [=====] - 0s 94ms/step
1/1 [=====] - 0s 88ms/step
1/1 [=====] - 0s 110ms/step
1/1 [=====] - 0s 103ms/step
1/1 [=====] - 0s 90ms/step
1/1 [=====] - 0s 86ms/step
1/1 [=====] - 0s 133ms/step
1/1 [=====] - 0s 87ms/step
1/1 [=====] - 0s 93ms/step
1/1 [=====] - 0s 95ms/step
1/1 [=====] - 0s 90ms/step
1/1 [=====] - 0s 86ms/step
1/1 [=====] - 0s 89ms/step
1/1 [=====] - 0s 89ms/step
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1/1 [=====] - 0s 91ms/step
1/1 [=====] - 0s 88ms/step
1/1 [=====] - 0s 94ms/step
1/1 [=====] - 0s 89ms/step
1/1 [=====] - 0s 89ms/step
1/1 [=====] - 0s 99ms/step
1/1 [=====] - 0s 90ms/step
1/1 [=====] - 0s 91ms/step

```

```

1/1 [=====] - 0s 87ms/step
1/1 [=====] - 0s 86ms/step
1/1 [=====] - 0s 88ms/step
1/1 [=====] - 0s 93ms/step
1/1 [=====] - 0s 101ms/step
1/1 [=====] - 0s 81ms/step
1/1 [=====] - 0s 82ms/step
1/1 [=====] - 0s 85ms/step
1/1 [=====] - 0s 77ms/step
1/1 [=====] - 0s 76ms/step
1/1 [=====] - 0s 85ms/step
1/1 [=====] - 0s 86ms/step

```

```

def plot_confusion_matrix(cm,
                          target_names,
                          title='Confusion matrix',
                          cmap=None,
                          normalize=True):

    import matplotlib.pyplot as plt
    import numpy as np
    import itertools

    accuracy = np.trace(cm) / float(np.sum(cm))
    misclass = 1 - accuracy

    if cmap is None:
        cmap = plt.get_cmap('Blues')

    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()

    if target_names is not None:
        tick_marks = np.arange(len(target_names))
        plt.xticks(tick_marks, target_names, rotation=45)
        plt.yticks(tick_marks, target_names)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    thresh = cm.max() / 1.5 if normalize else cm.max() / 2
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        if normalize:
            plt.text(j, i, "{:0.4f}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")
        else:
            plt.text(j, i, "{:,}".format(cm[i, j]),
                     horizontalalignment="center",

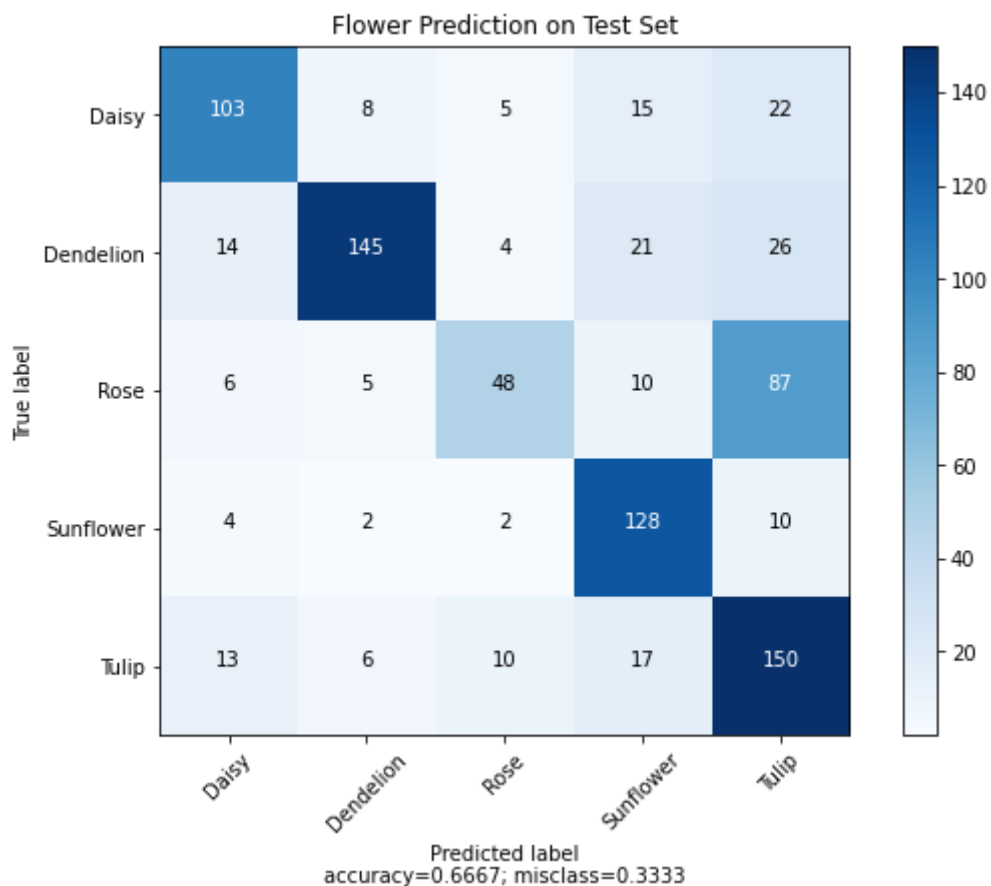
```



```
color="white" if cm[i, j] > thresh else "black")
```

```
plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accuracy,
plt.show())
```

```
plot_confusion_matrix(cm = tf.math.confusion_matrix(labels=true_labels, predictions=p
normalize      = False,
target_names   = ['Daisy', 'Dandelion', 'Rose', 'Sunflower', 'Tul
title          = "Flower Prediction on Test Set")
```



```
def target_translator (input_number) :
```

```
    if (input_number == 0) :
        return 'Daisy'
```

```
    elif (input_number == 1) :
        return 'Dandelion'
```

```
    elif (input_number == 2) :
        return 'Rose'
```

```
    elif (input_number == 3) :
```

```
        return 'Sunflower'

    elif (input_number == 4) :
        return 'Tulip'

breaker = 0

for counter in range (100) :
    if (true_labels[counter] != predicted_labels[counter]) :

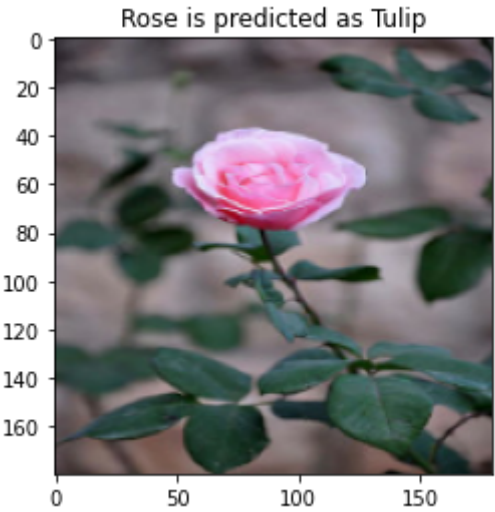
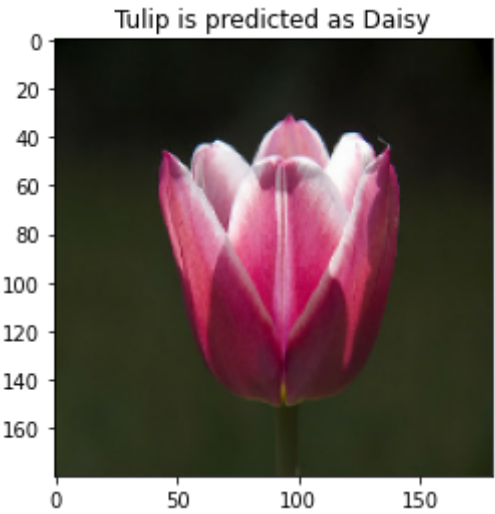
        plt.title(target_translator(true_labels[counter]) + ' is predicted as ' + tar

        plt.imshow(images[counter].numpy().astype("uint8"))

        plt.show()

        breaker = breaker + 1

    if (breaker > 2) :
        break
```



✓ 0s completed at 10:11 PM

