WuBenjaminAssignment8

April 20, 2022

1 CS156 (Introduction to AI), Spring 2022

2 Homework 8 submission

2.0.1 Roster Name: Benjamin Wu

2.0.2 Student ID: 013607880

2.0.3 Email address: benjamin.wu01@sjsu.edu

2.1 Solution

2.2 Import libraries, setup random seed

[ ]:

```python
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import random
```

[ ]:

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

2.3 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.

2.4 Code the solution

[ ]:

```python
image_size = (180, 180)
batch_size = 32

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "./homework8_input_data/flowers/training",
    labels="inferred",
    label_mode="categorical",
    validation_split=0.2,
    subset="training",
    seed=42,
    image_size=image_size,
    batch_size=batch_size,
)
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "./homework8_input_data/flowers/training",
    labels="inferred",
    label_mode="categorical",
    validation_split=0.2,
    subset="validation",
    seed=42,
    image_size=image_size,
    batch_size=batch_size,
)
test_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "./homework8_input_data/flowers/test",
    labels="inferred",
    label_mode="categorical",
    seed=42,
    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),
    ]
)
```

[ ]:

```
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)
```

```python
    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 = 2
    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)
```

[ ]:

```
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 [==============================] - 361s 4s/step - loss: 1.2679 - accuracy:
0.5306 - val_loss: 1.7036 - val_accuracy: 0.2590
Epoch 2/20
87/87 [==============================] - 350s 4s/step - loss: 1.0068 - accuracy:
0.6264 - val_loss: 2.2392 - val_accuracy: 0.2590
Epoch 3/20
87/87 [==============================] - 330s 4s/step - loss: 0.8816 - accuracy:
0.6702 - val_loss: 3.1702 - val_accuracy: 0.2590
Epoch 4/20
87/87 [==============================] - 329s 4s/step - loss: 0.8406 - accuracy:
0.6875 - val_loss: 3.6277 - val_accuracy: 0.2590
Epoch 5/20
87/87 [==============================] - 330s 4s/step - loss: 0.7492 - accuracy:
0.7226 - val_loss: 4.0123 - val_accuracy: 0.2590
Epoch 6/20
87/87 [==============================] - 334s 4s/step - loss: 0.7332 - accuracy:
0.7251 - val_loss: 2.5233 - val_accuracy: 0.2808
Epoch 7/20
87/87 [==============================] - 330s 4s/step - loss: 0.6712 - accuracy:
0.7533 - val_loss: 1.1421 - val_accuracy: 0.6064
Epoch 8/20
87/87 [==============================] - 330s 4s/step - loss: 0.6214 - accuracy:
0.7656 - val_loss: 1.8629 - val_accuracy: 0.6165
Epoch 9/20
87/87 [==============================] - 332s 4s/step - loss: 0.6223 - accuracy:
0.7765 - val_loss: 1.5189 - val_accuracy: 0.5774
Epoch 10/20
87/87 [==============================] - 355s 4s/step - loss: 0.5655 - accuracy:
0.7870 - val_loss: 0.7508 - val_accuracy: 0.7525
Epoch 11/20
87/87 [==============================] - 357s 4s/step - loss: 0.5547 - accuracy:
0.7960 - val_loss: 0.9861 - val_accuracy: 0.6918
```

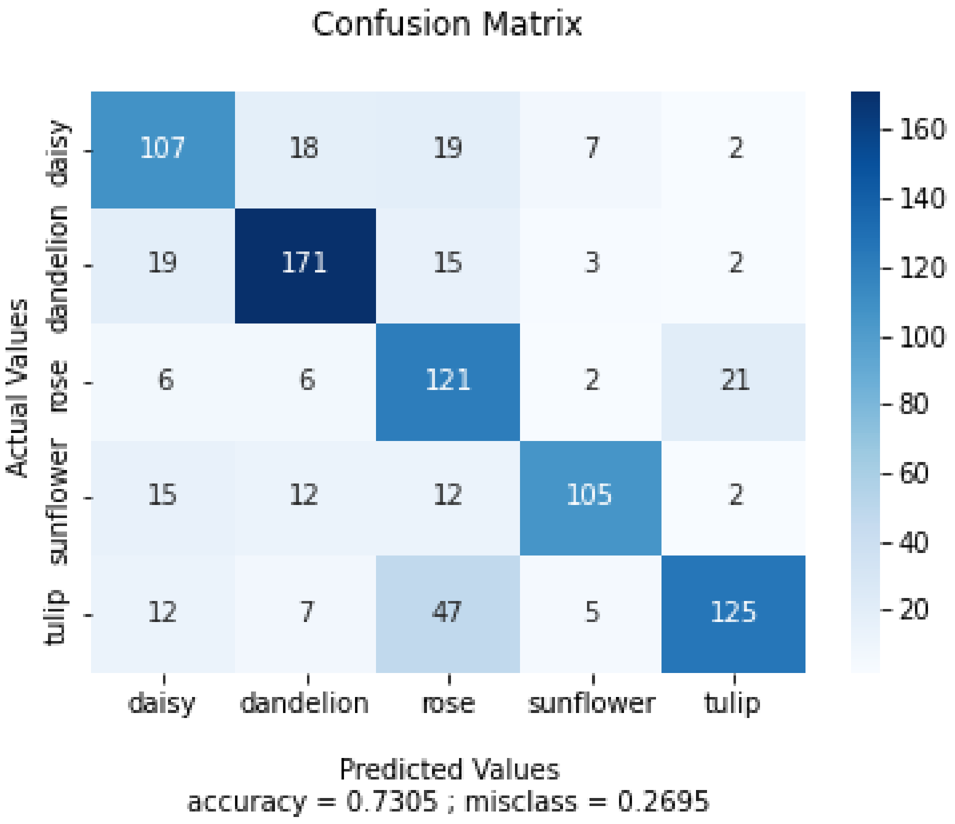
```
Epoch 12/20
87/87 [==============================] - 331s 4s/step - loss: 0.5247 - accuracy:
0.8058 - val_loss: 1.3166 - val_accuracy: 0.6411
Epoch 13/20
87/87 [==============================] - 331s 4s/step - loss: 0.5022 - accuracy:
0.8119 - val_loss: 0.7429 - val_accuracy: 0.7482
Epoch 14/20
87/87 [==============================] - 331s 4s/step - loss: 0.4761 - accuracy:
0.8235 - val_loss: 0.8396 - val_accuracy: 0.7496
Epoch 15/20
87/87 [==============================] - 330s 4s/step - loss: 0.4624 - accuracy:
0.8347 - val_loss: 0.8284 - val_accuracy: 0.7612
Epoch 16/20
87/87 [==============================] - 330s 4s/step - loss: 0.4864 - accuracy:
0.8156 - val_loss: 0.5827 - val_accuracy: 0.8032
Epoch 17/20
87/87 [==============================] - 332s 4s/step - loss: 0.4241 - accuracy:
0.8416 - val_loss: 0.5511 - val_accuracy: 0.8148
Epoch 18/20
87/87 [==============================] - 330s 4s/step - loss: 0.4174 - accuracy:
0.8416 - val_loss: 0.7066 - val_accuracy: 0.7641
Epoch 19/20
87/87 [==============================] - 331s 4s/step - loss: 0.4272 - accuracy:
0.8488 - val_loss: 1.0955 - val_accuracy: 0.6874
Epoch 20/20
87/87 [==============================] - 330s 4s/step - loss: 0.3906 - accuracy:
0.8568 - val_loss: 0.6308 - val_accuracy: 0.8075
```

```
[ ]: <keras.callbacks.History at 0x210df9e7bb0>
```

```
[ ]: labels = ["daisy", "dandelion", "rose", "sunflower", "tulip"]
     true_labels = []
     predicted_labels = []
     wrong_images = []
     wrong_labels = []
     actual_labels = []


     for x,y in test_ds:
         pred = model.predict(x)[0]
         predicted_labels.append(np.where(np.max(pred) == pred)[0][0])
         true_labels.append(np.where(np.max(y.numpy()[0]) == y.numpy()[0])[0][0])
         if(true_labels[len(true_labels) - 1] !=␣
      ↪predicted_labels[len(predicted_labels) - 1]):
             wrong_images.append(x)
             wrong_labels.append(labels[np.where(np.max(pred) == pred)[0][0]])
```

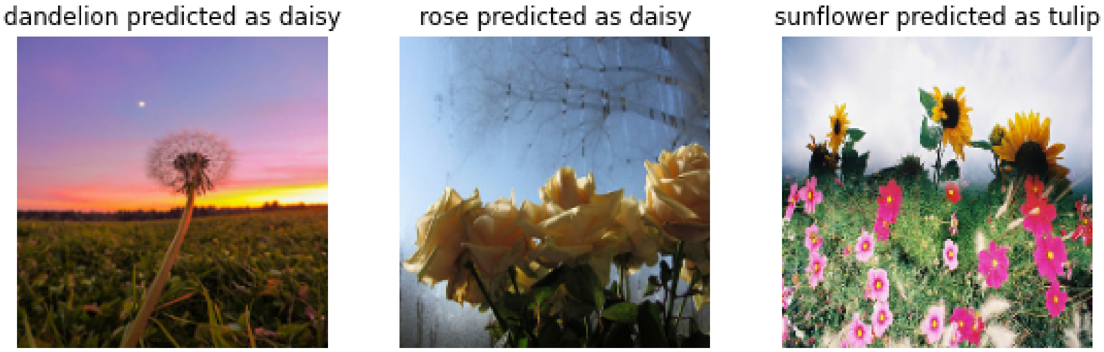
```
        actual_labels.append(labels[np.where(np.max(y.numpy()[0]) == y.
 ↪numpy()[0])[0][0]])
```

```
[ ]: cm = tf.math.confusion_matrix(labels=true_labels, predictions=predicted_labels).
      ↪numpy()
     ax = sns.heatmap(cm, annot=True, cmap='Blues', fmt='d')

     acc = ("accuracy = " + str(round((len(test_ds) - len(wrong_images)) /␣
      ↪len(test_ds), 4)) + " ; misclass = " + str(round(len(wrong_images) /␣
      ↪len(test_ds), 4)))

     ax.set_title('Confusion Matrix\n');
     ax.set_xlabel('\nPredicted Values\n' + acc)
     ax.set_ylabel('Actual Values ');

     ## Ticket labels - List must be in alphabetical order
     ax.xaxis.set_ticklabels(labels)
     ax.yaxis.set_ticklabels(labels)

     ## Display the visualization of the Confusion Matrix.
     plt.show()
```



[ ]:

```python
plt.figure(figsize=(10, 10))
for i in range(3):
    plt.subplot(3, 3, i + 1)
    x = random.randint(0, len(wrong_images))
    plt.imshow(wrong_images[x][0].numpy().astype("uint8"))
    plt.title(actual_labels[x] + " predicted as " + wrong_labels[x])
    plt.axis('off')
```



dandelion predicted as daisy

rose predicted as daisy

sunflower predicted as tulip