CarStyle

October 1, 2024

[1]:
```python
import tensorflow as tf
import os
import cv2
import math
import json
import numpy as np
from matplotlib import pyplot as plt
from keras.applications import VGG16
from keras.models import Model
from keras.layers import Dense, GlobalAveragePooling2D
from keras.metrics import Precision, Recall, SparseCategoricalAccuracy
```

[2]:
```python
print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
gpus = tf.config.experimental.list_physical_devices('GPU')
if gpus:
    try:
        for gpu in gpus:
            tf.config.experimental.set_memory_growth(gpu, True)
        logical_gpus = tf.config.experimental.list_logical_devices('GPU')
        print(len(gpus), "Physical GPUs,", len(logical_gpus), "Logical GPUs")
    except RuntimeError as e:
        print(e)
```

```
Num GPUs Available:  1
1 Physical GPUs, 1 Logical GPUs
```

[3]:
```python
base_dir = 'Styles'
train_dir = os.path.join(base_dir, 'train')
val_dir = os.path.join(base_dir, 'valid')
test_dir = os.path.join(base_dir, 'test')

img_size = (224, 224)
batch_size = 32

train_data = tf.keras.utils.image_dataset_from_directory(
    train_dir,
    image_size=img_size,
    batch_size=batch_size,
```

```
    label_mode='int',
    interpolation='bilinear'
)

val_data = tf.keras.utils.image_dataset_from_directory(
    val_dir,
    image_size=img_size,
    batch_size=batch_size,
    label_mode='int',
    interpolation='bilinear'
)

test_data = tf.keras.utils.image_dataset_from_directory(
    test_dir,
    image_size=img_size,
    batch_size=batch_size,
    label_mode='int',
    interpolation='bilinear'
)
```

```
Found 5350 files belonging to 7 classes.
Found 1397 files belonging to 7 classes.
Found 802 files belonging to 7 classes.
```

[4]:

```
class_names = train_data.class_names
print("Class names test:", class_names)

with open('CarStyle map.json', 'w') as f:
    json.dump(class_names, f)

data_iterator = train_data.as_numpy_iterator()
```

```
Class names test: ['Convertible', 'Coupe', 'Hatchback', 'Pick-Up', 'SUV',
'Sedan', 'VAN']
```

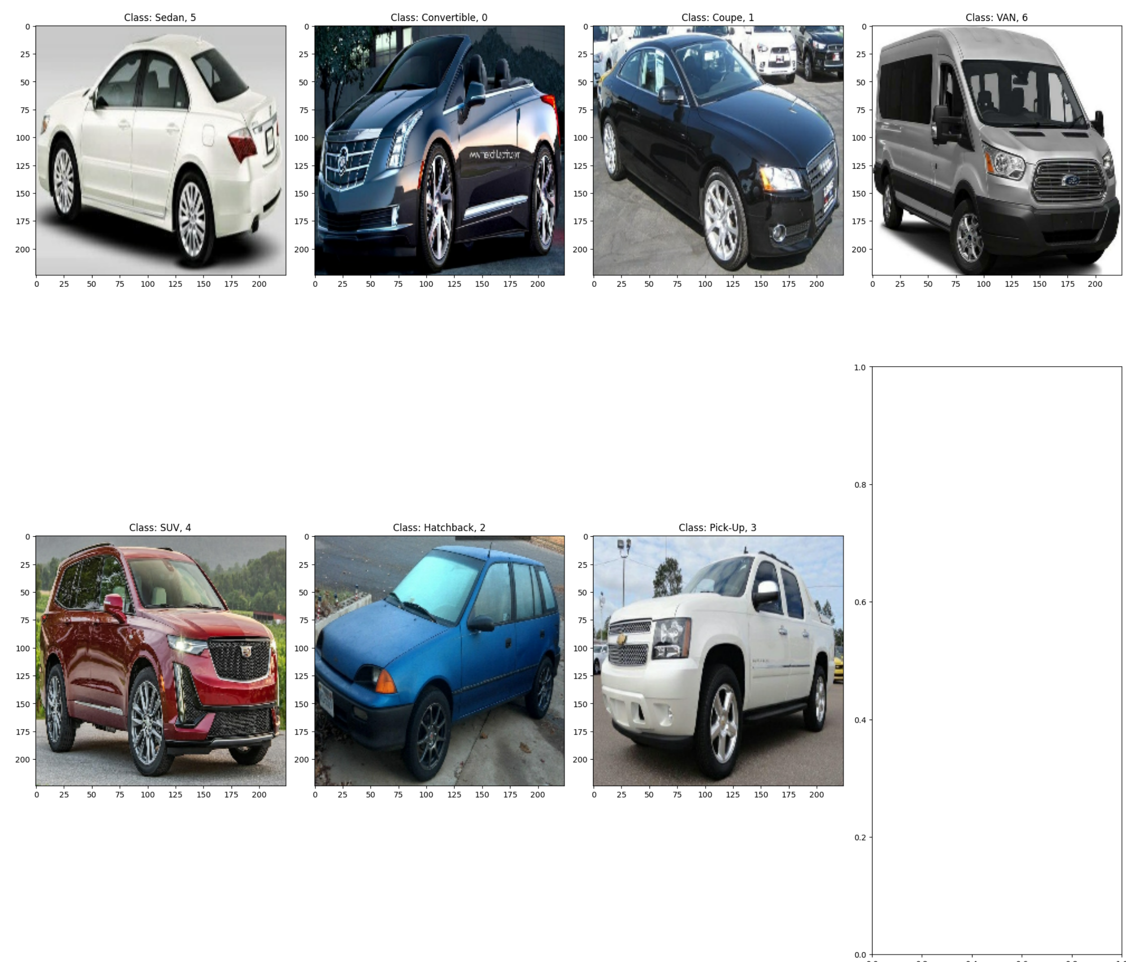
[5]:

```
batch = data_iterator.next()
num_classes = len(class_names)
```

[6]:

```
ncols = 4
nrows = math.ceil(num_classes / ncols)
fig, ax = plt.subplots(nrows=nrows, ncols=ncols, figsize=(20, 20))

if nrows == 1:
    ax = ax.flatten()
elif ncols == 1:
    ax = ax.flatten()

plotted = set()
```

```
count = 0
while count < num_classes:
    batch = next(data_iterator)

    for idx, img in enumerate(batch[0]):
        label = batch[1][idx]
        if label not in plotted:
            ax_idx = count if nrows == 1 or ncols == 1 else (count // ncols, count % ncols)
            ax[ax_idx].imshow(img.astype(int))
            ax[ax_idx].title.set_text(f"Class: {class_names[label]}, {label}")
            plotted.add(label)
            count += 1

        if count == num_classes:
            break

plt.tight_layout()
plt.show()
```



[7]:
```
base_model = VGG16(
    weights='imagenet',
    include_top=False,
    input_shape=(224, 224, 3)
)
base_model.summary()
```

```
Model: "vgg16"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0

 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808
```

```
 block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

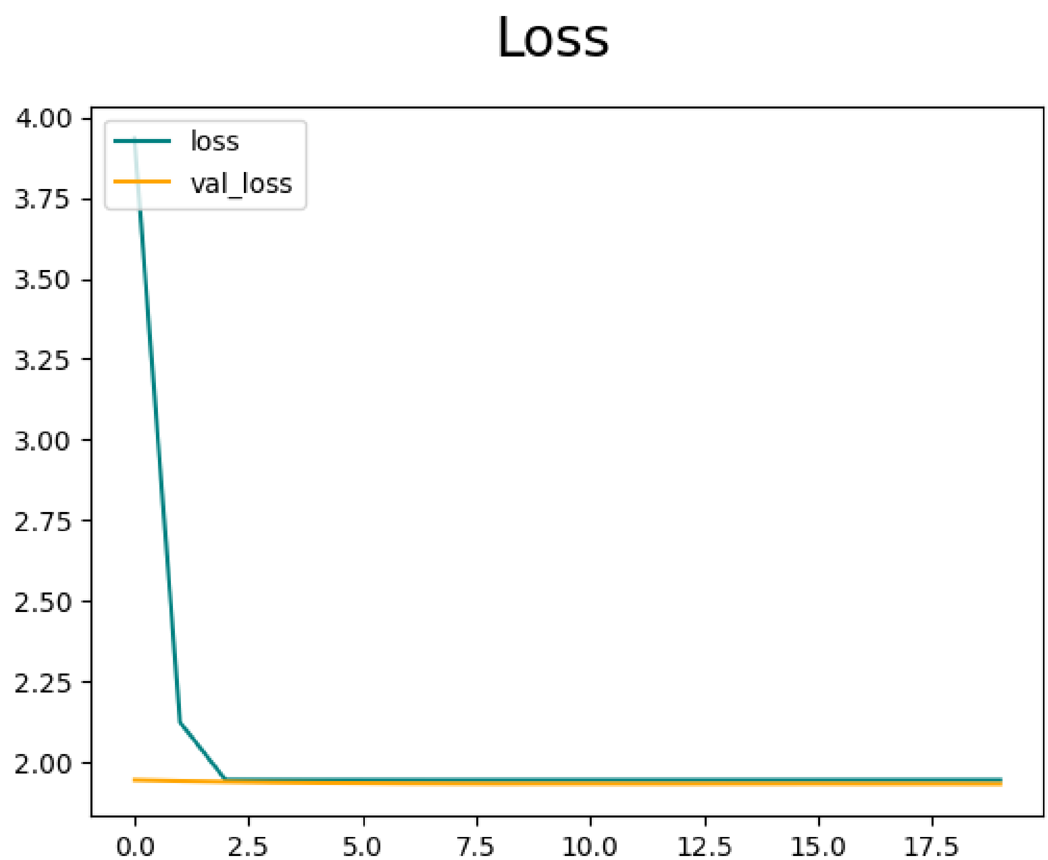
[8]:

```
x = base_model.output
x = GlobalAveragePooling2D()(x)
output = Dense(num_classes, activation='softmax')(x)
model = Model(inputs=base_model.input, outputs=output)

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

tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir='logs')

hist = model.fit(train_data, epochs=20, validation_data=val_data,␣
 ↪callbacks=[tensorboard_callback])
```

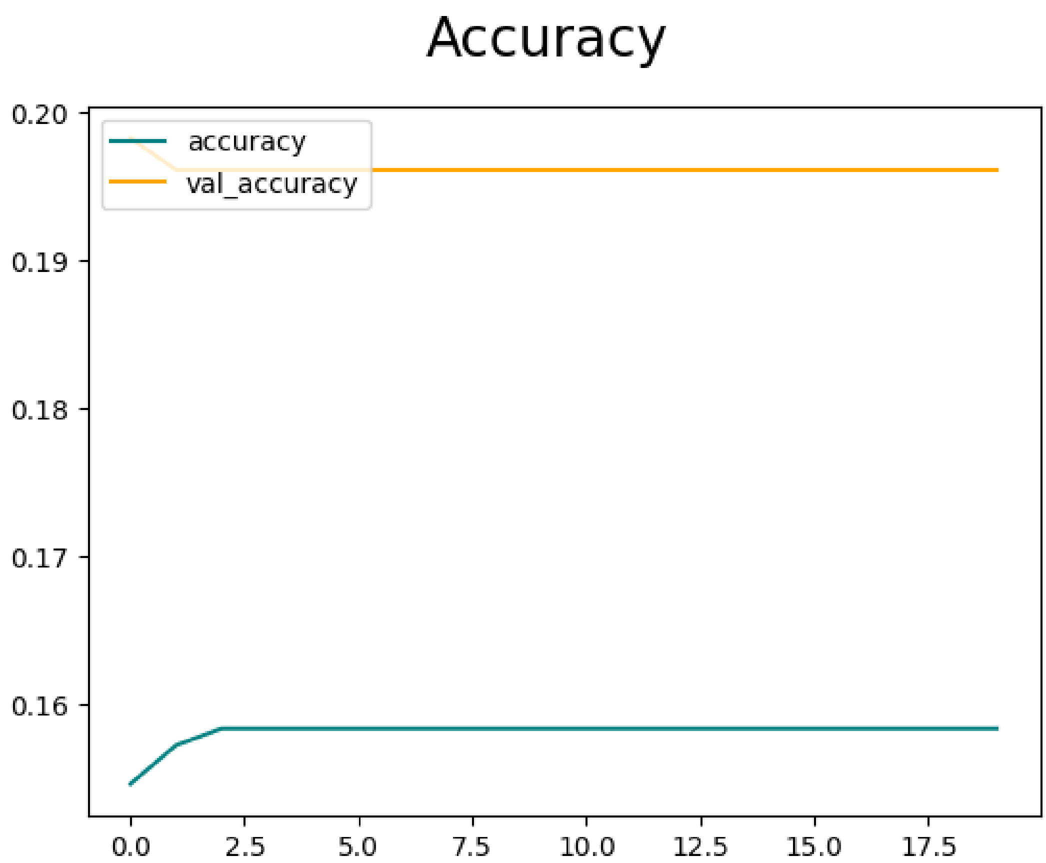
```
Epoch 1/20
168/168 [==============================] - 55s 180ms/step - loss: 3.9355 -
accuracy: 0.1546 - val_loss: 1.9441 - val_accuracy: 0.1983
Epoch 2/20
168/168 [==============================] - 28s 164ms/step - loss: 2.1236 -
accuracy: 0.1572 - val_loss: 1.9410 - val_accuracy: 0.1961
Epoch 3/20
168/168 [==============================] - 28s 163ms/step - loss: 1.9448 -
accuracy: 0.1583 - val_loss: 1.9387 - val_accuracy: 0.1961
Epoch 4/20
168/168 [==============================] - 27s 162ms/step - loss: 1.9445 -
accuracy: 0.1583 - val_loss: 1.9368 - val_accuracy: 0.1961
Epoch 5/20
168/168 [==============================] - 27s 162ms/step - loss: 1.9443 -
accuracy: 0.1583 - val_loss: 1.9355 - val_accuracy: 0.1961
Epoch 6/20
168/168 [==============================] - 28s 163ms/step - loss: 1.9442 -
accuracy: 0.1583 - val_loss: 1.9347 - val_accuracy: 0.1961
Epoch 7/20
168/168 [==============================] - 27s 162ms/step - loss: 1.9442 -
accuracy: 0.1583 - val_loss: 1.9338 - val_accuracy: 0.1961
Epoch 8/20
168/168 [==============================] - 28s 163ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9333 - val_accuracy: 0.1961
```

```
Epoch 9/20
168/168 [==============================] - 28s 167ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9329 - val_accuracy: 0.1961
Epoch 10/20
168/168 [==============================] - 30s 175ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9330 - val_accuracy: 0.1961
Epoch 11/20
168/168 [==============================] - 30s 175ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9330 - val_accuracy: 0.1961
Epoch 12/20
168/168 [==============================] - 30s 177ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9328 - val_accuracy: 0.1961
Epoch 13/20
168/168 [==============================] - 30s 176ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9327 - val_accuracy: 0.1961
Epoch 14/20
168/168 [==============================] - 29s 170ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9329 - val_accuracy: 0.1961
Epoch 15/20
168/168 [==============================] - 47s 281ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9329 - val_accuracy: 0.1961
Epoch 16/20
168/168 [==============================] - 30s 176ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9330 - val_accuracy: 0.1961
Epoch 17/20
168/168 [==============================] - 30s 178ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9327 - val_accuracy: 0.1961
Epoch 18/20
168/168 [==============================] - 30s 175ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9327 - val_accuracy: 0.1961
Epoch 19/20
168/168 [==============================] - 30s 176ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9326 - val_accuracy: 0.1961
Epoch 20/20
168/168 [==============================] - 31s 182ms/step - loss: 1.9441 -
accuracy: 0.1583 - val_loss: 1.9323 - val_accuracy: 0.1961
```

[9]:
```
fig = plt.figure()
plt .plot(hist.history['loss'], color='teal', label='loss')
plt.plot(hist.history['val_loss'], color='orange', label='val_loss')
fig.suptitle('Loss', fontsize=20)
plt.legend(loc="upper left")
plt.show()
```



[10]:
```
fig = plt.figure()
plt.plot(hist.history['accuracy'], color='teal', label='accuracy')
plt.plot(hist.history['val_accuracy'], color='orange', label='val_accuracy')
fig.suptitle('Accuracy', fontsize=20)
plt.legend(loc="upper left")
plt.show()
```



[11]:
```
pre = Precision()
re = Recall()
acc = SparseCategoricalAccuracy()
```

[12]:
```
for batch in test_data.as_numpy_iterator():
    X, y = batch
    yhat = model.predict(X)

    yhat_classes = tf.argmax(yhat, axis=1)

    pre.update_state(y, yhat_classes)
    re.update_state(y, yhat_classes)
    acc.update_state(y, yhat)
```

```
1/1 [==============================] - 0s 125ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 21ms/step
```

```
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 61ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 55ms/step
1/1 [==============================] - 0s 46ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 433ms/step
```

[13]:

```
print(f"Precision: {pre.result().numpy() * 100 : .2f}%")
print(f"Recall: {re.result().numpy() * 100 : .2f}%")
print(f"Accuracy: {acc.result().numpy() * 100 : .2f}%")
```

```
Precision:  78.30%
Recall:  100.00%
Accuracy:  15.59%
```

[14]:

```
img = cv2.imread('Styles/test/Hatchback/8_jpg.rf.
↪c314c1d6777942876503fa1482c82240.jpg')

img_resized = cv2.resize(img, img_size)
img_expanded = np.expand_dims(img_resized, axis=0)

yhat = model.predict(img_expanded)
predicted_class = tf.argmax(yhat, axis=1).numpy()[0]

plt.imshow(img)
plt.title(f'Predicted class: {predicted_class}')
plt.axis('off')
plt.show()
```

```
1/1 [==============================] - 0s 347ms/step
```

Predicted class: 4

[15]:
```python
print(f'Predicted class is: {class_names[predicted_class]}')
for idx, prob in enumerate(yhat[0]):
    print(f"Model probability for {class_names[idx]} is {prob * 100:.2f}%")
```

```
Predicted class is: SUV
Model probability for Convertible is 15.21%
Model probability for Coupe is 13.41%
Model probability for Hatchback is 13.18%
Model probability for Pick-Up is 14.10%
Model probability for SUV is 15.88%
Model probability for Sedan is 13.59%
Model probability for VAN is 14.61%
```

[16]:
```python
model_file_name = f"CarStyle{acc.result().numpy() * 100 : .2f}% VGG16.h5"
model.save(os.path.join('CarBackEnd/models/CarStyles', model_file_name))
```

[ ]:
```python

```