svm_cnn_analysis

December 12, 2024

[1]:
```
# Install basic modules and make sure they are available with the latest pip␣
↪version.
# Always updating PIP could be either good or bad, you just have to choose one␣
↪base on the situation around.

# I use --quiet and --no-warn-script-location to hide the output of my␣
↪directory paths
import sys
import os

!{sys.executable} -m pip install --upgrade pip matplotlib numpy␣
↪tensorflow-macos tensorflow-metal scikit-learn --quiet␣
↪--no-warn-script-location
```

[2]:
```
from tensorflow.keras import layers
from tensorflow.keras import Model
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.models import Model
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
import numpy as np
import os
from PIL import Image
import glob
```

[3]:
```
# Load all images and labels
dataset_path = os.path.join(os.getcwd().replace("investigation",␣
↪"kaggledataset"), 'garbage_classification')

image_data = []
labels = []
class_names = sorted(os.listdir(dataset_path))
print(f"Classes: {class_names}")

for class_idx, class_name in enumerate(class_names):
```

```
    class_folder = os.path.join(dataset_path, class_name)
    if os.path.isdir(class_folder):
        for img_file in glob.glob(os.path.join(class_folder, "*.jpg")):
            try:
                # Open the image, resize, and normalize
                img = Image.open(img_file).convert("RGB").resize((256, 256))
                image_data.append(np.array(img) / 255.0)  # Normalize to 0-1␣
↪range
                labels.append(class_idx)
            except Exception as e:
                print(f"Error loading image {img_file}: {e}")

# Convert to NumPy arrays
image_data = np.array(image_data, dtype="float32")
labels = np.array(labels)

# One-hot encode the labels for CNN training
labels_one_hot = to_categorical(labels, num_classes=len(class_names))

# Split data into train/test sets
train_data, test_data, train_labels, test_labels = train_test_split(
    image_data, labels_one_hot, test_size=0.2, random_state=42, stratify=labels
)
```

```
Classes: ['battery', 'biological', 'brown-glass', 'cardboard', 'clothes',
'green-glass', 'metal', 'paper', 'plastic', 'shoes', 'trash', 'white-glass']
```

[4]:

```
img_input = layers.Input(shape=(256, 256, 3))

# CNN architecture
x = layers.Conv2D(32, 3, activation=None)(img_input)
x = layers.BatchNormalization()(x)
x = layers.ReLU()(x)
x = layers.MaxPooling2D(2)(x)

x = layers.Conv2D(64, 3, activation=None)(x)
x = layers.BatchNormalization()(x)
x = layers.ReLU()(x)
x = layers.MaxPooling2D(2)(x)

x = layers.Conv2D(128, 3, activation=None)(x)
x = layers.BatchNormalization()(x)
x = layers.ReLU()(x)
x = layers.MaxPooling2D(2)(x)

x = layers.Flatten()(x)
x = layers.Dense(512, activation=None)(x)
```

```python
x = layers.BatchNormalization()(x)
x = layers.ReLU()(x)
output = layers.Dense(len(class_names), activation='softmax')(x)

cnn_model = Model(img_input, output)

cnn_model.compile(
    loss='categorical_crossentropy',
    optimizer=RMSprop(learning_rate=0.0001),
    metrics=['acc']
)

# Train CNN
cnn_model.fit(
    train_data,
    train_labels,
    epochs=30,  # Reduced for demonstration
    batch_size=32,
    validation_data=(test_data, test_labels)
)
```

```
2024-12-12 15:39:42.586247: I metal_plugin/src/device/metal_device.cc:1154]
Metal device set to: Apple M3 Max
2024-12-12 15:39:42.586272: I metal_plugin/src/device/metal_device.cc:296]
systemMemory: 48.00 GB
2024-12-12 15:39:42.586281: I metal_plugin/src/device/metal_device.cc:313]
maxCacheSize: 18.00 GB
2024-12-12 15:39:42.586294: I
tensorflow/core/common_runtime/pluggable_device/pluggable_device_factory.cc:305]
Could not identify NUMA node of platform GPU ID 0, defaulting to 0. Your kernel
may not have been built with NUMA support.
2024-12-12 15:39:42.586305: I
tensorflow/core/common_runtime/pluggable_device/pluggable_device_factory.cc:271]
Created TensorFlow device (/job:localhost/replica:0/task:0/device:GPU:0 with 0
MB memory) -> physical PluggableDevice (device: 0, name: METAL, pci bus id:
<undefined>)
```

```
Epoch 1/30
```

```
2024-12-12 15:39:50.303138: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:117]
Plugin optimizer for device_type GPU is enabled.
```

```
388/388              44s 108ms/step -
acc: 0.6094 - loss: 1.2758 - val_acc: 0.5450 - val_loss: 1.4117
Epoch 2/30
388/388              40s 102ms/step -
acc: 0.8611 - loss: 0.4477 - val_acc: 0.7390 - val_loss: 0.8195
Epoch 3/30
```

```
388/388              40s 104ms/step -
acc: 0.9510 - loss: 0.1778 - val_acc: 0.7396 - val_loss: 0.8717
Epoch 4/30
388/388              40s 102ms/step -
acc: 0.9841 - loss: 0.0731 - val_acc: 0.7325 - val_loss: 0.9369
Epoch 5/30
388/388              39s 102ms/step -
acc: 0.9913 - loss: 0.0417 - val_acc: 0.7535 - val_loss: 0.9677
Epoch 6/30
388/388              40s 102ms/step -
acc: 0.9966 - loss: 0.0240 - val_acc: 0.7042 - val_loss: 1.2862
Epoch 7/30
388/388              40s 102ms/step -
acc: 0.9970 - loss: 0.0161 - val_acc: 0.7580 - val_loss: 0.9367
Epoch 8/30
388/388              39s 101ms/step -
acc: 0.9993 - loss: 0.0075 - val_acc: 0.7470 - val_loss: 1.0077
Epoch 9/30
388/388              40s 102ms/step -
acc: 0.9986 - loss: 0.0085 - val_acc: 0.7564 - val_loss: 0.9552
Epoch 10/30
388/388              39s 100ms/step -
acc: 0.9996 - loss: 0.0056 - val_acc: 0.7341 - val_loss: 1.0580
Epoch 11/30
388/388              39s 100ms/step -
acc: 0.9993 - loss: 0.0046 - val_acc: 0.7609 - val_loss: 0.9937
Epoch 12/30
388/388              39s 101ms/step -
acc: 0.9995 - loss: 0.0040 - val_acc: 0.7441 - val_loss: 1.1035
Epoch 13/30
388/388              40s 102ms/step -
acc: 0.9994 - loss: 0.0040 - val_acc: 0.7473 - val_loss: 1.1447
Epoch 14/30
388/388              40s 102ms/step -
acc: 0.9990 - loss: 0.0049 - val_acc: 0.7631 - val_loss: 0.9834
Epoch 15/30
388/388              40s 103ms/step -
acc: 0.9995 - loss: 0.0037 - val_acc: 0.7651 - val_loss: 1.0743
Epoch 16/30
388/388              40s 102ms/step -
acc: 0.9997 - loss: 0.0026 - val_acc: 0.7618 - val_loss: 1.0169
Epoch 17/30
388/388              39s 101ms/step -
acc: 0.9997 - loss: 0.0025 - val_acc: 0.7586 - val_loss: 1.1095
Epoch 18/30
388/388              39s 101ms/step -
acc: 0.9992 - loss: 0.0039 - val_acc: 0.7538 - val_loss: 1.1540
Epoch 19/30
```

```
388/388          40s 102ms/step -
acc: 0.9998 - loss: 0.0018 - val_acc: 0.7058 - val_loss: 1.3810
Epoch 20/30
388/388          39s 101ms/step -
acc: 0.9994 - loss: 0.0028 - val_acc: 0.7596 - val_loss: 1.0664
Epoch 21/30
388/388          39s 101ms/step -
acc: 0.9996 - loss: 0.0021 - val_acc: 0.7612 - val_loss: 1.0729
Epoch 22/30
388/388          39s 101ms/step -
acc: 0.9998 - loss: 0.0012 - val_acc: 0.7618 - val_loss: 1.0754
Epoch 23/30
388/388          39s 101ms/step -
acc: 0.9994 - loss: 0.0032 - val_acc: 0.7580 - val_loss: 1.0902
Epoch 24/30
388/388          39s 102ms/step -
acc: 0.9982 - loss: 0.0075 - val_acc: 0.7689 - val_loss: 1.0264
Epoch 25/30
388/388          40s 102ms/step -
acc: 0.9997 - loss: 0.0015 - val_acc: 0.7651 - val_loss: 1.1445
Epoch 26/30
388/388          39s 101ms/step -
acc: 0.9992 - loss: 0.0039 - val_acc: 0.7612 - val_loss: 1.0925
Epoch 27/30
388/388          39s 100ms/step -
acc: 0.9993 - loss: 0.0031 - val_acc: 0.7583 - val_loss: 1.1288
Epoch 28/30
388/388          39s 100ms/step -
acc: 0.9999 - loss: 0.0011 - val_acc: 0.7573 - val_loss: 1.2308
Epoch 29/30
388/388          39s 101ms/step -
acc: 0.9997 - loss: 0.0012 - val_acc: 0.7506 - val_loss: 1.1876
Epoch 30/30
388/388          39s 101ms/step -
acc: 0.9994 - loss: 0.0040 - val_acc: 0.7676 - val_loss: 1.1025
```

[4]:
```
<keras.src.callbacks.history.History at 0x36a351a50>
```

[ ]:
```python
# Extract features using CNN
feature_extractor = Model(inputs=cnn_model.input, outputs=cnn_model.layers[-2].
 ↪output)

train_features = feature_extractor.predict(train_data)
test_features = feature_extractor.predict(test_data)

# Train an SVM on the extracted features
svm_model = SVC(kernel='linear', class_weight='balanced', probability=True)
```

```
svm_model.fit(train_features, np.argmax(train_labels, axis=1))

# Evaluate
y_pred = svm_model.predict(test_features)
print(f"Accuracy: {accuracy_score(np.argmax(test_labels, axis=1), y_pred)}")
print(classification_report(np.argmax(test_labels, axis=1), y_pred,␣
↪target_names=class_names))
```

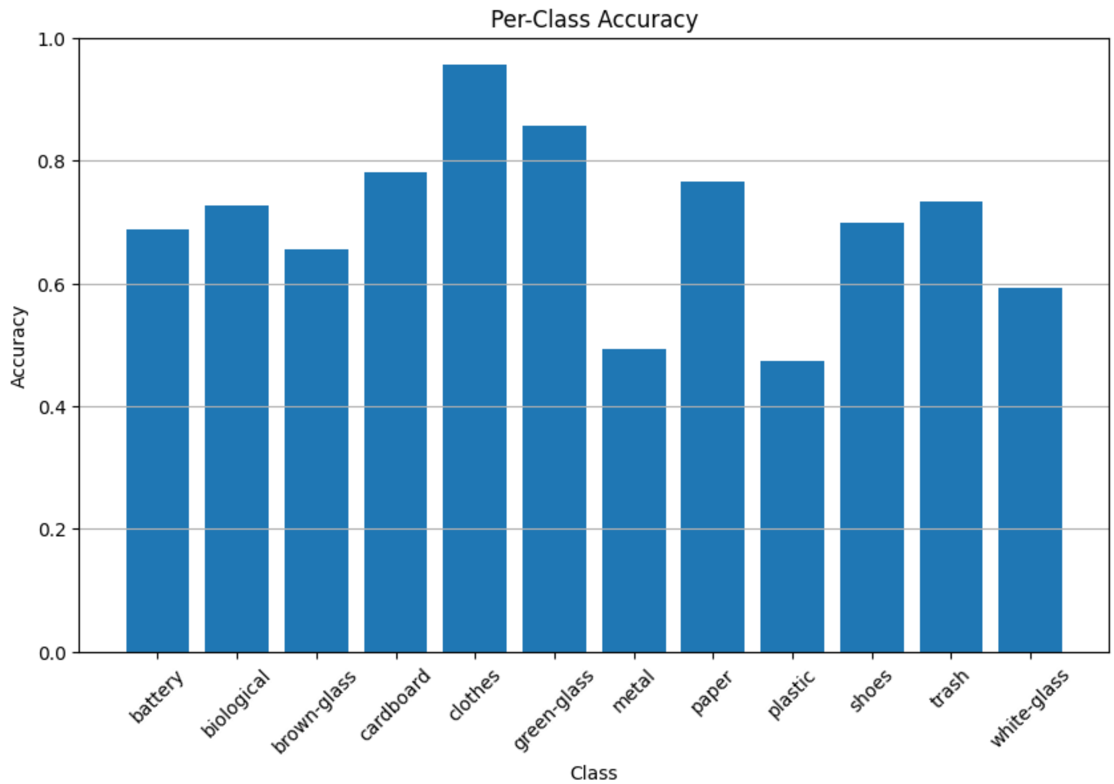
```
388/388              9s 22ms/step
97/97              2s 16ms/step
Accuracy: 0.7757009345794392
              precision    recall  f1-score   support

     battery       0.76      0.69      0.72       189
  biological       0.74      0.73      0.73       197
 brown-glass       0.75      0.66      0.70       122
   cardboard       0.78      0.78      0.78       178
     clothes       0.87      0.96      0.91      1065
 green-glass       0.84      0.86      0.85       126
       metal       0.64      0.49      0.56       154
       paper       0.80      0.77      0.78       210
     plastic       0.55      0.47      0.51       173
       shoes       0.72      0.70      0.71       395
       trash       0.69      0.73      0.71       139
 white-glass       0.59      0.59      0.59       155

    accuracy                           0.78      3103
   macro avg       0.73      0.70      0.71      3103
weighted avg       0.77      0.78      0.77      3103
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[7], line 16
     13 print(f"Accuracy: {accuracy_score(np.argmax(test_labels, axis=1),␣
↪y_pred)}")
     14 print(classification_report(np.argmax(test_labels, axis=1), y_pred,␣
↪target_names=class_names))
---> 16 svm_model.summary()

AttributeError: 'SVC' object has no attribute 'summary'
```

[8]:
```
import matplotlib.pyplot as plt
import numpy as np

# Use feature extractor to get features from the test data
```

```python
test_features = feature_extractor.predict(test_data)

# Get predictions for the test features
predicted_classes = svm_model.predict(test_features)

# Convert true labels from one-hot encoding to class indices
true_classes = np.argmax(test_labels, axis=1)

# Calculate overall accuracy
overall_accuracy = np.sum(predicted_classes == true_classes) / len(true_classes)
print(f"Overall Test Accuracy: {overall_accuracy:.2f}")

# Calculate per-class accuracy
num_classes = len(class_names)
class_accuracies = []
for class_index in range(num_classes):
    indices = np.where(true_classes == class_index)[0]
    class_correct = np.sum(predicted_classes[indices] == true_classes[indices])
    class_accuracy = class_correct / len(indices) if len(indices) > 0 else 0
    class_accuracies.append(class_accuracy)

# Plot per-class accuracy
plt.figure(figsize=(10, 6))
plt.bar(class_names, class_accuracies)
plt.title("Per-Class Accuracy")
plt.xlabel("Class")
plt.ylabel("Accuracy")
plt.ylim(0, 1)
plt.xticks(rotation=45)
plt.grid(axis="y")
plt.show()
```

```
97/97              2s 15ms/step
Overall Test Accuracy: 0.78
```


Per-Class Accuracy
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
battery
biological
brown-glass
cardboard
clothes
green-glass
metal
paper
plastic
shoes
trash
white-glass
Class

```
[ ]:
```