Applied Machine Learning

Homework 4

In [6]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
from PIL import Image
import tensorflow as tf
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.layers import Dense, Flatten, Dropout
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import layers, models
from sklearn.model_selection import train_test_split
```

Question 1

a. Take at least 100 images per class with at least 3 classes using your phone/camera (you can take advantage of spring in Bloomington and take photos of different trees, flowers, animals). Display 5 examples from each class.

We have taken 3 classes: bottle, car, and shoe. We have 100 images for each class. We will be displaying 5 examples from each class.

In [33]:
```
dir_path = r"C:\Users\jsubh\Desktop\AML\Homework4\data\bottle"

file_list = os.listdir(dir_path)
image_list = [file for file in file_list if file.endswith(('jpg'))]

print("Class: Bottle | Label: 0")

fig, axs = plt.subplots(1, 5, figsize=(15, 3))
for i in range(5):
    if i < len(image_list):
        image_path = os.path.join(dir_path, image_list[i])
        img = plt.imread(image_path)
        axs[i].imshow(img)
        axs[i].axis('off')
plt.show()
```

```
Class: Bottle | Label: 0
```

In [32]:
```
dir_path = r"C:\Users\jsubh\Desktop\AML\Homework4\data\car"

file_list = os.listdir(dir_path)
image_list = [file for file in file_list if file.endswith(('jpg'))]

print("Class: Car | Label: 1")

fig, axs = plt.subplots(1, 5, figsize=(15, 3))
for i in range(5):
    if i < len(image_list):
        image_path = os.path.join(dir_path, image_list[i])
        img = plt.imread(image_path)
        axs[i].imshow(img)
        axs[i].axis('off')
plt.show()
```

```
Class: Car | Label: 1
```

In [31]:
```
dir_path = r"C:\Users\jsubh\Desktop\AML\Homework4\data\shoe"

file_list = os.listdir(dir_path)
image_list = [file for file in file_list if file.endswith(('jpg'))]

print("Class: Shoe | Label: 2")

fig, axs = plt.subplots(1, 5, figsize=(15, 3))
for i in range(5):
    if i < len(image_list):
        image_path = os.path.join(dir_path, image_list[i])
        img = plt.imread(image_path)
        axs[i].imshow(img)
        axs[i].axis('off')
plt.show()
```

```
Class: Shoe | Label: 2
```

b. Build the input pipeline, including the appropriate preprocessing operations, and add data augmentation.

Data augmentation: It is the technique of adding more data to the existing dataset for better performance and accuracy. It is a pretty common preprocessing step for any kind of image classification. We are flipping each image left to right i.e. horizontal flipping, and then adding them to the same directory of original images. This augments our data and doubles the amount of data we have.

In [32]:
```
dir_path = r"C:\Users\jsubh\Desktop\AML\Homework4\data\bottle"
file_list = os.listdir(dir_path)
image_list = [file for file in file_list if file.endswith(('jpg'))]

cnt = 101
for image_name in image_list:
    image_path = os.path.join(dir_path, image_name)
    image = Image.open(image_path)
    flipped_image = image.transpose(method=Image.FLIP_LEFT_RIGHT)
    flipped_image.save(os.path.join(dir_path, "bottle_" + str(cnt) + ".jpg"))
    cnt+=1
```

In [151]:
```
dir_path = r"C:\Users\jsubh\Desktop\AML\Homework4\data\car"
file_list = os.listdir(dir_path)
image_list = [file for file in file_list if file.endswith(('jpg'))]

cnt = 101
for image_name in image_list:
    image_path = os.path.join(dir_path, image_name)
    image = Image.open(image_path)
    flipped_image = image.transpose(method=Image.FLIP_LEFT_RIGHT)
    flipped_image.save(os.path.join(dir_path, "car_" + str(cnt) + ".jpg"))
    cnt+=1
```

In [33]:
```
dir_path = r"C:\Users\jsubh\Desktop\AML\Homework4\data\shoe"
file_list = os.listdir(dir_path)
image_list = [file for file in file_list if file.endswith(('jpg'))]

cnt = 101
for image_name in image_list:
    image_path = os.path.join(dir_path, image_name)
    image = Image.open(image_path)
    flipped_image = image.transpose(method=Image.FLIP_LEFT_RIGHT)
    flipped_image.save(os.path.join(dir_path, "shoe_" + str(cnt) + ".jpg"))
    cnt+=1
```

Next we perform the following pre-processing steps:

1. Resizing: The images have been taken by all our team members using different phones i.e. not all images are guaranteed to have the same size. Also the images are all in the range of 3000x3000 pixels, which is computationally very expensive. So we resize all

the images to 32x32 pixels. We choose 32x32 because this size works the best and also most image classification datasets have 32x32 sized images.

2. Grayscaling: All our images were originally clicked in RGB. But since RGB is computationally expensive, we convert the images to grayscale using the convert() function from Pillow library.
3. Dataframing: We convert the images into pixel values and create a dataframe holding those values. There will be total 32x32 = 1024 pixels i.e. 1024 features for our models.

In [2]:
```
dir_path = r"C:\Users\jsubh\Desktop\AML\Homework4\data\bottle"
file_list = os.listdir(dir_path)
image_list = [file for file in file_list if file.endswith(('jpg'))]
pixel_values_list = []

for image_name in image_list:
    image_path = os.path.join(dir_path, image_name)
    with Image.open(image_path) as image:
        image = image.resize((32, 32))
        gray_image = image.convert('L')
        pixel_values = list(gray_image.getdata())
        pixel_values_list.append(pixel_values)

pixel_df_bottle = pd.DataFrame(np.array(pixel_values_list))
column_names = ["pixel_" + str(i) for i in range(pixel_df_bottle.shape[1])]
pixel_df_bottle.columns = column_names
```

In [3]:
```
dir_path = r"C:\Users\jsubh\Desktop\AML\Homework4\data\car"
file_list = os.listdir(dir_path)
image_list = [file for file in file_list if file.endswith(('jpg'))]
pixel_values_list = []

for image_name in image_list:
    image_path = os.path.join(dir_path, image_name)
    with Image.open(image_path) as image:
        image = image.resize((32, 32))
        gray_image = image.convert('L')
        pixel_values = list(gray_image.getdata())
        pixel_values_list.append(pixel_values)

pixel_df_car = pd.DataFrame(np.array(pixel_values_list))
column_names = ["pixel_" + str(i) for i in range(pixel_df_car.shape[1])]
pixel_df_car.columns = column_names
```

In [4]:
```
dir_path = r"C:\Users\jsubh\Desktop\AML\Homework4\data\shoe"
file_list = os.listdir(dir_path)
image_list = [file for file in file_list if file.endswith(('jpg'))]
pixel_values_list = []

for image_name in image_list:
    image_path = os.path.join(dir_path, image_name)
    with Image.open(image_path) as image:
        image = image.resize((32, 32))
        gray_image = image.convert('L')
        pixel_values = list(gray_image.getdata())
        pixel_values_list.append(pixel_values)

pixel_df_shoe = pd.DataFrame(np.array(pixel_values_list))
column_names = ["pixel_" + str(i) for i in range(pixel_df_shoe.shape[1])]
pixel_df_shoe.columns = column_names
```

c. Split the images into a training set, a validation set, and a test set.

First we create separate train, val and test datasets for each image class. Then we combine all the 3 train datasets to create the final train dataset. Similarly with val and test too.

In [7]:
```
# Bottle

zeros_list = [0] * 200
bottle_label = pd.DataFrame({'label': zeros_list})

x_bottle, x_test_bottle, y_bottle, y_test_bottle = train_test_split(pixel_df_bottle, bottle_label, test_size=
x_train_bottle, x_val_bottle, y_train_bottle, y_val_bottle = train_test_split(x_bottle, y_bottle, test_size=0
```

In [8]:
```
print(len(x_train_bottle))
print(len(x_val_bottle))
print(len(x_test_bottle))
```

```
180
10
10
```

In [9]:
```
# Car

ones_list = [1] * 200
car_label = pd.DataFrame({'label': ones_list})

x_car, x_test_car, y_car, y_test_car = train_test_split(pixel_df_car, car_label, test_size=0.05, random_state
x_train_car, x_val_car, y_train_car, y_val_car = train_test_split(x_car, y_car, test_size=0.05263, random_sta
```

In [10]:
```
print(len(x_train_car))
print(len(x_val_car))
print(len(x_test_car))
```

```
180
10
10
```

In [11]:
```
# Shoe

twos_list = [2] * 200
shoe_label = pd.DataFrame({'label': twos_list})

x_shoe, x_test_shoe, y_shoe, y_test_shoe = train_test_split(pixel_df_shoe, shoe_label, test_size=0.05, random
x_train_shoe, x_val_shoe, y_train_shoe, y_val_shoe = train_test_split(x_shoe, y_shoe, test_size=0.05263, rand
```

In [12]:
```
print(len(x_train_shoe))
print(len(x_val_shoe))
print(len(x_test_shoe))
```

```
180
10
10
```

In [13]:
```
# Combining train dataframes
x_train = x_train_bottle.append(x_train_car)
x_train = x_train.append(x_train_shoe)
y_train = y_train_bottle.append(y_train_car)
y_train = y_train.append(y_train_shoe)

# Combining val dataframes
x_val = x_val_bottle.append(x_val_car)
x_val = x_val.append(x_val_shoe)
y_val = y_val_bottle.append(y_val_car)
y_val = y_val.append(y_val_shoe)

# Combining test dataframes
x_test = x_test_bottle.append(x_test_car)
x_test = x_test.append(x_test_shoe)
y_test = y_test_bottle.append(y_test_car)
y_test = y_test.append(y_test_shoe)
```

```
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:2: FutureWarning: The frame.append method is
deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  x_train = x_train_bottle.append(x_train_car)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:3: FutureWarning: The frame.append method is
deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  x_train = x_train.append(x_train_shoe)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:4: FutureWarning: The frame.append method is
deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  y_train = y_train_bottle.append(y_train_car)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:5: FutureWarning: The frame.append method is
deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  y_train = y_train.append(y_train_shoe)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:8: FutureWarning: The frame.append method is
deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  x_val = x_val_bottle.append(x_val_car)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:9: FutureWarning: The frame.append method is
deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  x_val = x_val.append(x_val_shoe)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:10: FutureWarning: The frame.append method i
s deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  y_val = y_val_bottle.append(y_val_car)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:11: FutureWarning: The frame.append method i
s deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  y_val = y_val.append(y_val_shoe)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:14: FutureWarning: The frame.append method i
s deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  x_test = x_test_bottle.append(x_test_car)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:15: FutureWarning: The frame.append method i
s deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  x_test = x_test.append(x_test_shoe)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:16: FutureWarning: The frame.append method i
s deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  y_test = y_test_bottle.append(y_test_car)
C:\Users\jsubh\AppData\Local\Temp\ipykernel_24264\4218027531.py:17: FutureWarning: The frame.append method i
s deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  y_test = y_test.append(y_test_shoe)
```

In [14]:
```
print(len(x_train))
print(len(y_train))
print(len(x_test))
print(len(y_test))
print(len(x_val))
print(len(y_val))
```

```
540
540
30
30
30
30
```

In [15]:
```
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(540, 1024)
(540, 1)
(30, 1024)
(30, 1)
```

In [16]:
```
x_train = x_train.to_numpy()
x_test = x_test.to_numpy()
x_val = x_val.to_numpy()
```

d. Fine-tune a pretrained model of your choice on this dataset (the one you created in part c). Report classification accuracy and give a few examples of correct/incorrect classification (show a few images that were correctly/incorrectly classified).

In [17]:
```
input_shape = (32, 32, 3)
vgg16_base = VGG16(weights='imagenet', include_top=False, input_shape=input_shape)

x = vgg16_base.output
x = Flatten()(x)
x = Dense(512, activation='relu')(x)
x = Dropout(0.5)(x)
output = Dense(3, activation='softmax')(x)
model = Model(inputs=vgg16_base.input, outputs=output)

for layer in vgg16_base.layers:
    layer.trainable = False

opt = Adam(learning_rate=1e-4)
model.compile(optimizer=opt, loss='sparse_categorical_crossentropy', metrics=['accuracy'])

x_train = np.stack([x_train.reshape(-1, 32, 32)]*3, axis=-1)
x_test = np.stack([x_test.reshape(-1, 32, 32)]*3, axis=-1)
x_val = np.stack([x_val.reshape(-1, 32, 32)]*3, axis=-1)

history = model.fit(x_train.reshape(540, 32, 32, 3), y_train, epochs=10, batch_size=32, validation_data=(x_va

for i, acc in enumerate(history.history['accuracy']):
    print(f"Epoch {i+1} - Train Accuracy: {acc:.4f} - Val Accuracy: {history.history['val_accuracy'][i]:.4f}"
```

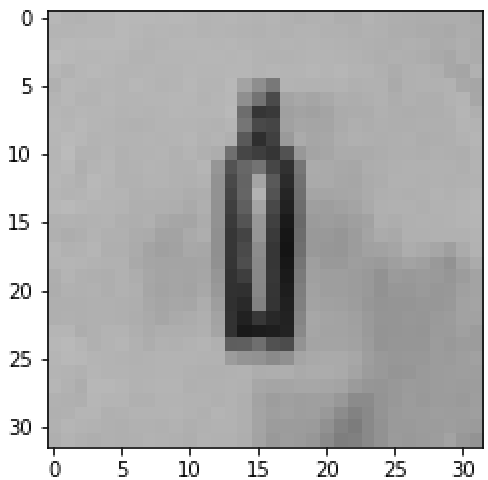
```
Epoch 1/10
17/17 [==============================] - 2s 75ms/step - loss: 6.1917 - accuracy: 0.5963 - val_loss: 0.0041 -
val_accuracy: 1.0000
Epoch 2/10
17/17 [==============================] - 1s 58ms/step - loss: 2.1080 - accuracy: 0.8093 - val_loss: 2.1060e-
06 - val_accuracy: 1.0000
Epoch 3/10
17/17 [==============================] - 1s 57ms/step - loss: 0.5573 - accuracy: 0.9463 - val_loss: 3.5763e-
08 - val_accuracy: 1.0000
Epoch 4/10
17/17 [==============================] - 1s 61ms/step - loss: 0.4922 - accuracy: 0.9574 - val_loss: 1.1921e-
08 - val_accuracy: 1.0000
Epoch 5/10
17/17 [==============================] - 1s 61ms/step - loss: 0.1175 - accuracy: 0.9759 - val_loss: 0.0000e+
00 - val_accuracy: 1.0000
Epoch 6/10
17/17 [==============================] - 1s 63ms/step - loss: 0.3417 - accuracy: 0.9667 - val_loss: 0.0000e+
00 - val_accuracy: 1.0000
Epoch 7/10
17/17 [==============================] - 1s 62ms/step - loss: 0.0970 - accuracy: 0.9778 - val_loss: 3.9736e-
09 - val_accuracy: 1.0000
Epoch 8/10
17/17 [==============================] - 1s 59ms/step - loss: 0.1991 - accuracy: 0.9815 - val_loss: 3.9736e-
09 - val_accuracy: 1.0000
Epoch 9/10
17/17 [==============================] - 1s 59ms/step - loss: 0.0208 - accuracy: 0.9926 - val_loss: 3.9736e-
09 - val_accuracy: 1.0000
Epoch 10/10
17/17 [==============================] - 1s 58ms/step - loss: 0.0889 - accuracy: 0.9852 - val_loss: 0.0000e+
00 - val_accuracy: 1.0000
Epoch 1 - Train Accuracy: 0.5963 - Val Accuracy: 1.0000
Epoch 2 - Train Accuracy: 0.8093 - Val Accuracy: 1.0000
Epoch 3 - Train Accuracy: 0.9463 - Val Accuracy: 1.0000
Epoch 4 - Train Accuracy: 0.9574 - Val Accuracy: 1.0000
Epoch 5 - Train Accuracy: 0.9759 - Val Accuracy: 1.0000
Epoch 6 - Train Accuracy: 0.9667 - Val Accuracy: 1.0000
Epoch 7 - Train Accuracy: 0.9778 - Val Accuracy: 1.0000
Epoch 8 - Train Accuracy: 0.9815 - Val Accuracy: 1.0000
Epoch 9 - Train Accuracy: 0.9926 - Val Accuracy: 1.0000
Epoch 10 - Train Accuracy: 0.9852 - Val Accuracy: 1.0000
```

In [18]:
```
y_test_reshaped = y_test.to_numpy()
```

In [19]:
```
y_pred = model.predict(x_test)
```

```
1/1 [==============================] - 0s 254ms/step
```

In [20]:
```
for z in range(0,len(y_pred)):
    img_arr_temp = x_test[z]
    plt.imshow(img_arr_temp)
    plt.show()
    print("Actual class:", int(y_test_reshaped[z]))
    print("Predicted class:", np.argmax(y_pred[z]))
```




```
Actual class: 0
Predicted class: 0
```

We use the VGG16 model as our pre-trained model. VGG16 is a convolutional neural network architecture designed for image classification tasks. The VGG16 network consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. The classification accuracies are given below:

Data	Accuracy
Train	98.52%

Data	Accuracy
Val	100.00%
Test	100.00%

We run the model for only 10 epochs, within which it produced great results. Val accuracy touches 100% after the first epoch itself. Train accuracy also goes high enough to 98.52%. We evaluate our trained model on the unseen test data, on which it also produces

Train from scratch (without pretraining) a deep neural network that contains convolutional layers on this dataset (the one you created in part c). Report classification accuracy and give a few examples of correct/incorrect classification (show a few images that were correctly/incorrectly classified). Note: The objective of this question is to illustrate that training deep networks from scratch requires a lot of data so it is ok if your classification accuracy is low.

In [21]:

```python
print(x_train.shape)
print(x_val.shape)
print(x_test.shape)
print(y_train.shape)
print(y_val.shape)
print(y_test.shape)
```

```
(540, 32, 32, 3)
(30, 32, 32, 3)
(30, 32, 32, 3)
(540, 1)
(30, 1)
(30, 1)
```

In [22]:

```python
cnn_model = models.Sequential()
cnn_model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
cnn_model.add(layers.MaxPooling2D((2, 2)))
cnn_model.add(layers.Conv2D(64, (3, 3), activation='relu'))
cnn_model.add(layers.MaxPooling2D((2, 2)))
cnn_model.add(layers.Flatten())
cnn_model.add(layers.Dense(64, activation='relu'))
cnn_model.add(layers.Dense(3, activation='softmax'))
```

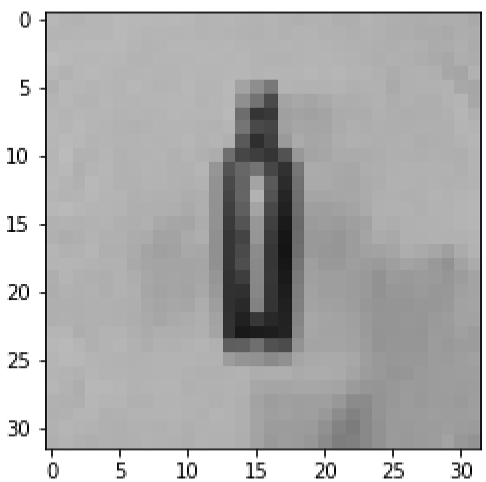
In [23]:
```
cnn_model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',metrics=['accuracy'])
history = cnn_model.fit(x_train, y_train, epochs=10, validation_data=(x_val, y_val))
test_loss, test_acc = cnn_model.evaluate(x_test, y_test)
print('Test accuracy:', test_acc)
```

```
Epoch 1/10
17/17 [==============================] - 1s 23ms/step - loss: 24.1280 - accuracy: 0.4296 - val_loss: 0.3473
- val_accuracy: 0.9000
Epoch 2/10
17/17 [==============================] - 0s 17ms/step - loss: 0.2534 - accuracy: 0.9185 - val_loss: 0.1524 -
val_accuracy: 0.9333
Epoch 3/10
17/17 [==============================] - 0s 17ms/step - loss: 0.0650 - accuracy: 0.9796 - val_loss: 0.0487 -
val_accuracy: 0.9667
Epoch 4/10
17/17 [==============================] - 0s 18ms/step - loss: 0.0199 - accuracy: 0.9981 - val_loss: 0.0140 -
val_accuracy: 1.0000
Epoch 5/10
17/17 [==============================] - 0s 16ms/step - loss: 0.0108 - accuracy: 1.0000 - val_loss: 0.0132 -
val_accuracy: 1.0000
Epoch 6/10
17/17 [==============================] - 0s 17ms/step - loss: 0.0067 - accuracy: 1.0000 - val_loss: 0.0077 -
val_accuracy: 1.0000
Epoch 7/10
17/17 [==============================] - 0s 16ms/step - loss: 0.0039 - accuracy: 1.0000 - val_loss: 0.0046 -
val_accuracy: 1.0000
Epoch 8/10
17/17 [==============================] - 0s 17ms/step - loss: 0.0016 - accuracy: 1.0000 - val_loss: 0.0044 -
val_accuracy: 1.0000
Epoch 9/10
17/17 [==============================] - 0s 15ms/step - loss: 0.0010 - accuracy: 1.0000 - val_loss: 0.0033 -
val_accuracy: 1.0000
Epoch 10/10
17/17 [==============================] - 0s 15ms/step - loss: 8.3275e-04 - accuracy: 1.0000 - val_loss: 0.00
27 - val_accuracy: 1.0000
1/1 [==============================] - 0s 28ms/step - loss: 1.7965e-04 - accuracy: 1.0000
Test accuracy: 1.0
```

In [24]:
```
y_pred = cnn_model.predict(x_test)
```

```
1/1 [==============================] - 0s 70ms/step
```

In [26]:
```
for z in range(0,len(y_pred)):
    img_arr_temp = x_test[z]
    plt.imshow(img_arr_temp)
    plt.show()
    print("Actual class:", int(y_test_reshaped[z]))
    print("Predicted class:", np.argmax(y_pred[z]))
```




```
Actual class: 0
Predicted class: 0
```

Our CNN model has the following structure. An input layer of shape 32x32x3, followed by 2 blocks of Conv2D + MaxPooling2D layers. The Conv2D layer uses ReLU activation function. The pooling layer works to reduce overfitting. It is followed by a Flatten layer, followed by 2 dense layers. The first dense layer has 64 neurons with ReLU activation function, and the second has 3 neurons (for 3 output classes) with softmax activation function. The softmax is a popular choice to use for the output layer since it uses probabilistic methods to determining the output class. We also run this CNN model for 10 epochs, and it also produces excellent results on our dataset. The training accuracy starts off low but ultimately reaches 100%.

Data	Accuracy
Train	100.00%

In [ ]: