ASSIGNMENT 2

Assignment Date	06 November 2022
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Maximum Marks	2 Marks

Traffic Signs Recognition – About the Python Project

In this Python project example, we will build a deep neural network model that can classify traffic signs present in the image into different categories. With this model, we are able to read and understand traffic signs which are a very important task for all autonomous vehicles.

Traffic Signs Dataset

The dataset contains more than 50,000 images of different traffic signs. It is further classified into 43 different classes. The dataset is quite varying, some of the classes have many images while some classes have few images. The size of the dataset is around 300 MB. The dataset has a train folder which contains images inside each class and a test folder which we will use for testing our model.

Step 1: Explore the dataset

Our 'train' folder contains 43 folders each representing a different class. The range of the folder is from 0 to 42. With the help of the OS module, we iterate over all the classes and append images and their respective labels in the data and labels list.

The PIL library is used to open image content into an array.

```python
[9]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
from PIL import Image
import os
from sklearn.model_selection import train_test_split
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Conv2D, MaxPool2D, Dense, Flatten, Dropout

data = []
labels = []
classes = 43
cur_path = os.getcwd()

for i in range(classes):
    path = os.path.join(cur_path,'train',str(i))
    images = os.listdir(path)

    for a in images:
        try:
            image = Image.open(path + '\\'+ a)
            image = image.resize((30,30))
            image = np.array(image)
            #sim = Image.fromarray(image)
            data.append(image)
            labels.append(i)
        except:
            print("Error loading image")
data = np.array(data)
labels = np.array(labels)
```

```python
[10]: print(data.shape, labels.shape)
X_train, X_test, y_train, y_test = train_test_split(data, labels, test_size=0.2, random_state=42)


print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)

y_train = to_categorical(y_train, 43)
y_test = to_categorical(y_test, 43)
```

```
(39209, 30, 30, 3) (39209,)
(31367, 30, 30, 3) (7842, 30, 30, 3) (31367,) (7842,)
```

Step 2: Build a CNN model

To classify the images into their respective categories, we will build a CNN. CNN is best for image classification purposes.
The architecture of our model is:

- 2 Conv2D layer (filter=32, kernel _size=(5,5), activation=”relu”)
- MaxPool2D layer (pool_ size=(2,2))
- Dropout layer (rate=0.25)
- 2 Conv2D layer (filter=64, kernel_ size=(3,3), activation=”relu”)
- MaxPool2D layer (pool _size=(2,2))

- Dropout layer (rate=0.25)
- Flatten layer to squeeze the layers into 1 dimension
- Dense Fully connected layer (256 nodes, activation="relu")
- Dropout layer (rate=0.5)
- Dense layer (43 nodes, activation="softmax")

```
[11]: model = Sequential()
model.add(Conv2D(filters=32, kernel_size=(5,5), activation='relu', input_shape=X_train.shape[1:]))
model.add(Conv2D(filters=32, kernel_size=(5,5), activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(rate=0.25))
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(rate=0.25))
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(rate=0.5))
model.add(Dense(43, activation='softmax'))

#Compilation of the model
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

Steps 3: Train and validate the model

After building the model architecture, we then train the model using model.fit(). I tried with batch size 32 and 64. Our model performed better with

After building the model architecture, we then train the model using

```
[12]: epochs = 15
      history = model.fit(X_train, y_train, batch_size=64, epochs=epochs,validation_data=(X_test, y_test))
```

```
Train on 31367 samples, validate on 7842 samples
Epoch 1/15
31367/31367 [==============================] - 82s 3ms/step - loss: 2.3108 - accuracy: 0.4369 - val_lo
ss: 0.6590 - val_accuracy: 0.8234
Epoch 2/15
31367/31367 [==============================] - 82s 3ms/step - loss: 0.8266 - accuracy: 0.7606 - val_lo
ss: 0.3468 - val_accuracy: 0.9100
Epoch 3/15
31367/31367 [==============================] - 83s 3ms/step - loss: 0.5738 - accuracy: 0.8283 - val_lo
ss: 0.1882 - val_accuracy: 0.9504
Epoch 4/15
31367/31367 [==============================] - 85s 3ms/step - loss: 0.4282 - accuracy: 0.8720 - val_lo
ss: 0.1373 - val_accuracy: 0.9661
Epoch 5/15
31367/31367 [==============================] - 84s 3ms/step - loss: 0.3565 - accuracy: 0.8950 - val_lo
ss: 0.1068 - val_accuracy: 0.9702
Epoch 6/15
31367/31367 [==============================] - 81s 3ms/step - loss: 0.3081 - accuracy: 0.9074 - val_lo
ss: 0.1527 - val_accuracy: 0.9575
Epoch 7/15
31367/31367 [==============================] - 81s 3ms/step - loss: 0.2730 - accuracy: 0.9192 - val_lo
ss: 0.0888 - val_accuracy: 0.9753
Epoch 8/15
31367/31367 [==============================] - 81s 3ms/step - loss: 0.2429 - accuracy: 0.9271 - val_lo
ss: 0.0934 - val_accuracy: 0.9737
Epoch 9/15
31367/31367 [==============================] - 84s 3ms/step - loss: 0.2429 - accuracy: 0.9299 - val_lo
ss: 0.0772 - val_accuracy: 0.9763
Epoch 10/15
31367/31367 [==============================] - 81s 3ms/step - loss: 0.2176 - accuracy: 0.9364 - val_lo
ss: 0.1133 - val_accuracy: 0.9663
Epoch 11/15
31367/31367 [==============================] - 82s 3ms/step - loss: 0.2200 - accuracy: 0.9360 - val_lo
ss: 0.0823 - val_accuracy: 0.9786
Epoch 12/15
31367/31367 [==============================] - 80s 3ms/step - loss: 0.2046 - accuracy: 0.9406 - val_lo
ss: 0.0806 - val_accuracy: 0.9787
Epoch 13/15
31367/31367 [==============================] - 80s 3ms/step - loss: 0.1876 - accuracy: 0.9452 - val_lo
ss: 0.0569 - val_accuracy: 0.9852
Epoch 14/15
31367/31367 [==============================] - 81s 3ms/step - loss: 0.2007 - accuracy: 0.9430 - val_lo
ss: 0.0629 - val_accuracy: 0.9811
Epoch 15/15
31367/31367 [==============================] - 81s 3ms/step - loss: 0.1914 - accuracy: 0.9463 - val_lo
ss: 0.0676 - val_accuracy: 0.9813
```