Self-Driving Car Engineer Nanodegree

Deep Learning

Project: Build a Traffic Sign Recognition Classifier

In this notebook, a template is provided for you to implement your functionality in stages which is required to successfully complete this project. If additional code is required that cannot be included in the notebook, be sure that the Python code is successfully imported and included in your submission, if necessary. Sections that begin with **'Implementation'** in the header indicate where you should begin your implementation for your project. Note that some sections of implementation are optional, and will be marked with **'Optional'** in the header.

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. In addition, Markdown cells can be edited by typically double-clicking the cell to enter edit mode.

Step 0: Load The Data

In [1]:
```
# Load pickled data
import pickle
import csv
import cv2
import numpy as np
import math
import matplotlib.pyplot as plt

signnames = []
with open("signnames.csv", 'r') as f:
    next(f)
    reader = csv.reader(f)
    signnames = list(reader)
n_classes = len(signnames)

training_file = "./train.p"
testing_file = "./test.p"

with open(training_file, mode='rb') as f:
    train = pickle.load(f)
with open(testing_file, mode='rb') as f:
    test = pickle.load(f)
```

Preprocess Data

In [2]:
```
from sklearn import cross_validation
X_train, X_test = [], []
y_train, y_test = [], test['labels']

for i, img in enumerate(train['features']):
    img = cv2.resize(img,(48, 48), interpolation = cv2.INTER_CUBIC)
    X_train.append(img)
    y_train.append(train['labels'][i])
    # Adaptive Histogram (CLAHE)
    imgLab = cv2.cvtColor(img, cv2.COLOR_RGB2Lab)
    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8,8))
    l, a, b = cv2.split(imgLab)
    l = clahe.apply(l)
    imgLab = cv2.merge((l, a, b))
    imgLab = cv2.cvtColor(imgLab, cv2.COLOR_Lab2RGB)
    X_train.append(imgLab)
    y_train.append(train['labels'][i])
    # Rotate -15
    M = cv2.getRotationMatrix2D((24, 24), -15.0, 1)
    imgL = cv2.warpAffine(img, M, (48, 48))
    X_train.append(imgL)
    y_train.append(train['labels'][i])
    # Rotate 15
    M = cv2.getRotationMatrix2D((24, 24), 15.0, 1)
    imgR = cv2.warpAffine(img, M, (48, 48))
    X_train.append(imgR)
    y_train.append(train['labels'][i])


for img in test['features']:
    X_test.append(cv2.resize(img,(48, 48), interpolation = cv2.INTER_
CUBIC))

X_train, X_validation, y_train, y_validation = cross_validation.train
_test_split(X_train, y_train, test_size=0.2, random_state=7)

from sklearn.utils import shuffle
X_train, y_train = shuffle(X_train, y_train)
```

```
/home/carnd/anaconda3/envs/carnd-term1/lib/python3.5/site-packages/sk
learn/cross_validation.py:44: DeprecationWarning: This module was dep
recated in version 0.18 in favor of the model_selection module into w
hich all the refactored classes and functions are moved. Also note th
at the interface of the new CV iterators are different from that of t
his module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

Step 1: Dataset Summary & Exploration

The pickled data is a dictionary with 4 key/value pairs:

- `'features'` is a 4D array containing raw pixel data of the traffic sign images, (num examples, width, height, channels).
- `'labels'` is a 2D array containing the label/class id of the traffic sign. The file `signnames.csv` contains id -> name mappings for each id.
- `'sizes'` is a list containing tuples, (width, height) representing the the original width and height the image.
- `'coords'` is a list containing tuples, (x1, y1, x2, y2) representing coordinates of a bounding box around the sign in the image. **THESE COORDINATES ASSUME THE ORIGINAL IMAGE. THE PICKLED DATA CONTAINS RESIZED VERSIONS (32 by 32) OF THESE IMAGES**

Complete the basic data summary below.

In [3]:
```
n_train = len(X_train)
n_test = len(X_test)
image_shape = X_train[0].shape

print("Number of training examples =", n_train)
print("Number of testing examples =", n_test)
print("Image data shape =", image_shape)
print("Number of classes =", n_classes)

print("Number of X_train = ", len(X_train))
print("Number of X_validation = ", len(X_validation))
print("Number of y_train = ", len(y_train))
print("Number of y_validation = ", len(y_validation))
```

```
Number of training examples = 125468
Number of testing examples = 12630
Image data shape = (48, 48, 3)
Number of classes = 43
Number of X_train =  125468
Number of X_validation =  31368
Number of y_train =  125468
Number of y_validation =  31368
```

Visualize the German Traffic Signs Dataset using the pickled file(s). This is open ended, suggestions include: plotting traffic sign images, plotting the count of each sign, etc.

The Matplotlib (http://matplotlib.org/) examples (http://matplotlib.org/examples/index.html) and gallery (http://matplotlib.org/gallery.html) pages are a great resource for doing visualizations in Python.

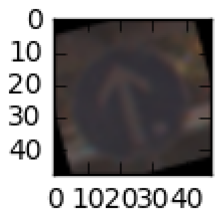
NOTE: It's recommended you start with something simple first. If you wish to do more, come back to it after you've completed the rest of the sections.

In [4]:
```
import random
# Visualizations will be shown in the notebook.
%matplotlib inline

index = random.randint(0, len(X_train))
image = X_train[index].squeeze()

plt.figure(figsize=(1,1))
plt.imshow(image)
print(y_train[index], signnames[y_train[index]][1])
```

```
35 Ahead only
```



Step 2: Design and Test a Model Architecture

Design and implement a deep learning model that learns to recognize traffic signs. Train and test your model on the German Traffic Sign Dataset (http://benchmark.ini.rub.de/?section=gtsrb&subsection=dataset).

There are various aspects to consider when thinking about this problem:

- Neural network architecture
- Play around preprocessing techniques (normalization, rgb to grayscale, etc)
- Number of examples per label (some have more than others).
- Generate fake data.

Here is an example of a published baseline model on this problem (http://yann.lecun.com/exdb/publis/pdf/sermanet-ijcnn-11.pdf). It's not required to be familiar with the approach used in the paper but, it's good practice to try to read papers like these.

NOTE: The LeNet-5 implementation shown in the classroom (https://classroom.udacity.com/nanodegrees/nd013/parts/fbf77062-5703-404e-b60c-95b78b2f3f9e/modules/6df7ae49-c61c-4bb2-a23e-6527e69209ec/lessons/601ae704-1035-4287-8b11-e2c2716217ad/concepts/d4aca031-508f-4e0b-b493-e7b706120f81) at the end of the CNN lesson is a solid starting point. You'll have to change the number of classes and possibly the preprocessing, but aside from that it's plug and play!

Implementation

Use the code cell (or multiple code cells, if necessary) to implement the first step of your project. Once you have completed your implementation and are satisfied with the results, be sure to thoroughly answer the questions that follow.

In [5]:

```
import tensorflow as tf
from tensorflow.contrib.layers import flatten

EPOCHS = 10
BATCH_SIZE = 128

def ConvNet(x):
    mu = 0
    sigma = 0.1

    # Layer 1: Convolutional. Input = 48x48x3. Output = 42x42x100.
    c1_W = tf.Variable(tf.truncated_normal([7, 7, 3, 100], mean=mu, s
tddev=sigma))
    c1_b = tf.Variable(tf.zeros(100))
    c1 = tf.nn.conv2d(x, c1_W, strides=[1, 1, 1, 1], padding='VALID')
    c1 = tf.nn.bias_add(c1, c1_b)
    c1 = tf.nn.relu(c1)

    # Layer 2: Max Pooling. Input = 42x42x100. Output = 21x21x100.
    s2 = tf.nn.max_pool(c1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1],
 padding='SAME')

    # Layer 3: Convolutional. Input = 21x21x100. Output = 18x18x150.
    c3_W = tf.Variable(tf.truncated_normal([4, 4, 100, 150], mean=mu,
 stddev=sigma))
    c3_b = tf.Variable(tf.zeros(150))
    c3 = tf.nn.conv2d(s2, c3_W, strides=[1, 1, 1, 1],
padding='VALID')
    c3 = tf.nn.bias_add(c3, c3_b)
    c3 = tf.nn.relu(c3)

    # Layer 4: Max Pooling. Input = 18x18x150. Output = 9x9x150
    s4 = tf.nn.max_pool(c3, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1],
 padding='SAME')

    # Layer 5: Convolutional. Input = 9x9x150. Output = 6x6x250.
    c5_W = tf.Variable(tf.truncated_normal([4, 4, 150, 250], mean=mu,
 stddev=sigma))
    c5_b = tf.Variable(tf.zeros(250))
    c5 = tf.nn.conv2d(s4, c5_W, strides=[1, 1, 1, 1],
padding='VALID')
    c5 = tf.nn.bias_add(c5, c5_b)
    c5 = tf.nn.relu(c5)

    # Layer 6: Max Pooling. Input = 6x6x250. Output = 3x3x250.
    s6 = tf.nn.max_pool(c5, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1],
 padding='SAME')

    # Layer 6: Flatten. Input = 3x3x250. Output = 2250
    s6 = flatten(s6)

    # Layer 7: Fully Connected. Input = 2250. Output = 300.
    fc7_W = tf.Variable(tf.truncated_normal([2250, 300], mean=mu, std
dev=sigma))
    fc7_b = tf.Variable(tf.zeros(300))
    fc7 = tf.add(tf.matmul(s6, fc7_W), fc7_b)
    fc7 = tf.nn.relu(fc7)
```

```
    # Layer 8: Fully Connected. Input = 300. Output = 43.
    fc8_W = tf.Variable(tf.truncated_normal([300, 43], mean=mu, stdde
v=sigma))
    fc8_b = tf.Variable(tf.zeros(43))
    fc8 = tf.add(tf.matmul(fc7, fc8_W), fc8_b)

    return fc8
```

Features and Labels

In [6]:
```
x = tf.placeholder(tf.float32, (None, 48, 48, 3))
y = tf.placeholder(tf.int32, (None))
one_hot_y = tf.one_hot(y, n_classes)
```

Training Pipeline

In [7]:
```
rate = 0.001

logits = ConvNet(x)
cross_entropy = tf.nn.softmax_cross_entropy_with_logits(logits, one_h
ot_y)
loss_operation = tf.reduce_mean(cross_entropy)
optimizer = tf.train.AdamOptimizer(learning_rate = rate)
training_operation = optimizer.minimize(loss_operation)
```

Model Evaluation

In [8]:
```
correct_prediction = tf.equal(tf.argmax(logits, 1), tf.argmax(one_hot
_y, 1))
accuracy_operation = tf.reduce_mean(tf.cast(correct_prediction, tf.fl
oat32))

def evaluate(X_data, y_data):
    num_examples = len(X_data)
    total_accuracy = 0
    sess = tf.get_default_session()
    for offset in range(0, num_examples, BATCH_SIZE):
        batch_x, batch_y = X_data[offset:offset+BATCH_SIZE], y_data[o
ffset:offset+BATCH_SIZE]
        accuracy = sess.run(accuracy_operation, feed_dict={x:
batch_x, y: batch_y})
        total_accuracy += (accuracy * len(batch_x))
    return total_accuracy / num_examples
```

Model Training

In [9]:
```
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    num_examples = len(X_train)

    print("Training...")
    print()
    for i in range(EPOCHS):
        X_train, y_train = shuffle(X_train, y_train)
        for offset in range(0, num_examples, BATCH_SIZE):
            end = offset + BATCH_SIZE
            batch_x, batch_y = X_train[offset:end], y_train[offset:en
d]
            sess.run(training_operation, feed_dict={x: batch_x, y: ba
tch_y})

        validation_accuracy = evaluate(X_validation, y_validation)
        print("EPOCH {} ...".format(i+1))
        print("Validation Accuracy = {:.3f}".format(validation_accura
cy))
        print()

    try:
        saver
    except NameError:
        saver = tf.train.Saver()
    saver.save(sess, 'convnet')
    print("Model saved")
```

```
Training...

EPOCH 1 ...
Validation Accuracy = 0.094

EPOCH 2 ...
Validation Accuracy = 0.160

EPOCH 3 ...
Validation Accuracy = 0.213

EPOCH 4 ...
Validation Accuracy = 0.522

EPOCH 5 ...
Validation Accuracy = 0.778

EPOCH 6 ...
Validation Accuracy = 0.857

EPOCH 7 ...
Validation Accuracy = 0.887

EPOCH 8 ...
Validation Accuracy = 0.906

EPOCH 9 ...
Validation Accuracy = 0.923

EPOCH 10 ...
Validation Accuracy = 0.935

Model saved
```

Model Evaluation

In [22]:

```
with tf.Session() as sess:
    loader = tf.train.import_meta_graph("convnet.meta")
    loader.restore(sess, tf.train.latest_checkpoint('./'))

    test_accuracy = evaluate(X_test, y_test)
    print("Test Accuracy = {:.3f}".format(test_accuracy))
```

```
Test Accuracy = 0.899
```

Question 1

Describe how you preprocessed the data. Why did you choose that technique?

Answer:

I did not preprocess the data.

Question 2

Describe how you set up the training, validation and testing data for your model. ***Optional****: If you generated additional data, how did you generate the data? Why did you generate the data? What are the differences in the new dataset (with generated data) from the original dataset?*

Answer:

I generate additional data using 3 methods:

```
1. Adaptive histogram
2. Rotate -15 degree
3. Rotate 15 degree
```

Additionally, I resize the images from 32x32 to 48x48 I took the action according to the paper Multi-Column Deep Neural Network for Traffic Sign Classification (for Adaptive histogram) and Traffic Sign Recognition with Multi-Scale Convolutional Networks (for rotation).

Finally, I split the training data into 2 parts following 80:20 for cross validation.

Question 3

What does your final architecture look like? (Type of model, layers, sizes, connectivity, etc.) For reference on how to build a deep neural network using TensorFlow, see [Deep Neural Network in TensorFlow (https://classroom.udacity.com/nanodegrees/nd013/parts/fbf77062-5703-404e-b60c-95b78b2f3f9e/modules/6df7ae49-c61c-4bb2-a23e-6527e69209ec/lessons/b516a270-8600-4f93-a0a3-20dfeabe5da6/concepts/83a3a2a2-a9bd-4b7b-95b0-eb924ab14432)](https://classroom.udacity.com/nanodegrees/nd013/parts/fbf77062-5703-404e-b60c-95b78b2f3f9e/modules/6df7ae49-c61c-4bb2-a23e-6527e69209ec/lessons/b516a270-8600-4f93-a0a3-20dfeabe5da6/concepts/83a3a2a2-a9bd-4b7b-95b0-eb924ab14432) from the classroom.

Answer:

I uses the architecture from Multi-Column Deep Neural Network for Traffic Sign Classification by Ciresan et. al. The following lines briefly describes the layers:

Input: 48x48x3 images Layer 1: Convolutional layer with 7x7 kernel which output 100 maps of 42x42 neurons Layer 2: Max-pooling layer with 2x2 kernel and 2 strides which output 100 maps of 21x21 neurons Layer 3: Convolutional layer with 4x4 kernel which output 150 maps of 18x18 neurons Layer 4: Max-pooling layer with 2x2 kernel and 2 strides which output 100 maps of 9x9 neurons Layer 5: Convolutional layer with 4x4 kernel which output 250 maps of 6x6 neurons Layer 6: Max-pooling layer with 2x2 kernel and 2 strides which output 100 maps of 3x3 neurons Layer 7: Fully-connected layer outputing 300 neurons Layer 8: Fully-connected layer outputing 43 neurons/logits

Question 4

How did you train your model? (Type of optimizer, batch size, epochs, hyperparameters, etc.)

Answer:

Optimizer: Adam-optimizer Batch size: 128 Epochs: 10 Hyperparameters: mu = 0, sigma = 0.1 Learning rate: 0.001

Question 5

What approach did you take in coming up with a solution to this problem? It may have been a process of trial and error, in which case, outline the steps you took to get to the final solution and why you chose those steps. Perhaps your solution involved an already well known implementation or architecture. In this case, discuss why you think this is suitable for the current problem.

Answer:

I tried Lenet-5 prior to the current architecture. The evaluation result is about 0.8. After changing the architecture, the result improved to above 0.9. I decided to add additional training images after viewing the images. Some of them are darkened, and some of them off-centered. Therefore, I took cue from 2 papers above to generate additional data by using adaptive histogram and rotation. The results improved.

Step 3: Test a Model on New Images

Take several pictures of traffic signs that you find on the web or around you (at least five), and run them through your classifier on your computer to produce example results. The classifier might not recognize some local signs but it could prove interesting nonetheless.

You may find `signnames.csv` useful as it contains mappings from the class id (integer) to the actual sign name.

Implementation

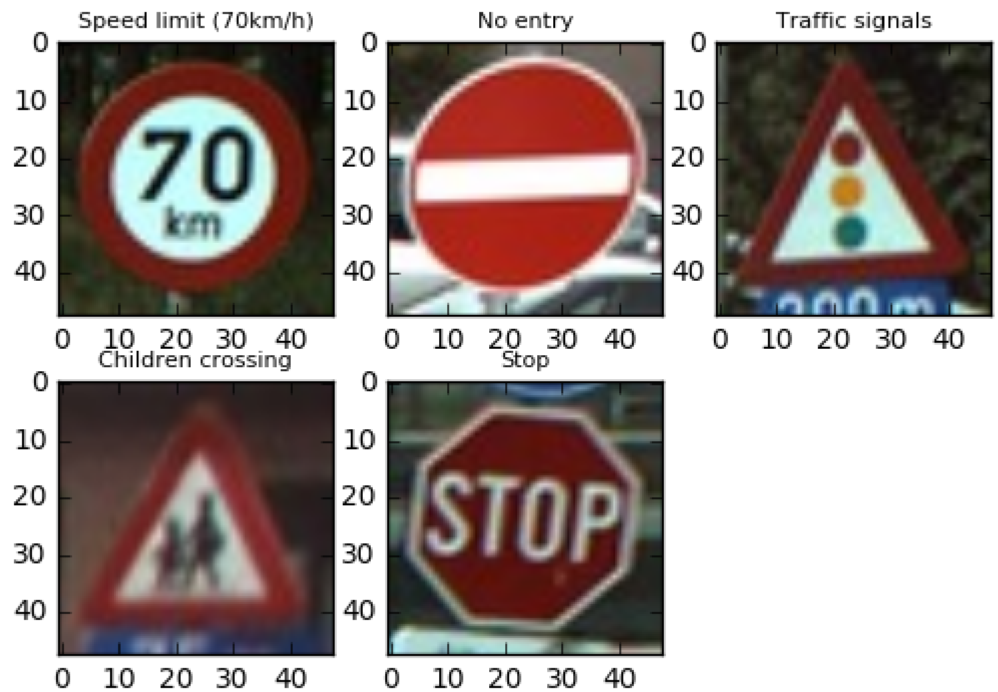
Use the code cell (or multiple code cells, if necessary) to implement the first step of your project. Once you have completed your implementation and are satisfied with the results, be sure to thoroughly answer the questions that follow.

In [64]:
```
from PIL import Image

# Visualizations will be shown in the notebook.
%matplotlib inline

new_images = []
new_labels = np.array([4, 17, 26, 28, 14])

fig = plt.figure()
for i in range(1, 6):
    subplot = fig.add_subplot(2,3,i)
    img = cv2.imread("./dataset/{}.png".format(i))
    img = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
    img = cv2.resize(img,(48, 48), interpolation = cv2.INTER_CUBIC)
    subplot.set_title(signnames[new_labels[i-1]][1],fontsize=8)
    subplot.imshow(img)
    new_images.append(img)
```



Question 6

Choose five candidate images of traffic signs and provide them in the report. Are there any particular qualities of the image(s) that might make classification difficult? It could be helpful to plot the images in the notebook.

Answer:

In [80]:
```
with tf.Session() as sess:
    loader = tf.train.import_meta_graph("convnet.meta")
    loader.restore(sess, tf.train.latest_checkpoint('./'))

    new_pics_classes = sess.run(logits, feed_dict={x: new_images})
    test_accuracy = evaluate(new_images, new_labels)
    print("Test Accuracy = {:.3f}".format(test_accuracy))

    top3 = sess.run(tf.nn.top_k(new_pics_classes, k=3, sorted=True))

    for i in range(len(top3[0])):
        labels = list(map(lambda x: signnames[x][1], top3[1][i]))
        print("Image {} predicted labels: {} with probabilities: 
{}".format(i+1, labels, top3[0][i]))
```

```
Test Accuracy = 0.800
Image 1 predicted labels: ['Speed limit (20km/h)', 'Speed limit (30k
m/h)', 'Speed limit (120km/h)'] with probabilities: [ 26.95365143  2
2.80621529  20.18837547]
Image 2 predicted labels: ['No entry', 'Stop', 'Yield'] with probabil
ities: [ 70.85643768  30.94743347  25.64486122]
Image 3 predicted labels: ['Traffic signals', 'Bicycles crossing', 'B
umpy road'] with probabilities: [ 52.54760361  47.56761551  44.685985
57]
Image 4 predicted labels: ['Children crossing', 'Bicycles crossing',
 'Slippery road'] with probabilities: [ 29.35030365  25.48864365  21.
97713089]
Image 5 predicted labels: ['Stop', 'General caution', 'No entry'] wit
h probabilities: [ 41.55501175  31.83267975  21.79871941]
```

Question 7

Is your model able to perform equally well on captured pictures when compared to testing on the dataset? The simplest way to do this check the accuracy of the predictions. For example, if the model predicted 1 out of 5 signs correctly, it's 20% accurate.

NOTE: *You could check the accuracy manually by using `signnames.csv` (same directory). This file has a mapping from the class id (0-42) to the corresponding sign name. So, you could take the class id the model outputs, lookup the name in `signnames.csv` and see if it matches the sign from the image.*

Answer:

The accuracy is 80%. With only 1 minor mistake which the model mistaken 70 as 20 which is incredible narrow because 2 is very similar to 7 in some perspective.

Question 8

Use the model's softmax probabilities to visualize the **certainty** *of its predictions, [`tf.nn.top_k` (https://www.tensorflow.org/versions/r0.12/api_docs/python/nn.html#top_k)](https://www.tensorflow.org/versions/r0.12/api_docs/python/nn.html#top_k) could prove helpful here. Which predictions is the model certain of? Uncertain? If the model was incorrect in its initial prediction, does the correct prediction appear in the top k? (k should be 5 at most)*

`tf.nn.top_k` will return the values and indices (class ids) of the top k predictions. So if k=3, for each sign, it'll return the 3 largest probabilities (out of a possible 43) and the correspoding class ids.

Take this numpy array as an example:

```
# (5, 6) array
a = np.array([[ 0.24879643,  0.07032244,  0.12641572,  0.34763842,  0.078934
97,
         0.12789202],
       [ 0.28086119,  0.27569815,  0.08594638,  0.0178669 ,  0.18063401,
         0.15899337],
       [ 0.26076848,  0.23664738,  0.08020603,  0.07001922,  0.1134371 ,
         0.23892179],
       [ 0.11943333,  0.29198961,  0.02605103,  0.26234032,  0.1351348 ,
         0.16505091],
       [ 0.09561176,  0.34396535,  0.0643941 ,  0.16240774,  0.24206137,
         0.09155967]])
```

Running it through `sess.run(tf.nn.top_k(tf.constant(a), k=3))` produces:

```
TopKV2(values=array([[ 0.34763842,  0.24879643,  0.12789202],
       [ 0.28086119,  0.27569815,  0.18063401],
       [ 0.26076848,  0.23892179,  0.23664738],
       [ 0.29198961,  0.26234032,  0.16505091],
       [ 0.34396535,  0.24206137,  0.16240774]]), indices=array([[3, 0, 5],
       [0, 1, 4],
       [0, 5, 1],
       [1, 3, 5],
       [1, 4, 3]], dtype=int32))
```

Looking just at the first row we get `[ 0.34763842,  0.24879643,  0.12789202]`, you can confirm these are the 3 largest probabilities in `a`. You'll also notice `[3, 0, 5]` are the corresponding indices.

Answer:

Looking at all the Top 3, the model predicted Image 2 with high confidence whereas the rest are very close. It is astonishing to see the model recognize Image 1 as a speed limit sign just that it wrongly predict the speed limit (70->20).