Write-up Report – Traffic Sign Classifier Project

Self-Driving Car Nano Degree Program – Term1, Project2

1. Ojective

   The objective of this project is to model a deep neural network that will predict the German traffic signs. Following are the steps of this project.

   - Load the data set (see below for links to the project data set)
   - Explore, summarize and visualize the data set
   - Design, train and test a model architecture
   - Use the model to make predictions on new images
   - Analyze the softmax probabilities of the new images
   - Summarize the results with a written report

2. Rubric Points

   2.1. Write-up / README

   2.1.1. Provide a Write-up / README that includes all the rubric points and how you addressed each one. You can submit your write up as markdown or pdf. You can use this template as a guide for writing the report. The submission includes the project code.

   This document is the write-up report. The link to the project code is https://github.com/sekar1232007/Traffic_Sign_Classification

   2.2. Data Set Summary & Exploration

   2.2.1. Provide a basic summary of the data set. In the code, the analysis should be done using python, numpy and/or pandas methods rather than hardcoding results manually

   I used basic python functions such as len, shape to find the length & dimensions of the training and test data set. I also wrote a small code to read in the signnames.csv file to find the no. of classes and to import the names of each traffic signs.

   Note: this information can be used later to print the name of the sign after predicting it.

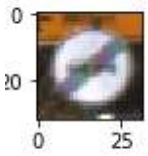
Following is the summary of the data set.

- Number of training examples = 34799
- Number of testing examples = 4410
- Image data shape = (32, 32, 3)
- Number of classes = 43

2.3. Design and Test a Model Architecture

2.3.1. Data preprocessing

- I decided not to convert the image to grayscale, as the color information may play a significant role in differentiating similar signs. Ex: there are minimum and maximum speed limit signs. Both the signs have numbers, but the background colors are different in both the cases.
- I plotted a random image to check it visually. This is how it looked like



- I normalized the input data between 0 and 0.9. This reduces the range of input values and as a result will help in converging (reaching local minima) weights and biases in a stable way.

2.3.2. Model Architecture

My final model architecture consists of following layers

Layer	Input Size	Output Size	Additional Info
Input	32*32*3	N.A	Input image (R.G.B values)
Convolution	32*32*3	28*28*18	Filter =5*5, strides=1*1, Valid padding
ReLu activation	N.A	N.A	N.A
Max pooling	28*28*18	14*14*18	Filter=2*2 strides=1*1
Convolution	14*14*18	10*10*54	Filter =5*5, strides=1*1, Valid padding
ReLu activation	N.A	N.A	N.A
Max pooling	10*10*18	5*5*54	Filter=2*2 strides=1*1
Flatten	5*5*54	1350	
Fully connected	1350	500	
Fully connected	500	250	
Output layer	250	43	

2.3.3. Model Tuning

At first I reused the Lenet model architecture from character recognition lab. During training the accuracy was very low. After debugging it was very clear that the model was under fitting. This model was designed only to predict 10 classes and also input feature was only one dimension. Where as in traffic recognition, I used an input with 3 features and also there are 43 classes to predict.

I tried increasing the features of my convolutions layer, after some iterations I was able to achieve 93% of accuracy on the training set with 18 & 54 features respectively at convolution layers 1 & 2.

2.3.4. Parameters used

Batch size=128

Learning rate = 0.001

Weights and Biases initialized with a random normal distribution with mu=0 & Sigma=0.1

Epochs =10

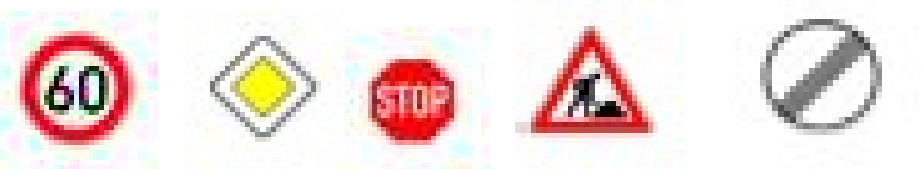
2.3.5. Accuracy

Validation: 94.6%

Test: 92.4%

2.4. Test a Model on New Images

2.4.1. German Traffic sign used for testing



2.4.2. Image resizing

After downloading, I resized the images to 32*32 manually using paint brush application and renamed the file names with their corresponding labels

2.4.3. Image prediction

- At first, all the images were predicted wrongly by my model. After a long debugging session I found the reason for wrong prediction.
- Reason:
  I used imread function to read the png files and then normalized them using the same algorithm used for training images.
- The imread function has already normalized the data between 0 & 1. This has led to the double normalization and all the input values scaled almost close to 0.
- Once I corrected the double normalization, the model predicted all the 5 images correctly. The accuracy was 100%

2.4.4. Top 5 softmax probabilities

Almost 100% for all the five images.

```
TopKV2(values=array([[  1.00000000e+00,   1.46327493e-21,   3.05450887e-23,
          7.43973458e-24,   2.94495912e-27],
       [  1.00000000e+00,   1.08557615e-16,   2.50128416e-17,
          1.05531024e-19,   6.87636665e-20],
       [  1.00000000e+00,   1.94675594e-15,   4.83798543e-18,
          6.49346959e-21,   2.72215300e-22],
       [  1.00000000e+00,   9.08220493e-13,   1.89497750e-13,
          2.09174249e-18,   1.10104791e-18],
       [  5.06199956e-01,   4.93799031e-01,   1.00174452e-06,
          7.87055754e-10,   2.73833300e-12]], dtype=float32), indices=array([[ 3,  2,  5, 29,  1],
       [12, 26, 11, 30, 29],
       [14, 17,  8,  1,  5],
       [25, 31, 30, 14, 24],
       [32,  6, 41,  5,  3]]))
```