Traffic Sign Recognition : Build a Traffic Sign Recognition Project

The goals / steps of this project are the following:
* 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

Writeup / README

Data Set Summary & Exploration

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.

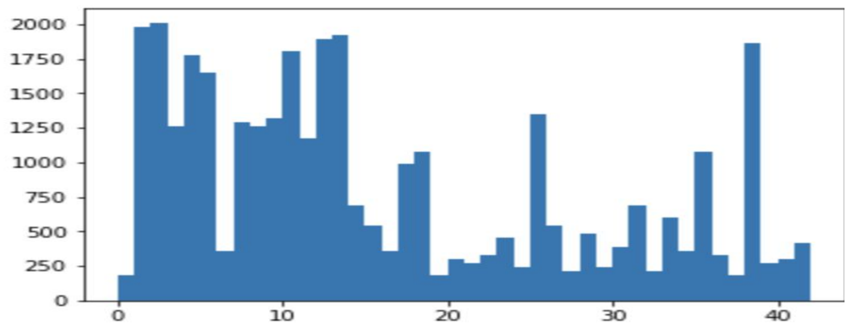
After reading the .pkl files I performed the following

Number of training examples = 34799
Number of testing examples = 12630
Image data shape = (32, 32, 3)
Number of classes = 43

2. Include an exploratory visualization of the dataset.

Here is an exploratory visualization of the data set. The following bar chart shows the frequency of training examples for each of the 43 class labels (traffic signs).

The bar chart shows a very uneven distribution of classes.



Design and Test a Model Architecture

1. Describe how you preprocessed the image data. What techniques were chosen and why did you choose these techniques? Consider including images showing the output of each preprocessing technique. Pre-processing refers to techniques such as converting to grayscale, normalization, etc. (OPTIONAL: As described in the "Stand Out Suggestions" part of the rubric, if you generated additional data for training, describe why you decided to generate additional data, how you generated the data, and provide example images of the additional data. Then describe the characteristics of the augmented training set like number of images in the set, number of images for each class, etc.)

I first decided to standardize all the data by converting it to zero mean and unit variance. This alone did not bring the accuracy above the minimum criterion (93 percent). On further reading I found that this normalization technique is most effective to remove the bias of multiple units of measurement of the data. The lack of improvement with this technique indicated that the data was collected in a consistent fashion.

Then I decided to perform scaling, between -1.0 to 1.0. This led to an improvement in performance.

After this I read online that brightness normalization improves performance when working with images that are captured any time during the day.

This did lead to a substantial improvement. I finally settled with brightness normalization and scaling between -0.5 to 0.5.

Since neural nets benefit from more data, I also performed data augmentation by applying small amounts of translations, brightness changes and rotations. This also teaches the network that the ideal function is agnostic to where in the overall image the traffic sign is present, its orientation and the time of the day it was captured.

With this augmentation the training data set became 4 times the original size.

2. Describe what your final model architecture looks like including model type, layers, layer sizes, connectivity, etc.) Consider including a diagram and/or table describing the final model.

I did not make any changes to the original LeNET architecture other than change the input image channel number to three and the output class number to 43. I also added dropout before the last fully connected layer to avoid overfitting. A probability of 0.5 gave good accuracy on the test set.

This is a description of the model used.

Layer	**Description**
Input	32x32x3 RGB image
Convolution 5x5	1x1 stride, valid padding, outputs 28x28x6
RELU	
Max pooling 2x2	2x2 stride, valid padding, outputs 14x14x6
Convolution 5x5	1x1 stride, valid padding, outputs 10x10x16
RELU	
Max pooling 2x2	2x2 stride, valid padding, outputs 5x5x16
Flatten	Output 400
Fully connected	Output 120
RELU	
Fully connected	Output 84
RELU	

Dropout	Keep Probability: 0.5
Fully connected	Output 43

3. Describe how you trained your model. The discussion can include the type of optimizer, the batch size, number of epochs and any hyperparameters such as learning rate.

I used the adamOptimizer which works well because of the inbuilt momentum.
The other hyperparameters that I used are:
EPOCHS = 20
BATCH_SIZE = 64
Learning rate = 0.001

4. Describe the approach taken for finding a solution and getting the validation set accuracy to be at least 0.93. Include in the discussion the results on the training, validation and test sets and where in the code these were calculated. Your approach may have been an iterative process, 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 the architecture is suitable for the current problem.

My final model results were:
* training set accuracy of **0.993**
* validation set accuracy of **0.949**
* test set accuracy of **0.931**

The validation accuracy is calculated after every epoch in cell “Train, Validate and Test the Model”.
The test and training accuracy is in cell “Load and Output the Images”.

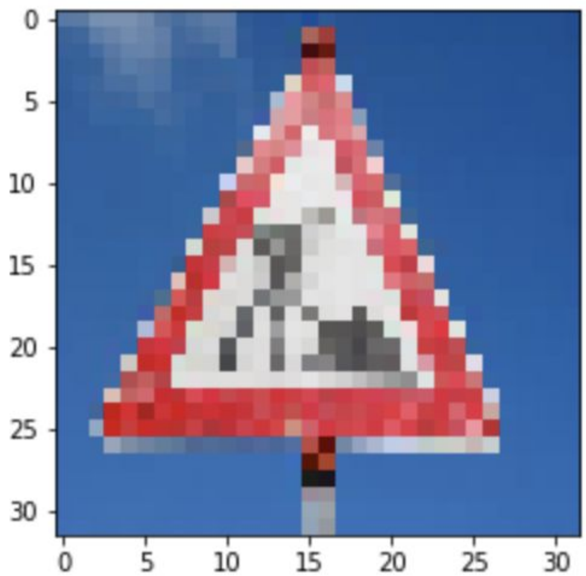
I started with the LeNet architecture as it is known to perform well on image data.
My approach to improving the performance was focused around picking the right normalization technique.
I also experimented with batch sizes of 64, 32, and 8. I did not find any significant improvements with dropping the batch size.
Further when I noticed that the accuracy tends to jump around a lot, I dropped the learning rate to 0.0005 and 0.0001. While these rates made the training slower, they did not help with the fluctuation.
Initially I did not have good results on the test set and thus decided to use dropout. A dropout param of 0.5 seems to work well.

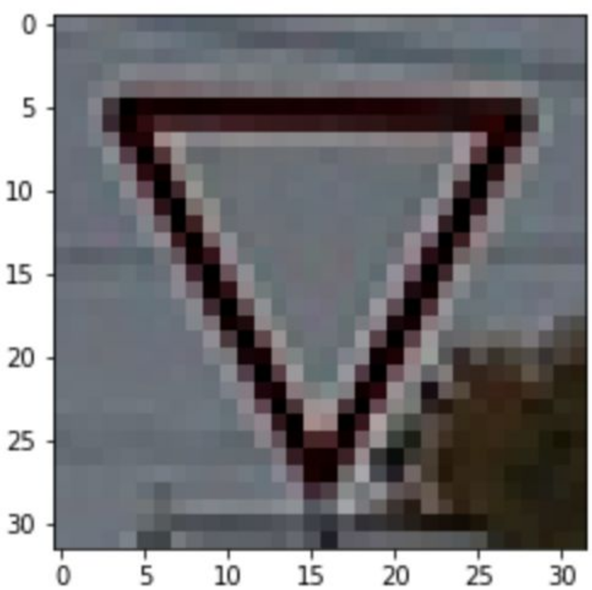
However given that the training accuracy is much higher than the validation accuracy, it is possible that the model has overfit on the training data. However increasing the dropout parameter was not very helpful with this problem.

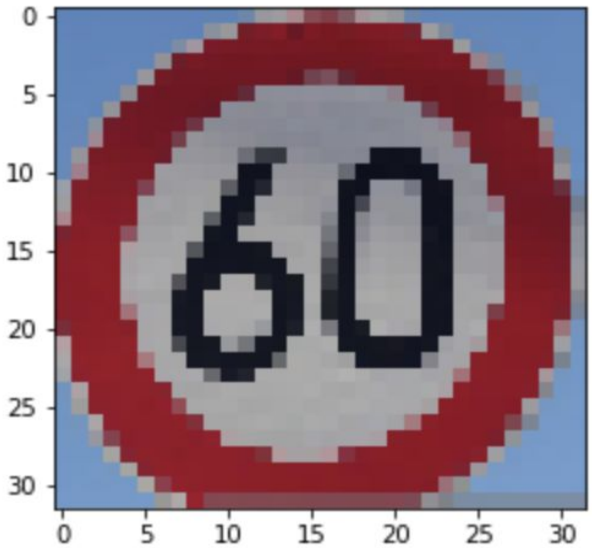
Test a Model on New Images

1. Choose five German traffic signs found on the web and provide them in the report. For each image, discuss what quality or qualities might be difficult to classify.

These are the images I chose for testing. All of these images are challenging because of the presence varying background.



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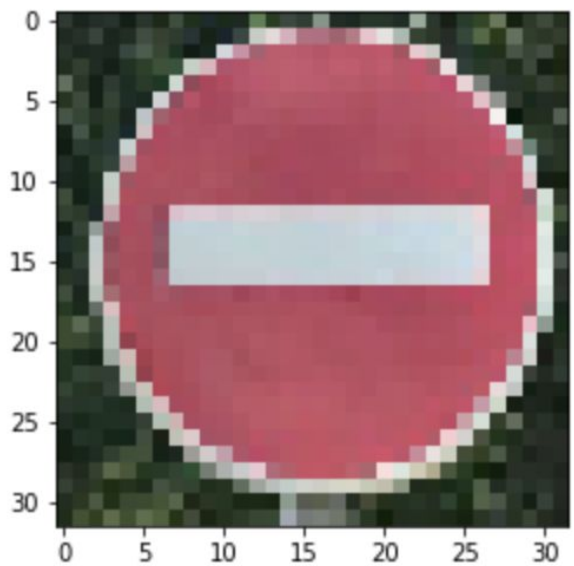
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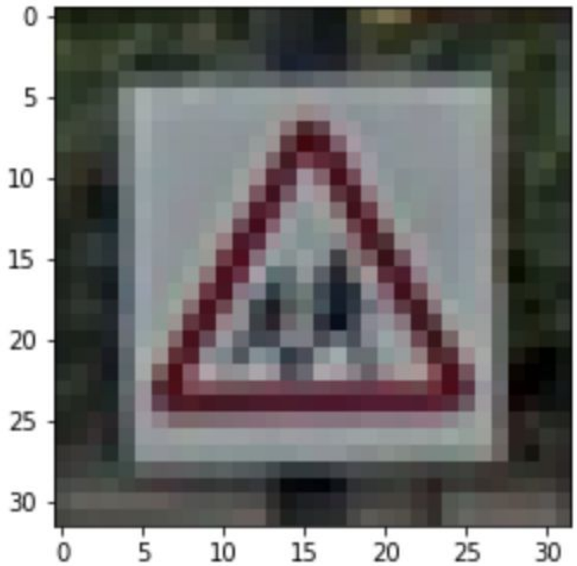

2. Discuss the model's predictions on these new traffic signs and compare the results to predicting on the test set. At a minimum, discuss what the predictions were, the accuracy on these new predictions, and compare the accuracy to the accuracy on the test set (OPTIONAL: Discuss the results in more detail as described in the "Stand Out Suggestions" part of the rubric).

The model was only able to correctly guess 2 of the 5 images. That gives it a accuracy of 40 percent. The results indicated that the network did not generalize properly.

I believe this result was much different than the test set as these images were not preprocessed. That is the images were not centred around the traffic sign etc. This is indicative of the challenges one might expect when running inference online.

The results were as follows:

Image Number	**Correct label**	**Predicted label**
1	Road Work	Double Curve
2	Yield	Yiled
3	Speed Limit (60km/h)	Go Straight or Left
4	No entry	No Entry
5	Children crossing	Double Curve

3. Describe how certain the model is when predicting on each of the five new images by looking at the softmax probabilities for each prediction. Provide the top 5 softmax probabilities for each image along with the sign type of each probability. (OPTIONAL: as described in the "Stand Out Suggestions" part of the rubric, visualizations can also be provided such as bar charts)

The softmax probabilities are as follows:

Correct label	**Predicted label**	**Highest probability**	**All softmax probabilities**
Road Work	Double Curve	9.91216421e-01	[9.91216421e-01, 8.77036247e-03, 6.60603837e-06, 3.45797275e-06, 2.84339308e-06]
Yield	Yiled	1.00000000e+00	[1.00000000e+00, 7.48112035e-15, 7.35917114e-18, 2.39014717e-19, 1.93508332e-19]
Speed Limit (60km/h)	Go Straight or Left	9.99995828e-01	[9.99995828e-01, 2.23388201e-06, 1.63432901e-06, 2.20761322e-07, 1.10794822e-08]
No entry	No Entry	9.98303294e-01	[9.98303294e-01, 1.66159414e-03, 2.64457158e-05, 8.41300698e-06, 1.05788963e-07]
Children crossing	Double Curve	5.61124504e-01	[5.61124504e-01, 4.01612341e-01, 2.26115156e-02, 8.74723401e-03, 2.64168018e-03]

After analyzing the softmax probabilities, it seems to me that the model is very confident about its correct predictions as well as the wrong ones. In the ones that it classified incorrectly I think it made the decision based on the surrounding of the sign rather than the sign itself.