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Udacity Self-Driving Car Nanodegree

P3 Reflection - Build a Traffic Sign Recognition Classifier

Overview

The goals / steps of this project are the following:

- Load the 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

My code for this project is publicly available and can be found here:

https://github.com/ednaldogoncalves/CarND-TrafficSignClassifier-P3

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1 - Data Set Summary & Exploration

1.1 - Basic Summary of the Data Set

I used the numpy library to calculate summary statistics of the traffic signs data set:

- The size of training set is 34799
- The size of test set is 12630
- The shape of a traffic sign image is (32, 32)
- The number of unique classes/labels in the data set is 43

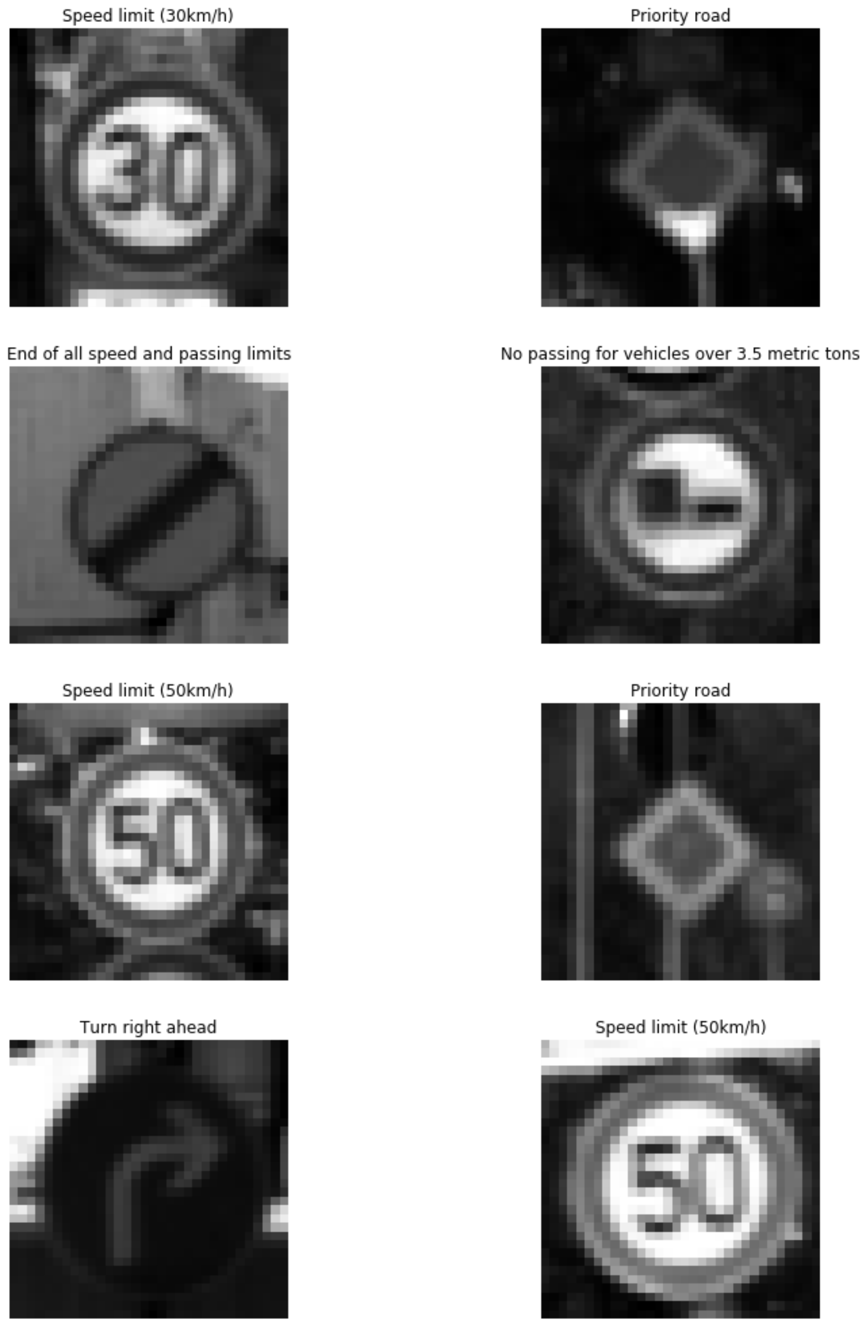
1.2 Exploratory visualization of the dataset

Here is an exploratory visualization of the data set. It pulls in a random set of eight images and labels them with the correct names in reference with the csv file to their respective id's.

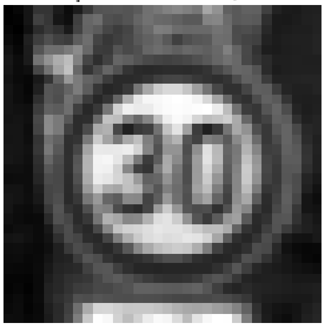
2 Design and Test a Model Architecture

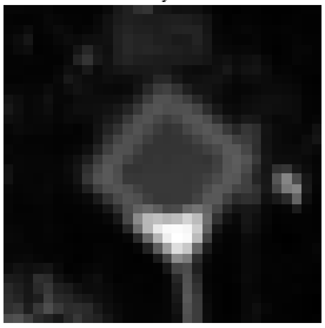
2.1 Pre-processing the Data Set

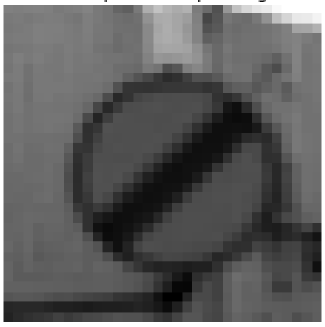
I converted the images to grayscale because in the technical paper it outlined several steps they used to achieve 93%. I assume this works better because the excess information only adds extra confusion into the learning process. After the grayscale I also normalized the image data because I've read it helps in speed of training and performance because of things like resources. Also added additional images to the datasets through randomized modifications.
Here is an example of a traffic sign images that were randomly selected.

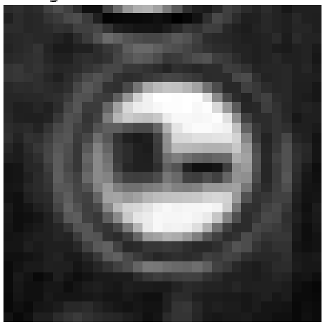


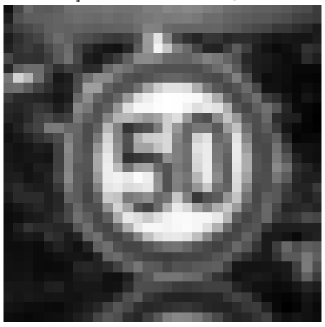
Here is a look at the normalized images. Which should look identical, but for some small random alterations such as opencv affine and rotation.

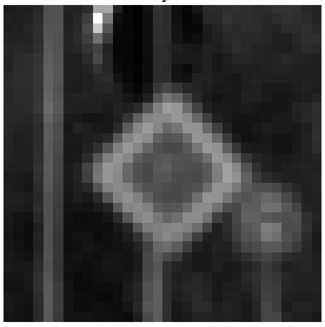

Speed limit (30km/h)


Priority road


End of all speed and passing limits


No passing for vehicles over 3.5 metric tons


Speed limit (50km/h)


Priority road

Turn right ahead

Speed limit (50km/h)

2.2 Model architecture

My final model consisted of the following layers:

Layer	Description
Input	32x32x1 grayscale image
Convolution 5x5	2x2 stride, valid padding, outputs 28x28x6
RELU	
Max pooling	2x2 stride, outputs 14x14x6
Convolution 5x5	2x2 stride, valid padding, outputs 10x10x16
RELU	
Max pooling	2x2 stride, outputs 5x5x16
Convolution 1x1	2x2 stride, valid padding, outputs 1x1x412
RELU	
Fully connected	input 412, output 122
RELU	
Dropout	50% keep
Fully connected	input 122, output 84
RELU	
Dropout	50% keep
Fully connected	input 84, output 43

2.3 Model Training

To train the model, I used an LeNet for the most part that was given, but I did add an additional convolution without a max pooling layer after. I used a learning rate of 0.00089. The epochs used was 35 while the batch size was 156. Other important parameters I learned were important was the number and distribution of additional data generated. I played around with various different distributions of image class counts and it had a dramatic effect on the training set accuracy. It didn't really have much of an effect on the test set accuracy, or real world image accuracy. Just using the default settings from the lesson leading up to this point I was able to get around 94% accuracy.

2.4 Solution Approach

My final model results were:

- Training set accuracy of 100.0%
- Validation set accuracy of 94.1%
- Test set accuracy of 93.5%

The first model is adapted from LeNet architecture. Since LeNet architecture has a great performance on recognizing handwritings, I think it would also work on classifying traffic signs.

I used the same parameter given in LeNet lab. Its training accuracy initially was around 90%, so I thought the filter depth was not large enough to capture images' shapes and contents. Previously the filter depth was low for the first and second layer. I increased them and accuracy increased to around 94%.

I also tuned epoch, batch_size, and rate parameters, and settled at:

- epoch 35
- batch_size 156
- learning rate 0.00089

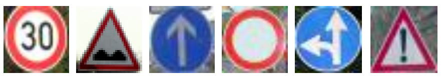
I have my explainations of the effect of the drop out layer after I've seen some of the training data. Some images are too dark to see the sign, so it seems that these images act as noises in the training data and drop out layer can reduce the negative effects on learning.

The final accuracy in validation set is around 0.941.

3 Test a Model on New Images

3.1 New Images

Here are five German traffic signs that I found on the web:



I used semi-easy images to classify and even modified them slightly. I made them all uniform in size and only had one partially cut off.

3.2 Performance on New Images

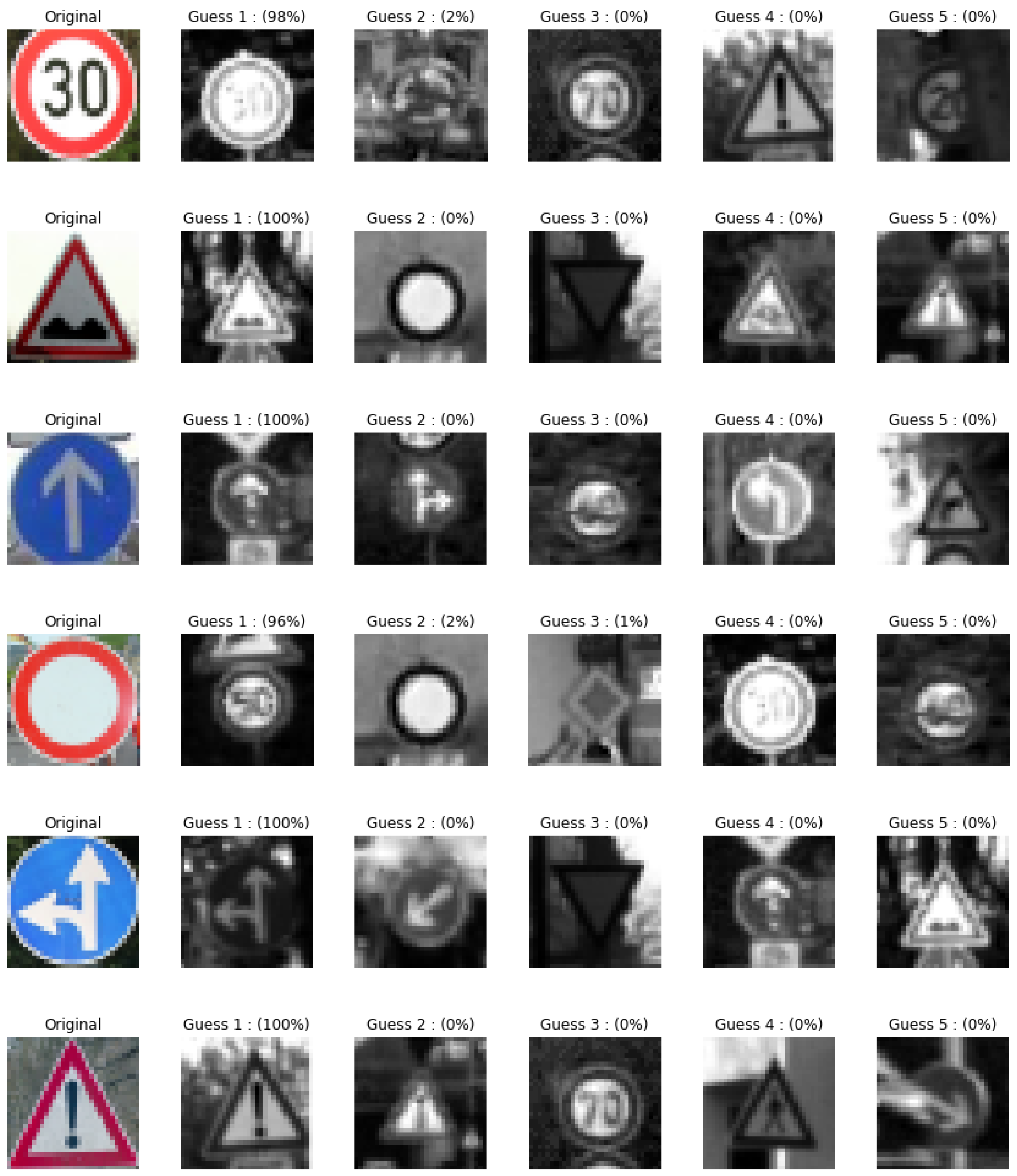
The accuracy on the new traffic signs is 66.7%, while it was 94% on the test set. This is a sign of underfitting. By looking at the virtualized result, I think this can be addressed by using more image preprocessing techniques on the training set.

By looking at the virtualized data. The prediction accuracy was 83,3%. I think to get the consistent correctness, I need more good data. One simple thing to do might be to preprocess the image by brightening dark ones.

Calculating the accuracy for these new images. The model predicted 3 out of 6 signs correctly, it's 50% accurate on these new images.

3.3 Model Certainty - Softmax Probabilities

This is the softmax probabilities for the predictions on the German traffic sign images found on the web:



The model was able to correctly guess 4 of the 6 traffic signs, which gives an accuracy of 67%. This compares favorably to the accuracy on the test set although I did throw it a softball.