[Project Writeup] Traffic Sign Classification 20-Sept-2017

Link to this Notebook: https://www.evernote.com/l/AC4sKKfM46VDwLoS0sAb90WrE648Sc4Z92A

Files Submitted

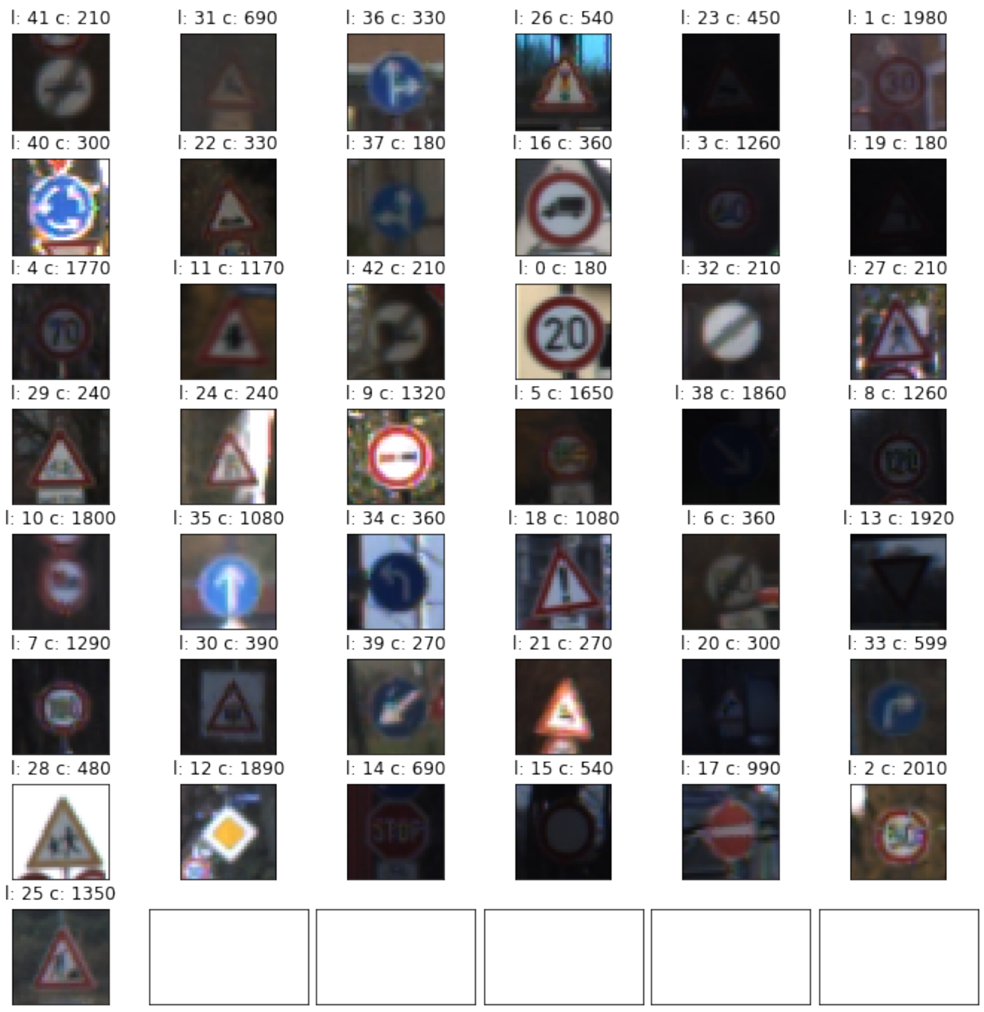
CRITERIA	MEETS SPECIFICATION
Submission Files	The Submission includes • *Traffic_Sign_Classifier.ipynb* files • *testSet/* test images • Writeup file as *writeup.pdf* • *Traffic_Sign_Classifier.html*

Dataset Exploration

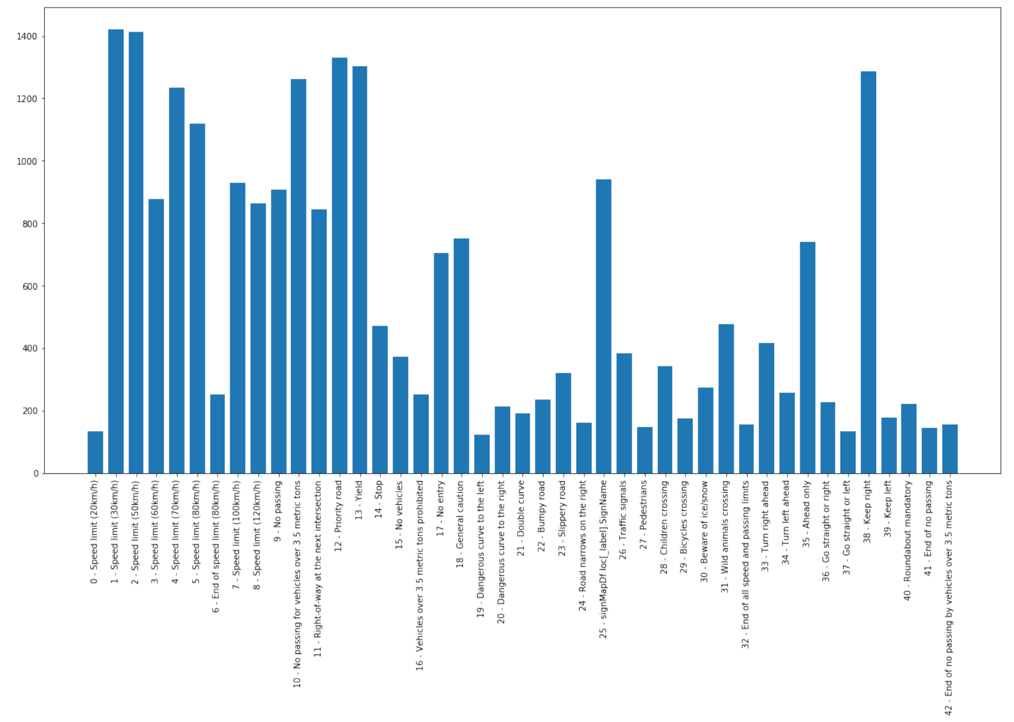
<table>
<tr><th>CRITERIA</th><th>MEETS SPECIFICATION</th></tr>
<tr><td>Dataset Summary</td><td>Database includes 3 files
• Train.p - training pickle file
• valid.p - validation pickle file
• Test.p - test pickle file

Each file is a pickle file,
It has features and labels in keys `features` and `labels`</td></tr>
<tr><td>Exploratory Visualization</td><td>The submission includes an exploratory visualization on the dataset.

Training data has 43 traffic signs, each sign differs in the number of samples available for training.



</td></tr>
</table>

Design and Test a Model Architecture

CRITERIA	MEETS SPECIFICATION

Preprocessing	• Just normalisation was done on data and that achieved 0.96 accuracy on Validation dataset.
	• Doing rotation, scaling based augmentation made the run time increase and the results where not better. A simple normalisation and adding of two convolutional layers before the LeNet architecture got better result,
	    ◦ Training Accuracy = 0.989
	    ◦ Validation Accuracy = 0.968

Model Architecture	PF the table below this table
Model Training	Learning rate of 0.001 was used. LeNet architecture was used for training a data set with images of shape (32, 32, 3) EPOCHS = 10 AdamOptimizer a variant of Stochastic Gradient Descent was used as optimiser.
Solution Approach (The submission describes the approach to finding a solution. Accuracy on the validation set is 0.93 or greater.)	Training Accuracy = 0.989 Validation Accuracy = 0.968 Initially the Lenet Architecture was used as suggested by Udacity. But that failed to give Validation accuracy above 0.89 - 0.90. Then two more convolution layers with Relu Activation was added to the beginning of the layer. These layers where given SAME padding so that the original Lenet Architecture gets the 32x32 image. These layers does adds to colour space transformation of images on its own. Normalisation was performed on images to values between 0 and 1. This help in case of High Contrast Variation among the images.

	The labels have been one hot encoded, so that the labels are converted into a, matrix with 0, 1 and the columns representing the label. In each column the unique placement of 1 identifies the label. Finally the Training accuracy came to 0.989 and Validation Accuracy to 0.968 which is good. Not a huge overfitting was observed. Though Test accuracy came to 0 .875 only, which shows a bit of overfitting. AdamOptimiser was used as it is faster in running. It us es moving averages of the parameters, which enables it t o use a larger effective step size and the algorithm wil l converge to this step size without fine tuning.

Model Architecture

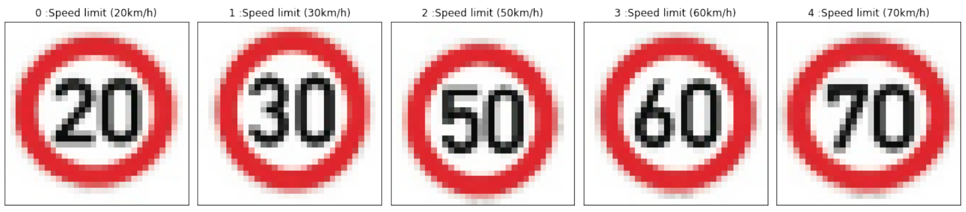
type	stride	size	filter/feature
conv	1 x 1 [padding=same]	5 x 5	3
conv	1 x 1 [padding=same]	5 x 5	7
conv	1 x 1 [padding=valid]	5 x 5	10
Max pooling	2 x 2 [padding=valid]	2 x 2	
conv	1 x 1	5 x 5	16
Max pool	2 x 2	2 x 2	
flatten			
Fully connected			120
Fully connected			80
Fully connected			43
softmax			43

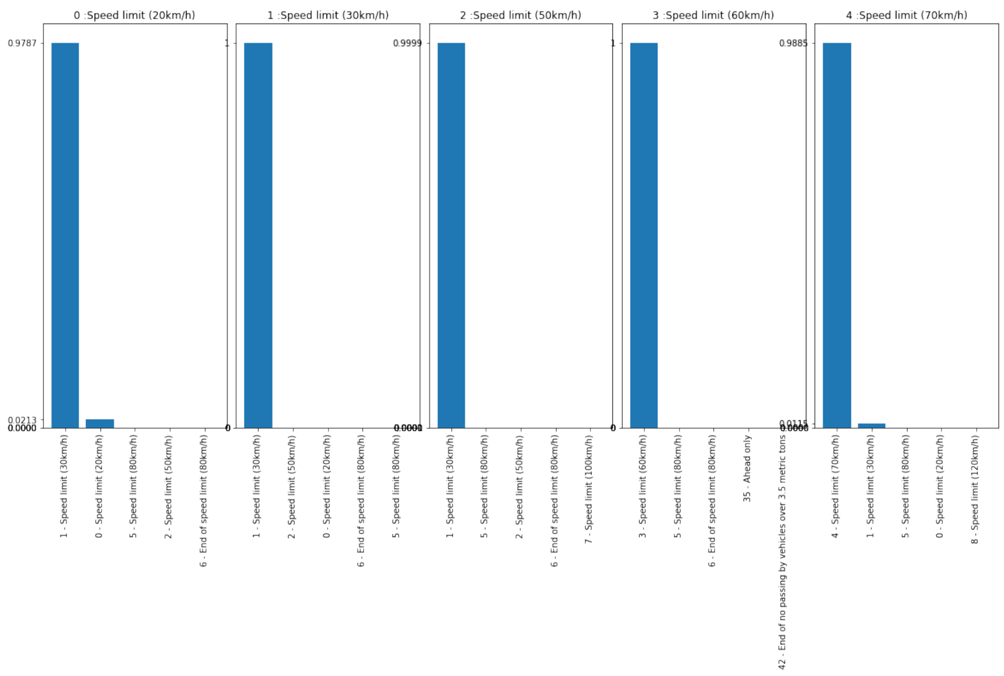
Test a Model on New Images

CRITERIA	MEETS SPECIFICATION
Acquiring New Images	The submission includes 2 * five new German Traffic signs found on the web. One set has clear images of the traffic signs. The other set has images taken in dark normal road conditions.
Performance on New Images	Images acquired from: http://benchmark.ini.rub.de/?

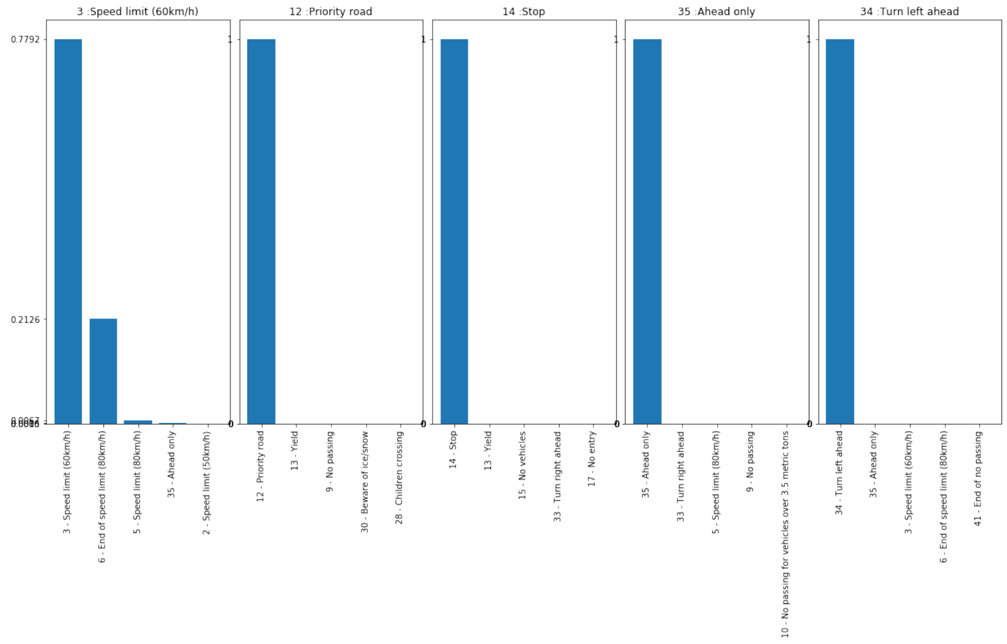
section=gtsrb&subsection=news

On a set of sample computer images acquired 60 % accuracy.





While the set with road conditions gave 100 accuracy.

Model Certainty - Softmax Probabilities	The top five softmax probabilities of the predictions on the captured images are outputted. The submission discusses how certain or uncertain the model is of its predictions.
	
	Signs [3, 12, 14, 35, 34]
	idx : 0 actual sign id: 3 kresults :[3 6 5 35 2]
	idx : 1 actual sign id: 12 kresults :[12 13 9 30 28]
	idx : 2 actual sign id: 14 kresults :[14 13 15 33 17]
	idx : 3 actual sign id: 35 kresults :[35 33 5 9 10]
	idx : 4 actual sign id: 34 kresults :[34 35 3 6 41]
	
	probability values: [[7.79210031e-01 2.12574050e-01 6.73343660e-03 1.46997254e-03
	    1.12289672e-05]
	[9.99997377e-01 2.48175047e-06 1.00112359e-07
	1.19281074e-08
	    5.15492271e-09]
	[1.00000000e+00 4.18616197e-10 2.00481623e-12
	1.31609459e-13
	    8.68164929e-14]
	[1.00000000e+00 4.35256432e-13 2.61120234e-14
	1.51658420e-14
	    5.16598843e-17]
	[1.00000000e+00 2.66956119e-12 9.65861180e-13
	1.26950073e-13
	    1.07681291e-14]]

Suggestions to Make Your Project Stand Out!

Here are a few ideas for going beyond the requirements outlined in the rubric.

AUGMENT THE TRAINING DATA

Augmenting the training set might help improve model performance. Common data augmentation techniques include rotation, translation, zoom, flips, and/or color perturbation. These techniques can be used individually or combined.

ANALYZE NEW IMAGE PERFORMANCE IN MORE DETAIL

Calculating the accuracy on these five German traffic sign images found on the web might not give a comprehensive overview of how well the model is performing. Consider ways to do a more detailed analysis of model performance by looking at predictions in more detail. For example, calculate the precision and recall for each traffic sign type from the test set and then compare performance on these five new images..

If one of the new images is a stop sign but was predicted to be a bumpy road sign, then we might expect a low recall for stop signs. In other words, the model has trouble predicting on stop signs. If one of the new images is a 100 km/h sign but was predicted to be a stop sign, we might expect precision to be low for stop signs. In other words, if the model says something is a stop sign, we're not very sure that it really is a stop sign.

Looking at performance of individual sign types can help guide how to better augment the data set or how to fine tune the model.

CREATE VISUALIZATIONS OF THE SOFTMAX PROBABILITIES

For each of the five new images, create a graphic visualization of the soft-max probabilities. Bar charts might work well.

VISUALIZE LAYERS OF THE NEURAL NETWORK

See Step 4 of the Iptyon notebook for details about how to do this.