CarND Project 2: Traffic Sign Recognition

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Summary

This below outlines the work performed for analyzing the German Traffic Sign Benchmark Dataset (http://benchmark.ini.rub.de/) from the Ruhr-University, Bochum, Germany, as part of the Self Driving Car Engineer (https://www.udacity.com/) nanodegree from Udacity. A convolutional neural network was trained with a validation accuracy of ~94% and testing accuracy of ~95%. Real-world testing with images from the internet showed results approaching 30% accuracy.

Introduction

One of the main characteristics of a legalized road are its signs and markings. It is therefore of great interest to the self-driving car research domain to find accurate, fast and resilient algorithms for image based road sign detection and classification. This work details the ***classification*** aspect, assuming the signs were already detected.

Methods

Data Summary

The dataset consists of labeled images organized in train, test and validation sets:

- Number of training examples: **34799**
- Number of testing examples: **4410**
- Image data shape: **32, 32, 3**
- Number of classes: **43**

It is evident from the above figure, that there is a great variation of brightness, contrast and resolution in the data. However, the targets/sings are brought to the image foreground and populate the centre of every sample with the majority of pixels, in most cases, belonging to the signs.

The samples per class distribution of all the sets can be seen below:

As can be seen, the distributions along the different sets are very close, but the distribution of samples among classes is of great variance. It was therefore necessary to balance-out the classes by generating *surrogate* data, based on the existing dataset.

Pre-processing Steps

Although the images have already undergone preprocessing steps (ROI cropping), further preprocessing was seen an efficient method for optimizing performance.

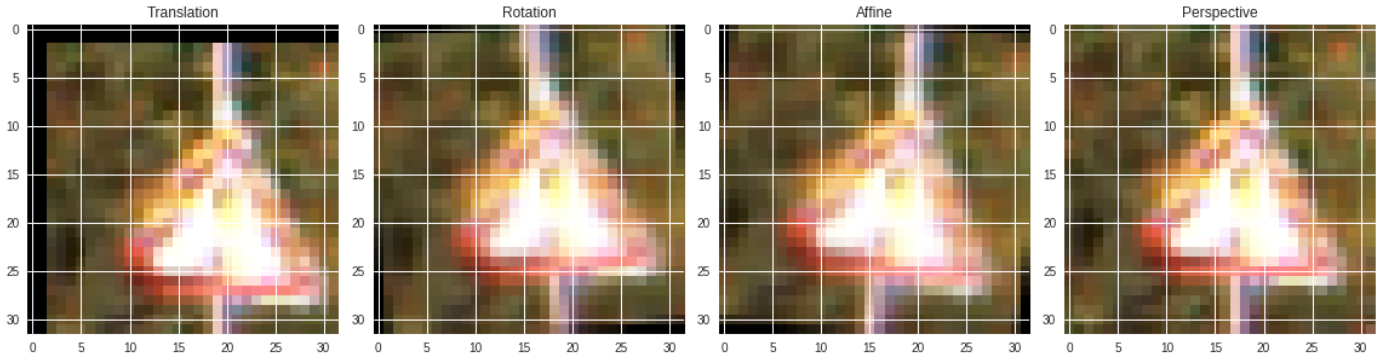
Class Balancing with Surrogate data

Since sample distribution among classes was seen to be greatly varying, it was decided to augment the lower-sample-count classes with artificially created data.

Another benefitial aspect in adding perturbations to the data is that in this manner the network becomes more robust and less likely to overfit.

The methods for creation of this data where all based on perturbing the existing samples, where the perturbations chosen where:

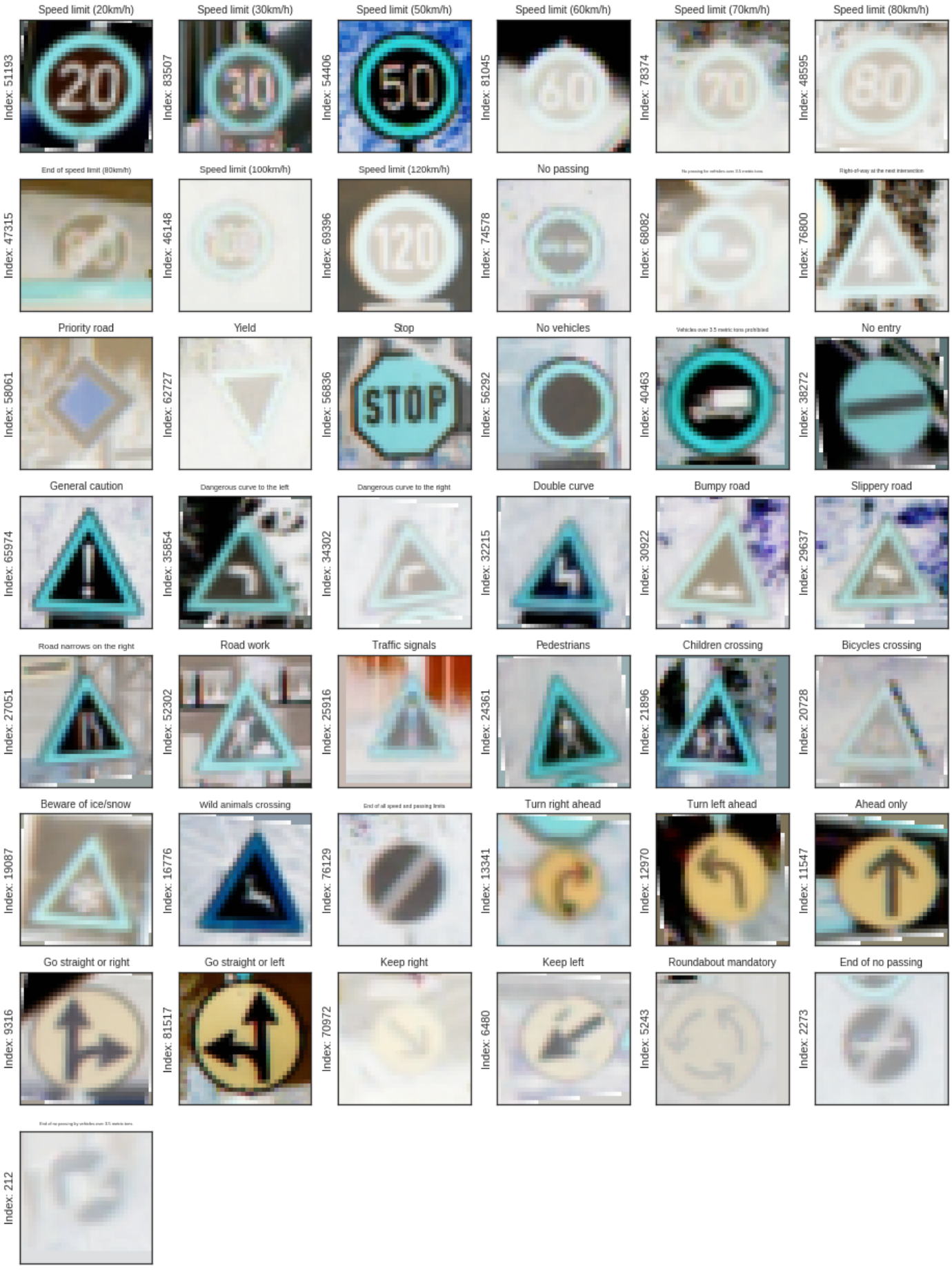
1. Image **Rotation** by +- 6 to 9 degrees around the image centre
2. Image **Translation** by +- 3 pixels along the x and y axes
3. Image **Affine** transformation
4. Image **Perspective** warping



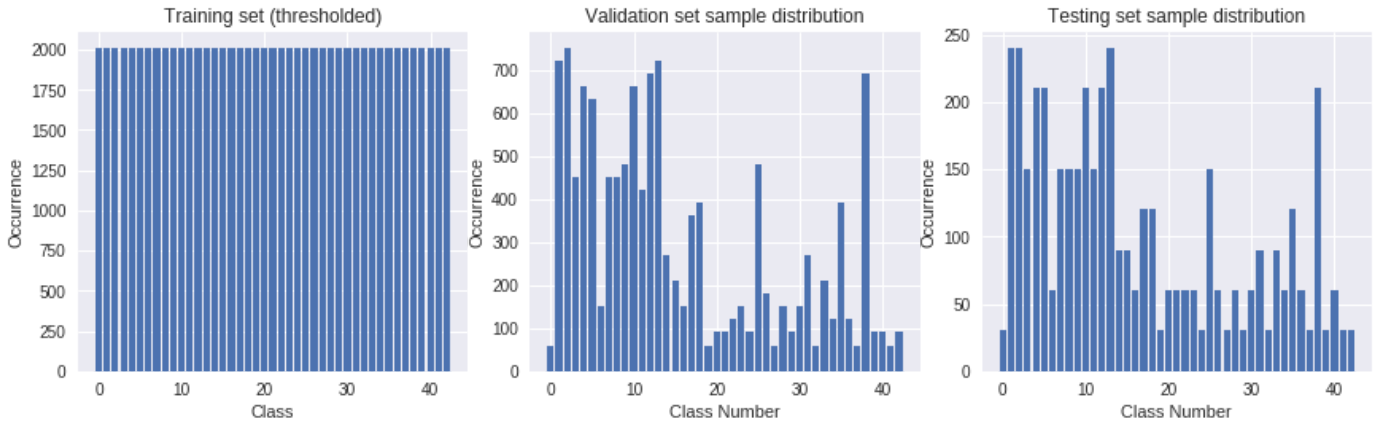
Using these techniques for image generation and class balancing, several balancing thresholds where tested, namely **median**, **mean** and **max** counts of all samples among the classes and the **max** threshold was chosen as final.

The results from class balancing can be seen below.

NOTE: Images where converted to float32 and therefore their colorspace is depicted differently by matplotlib.



The resulting distribution for the training is shown below, where the total training set size changed from 34799 to 86429, hence the surrogate data represents **~60%** of all training data!



Grayscale and Normalization

Images where then converted to grayscale and normalized between 0 and 1.

Network Architecture

Sevaral network architectures were iterated through. First, the LeNet convolutional network was taken and adapted to work with the traffic sign data set - adapting it to 43 categories, instead of 10. On the first iterations it was observed that the 3 channels of the image do not contribute towards better accuracy and the pre-processing now included not only normalization, but also a colorspace conversion to grayscale. In addition, multiple filter sizes where tested with the LeNet architecture, when the necessity of paramtrization was recognized (see below). Further, two dropout layers were added after the first two Fully-Connected layers which brought the accuracy towards 0.8-0.9. Multiple filter depths were tested, and with filter depths of (64, 128) for the first two convolutional layers, the network reached 0.91 accuracy. A further test was made with addition of a third convolutional layer, where final results came to ~0.95 accuracy.

Details of the layers dimensions can be found below.

In order to iterate through multiple network architectures, it is necessary to make the network models parametric, so interdependencies between variables can be solved dynamically.

Fist, the layer dimensions are sequentially defined. Example:

```
    layers = {}
    layers.update({
        'c1':{
            'd': n_channels * 9,
            'fx': 5,
            'fy': 5
        }
    })
    layers.update({
        'c2':{
            'd': layers['c1']['d'] * 6,
            'fx': 5,
            'fy': 5
        }
    })
    layers.update({
        'c3':{
            'd': layers['c2']['d'] * 4,
            'fx': 5,
            'fy': 5
        }
    })
    layers.update({
        'f0': {
            # Resulting flat size = n_channels * 9 * 6 * 4 = 1 * 9 * 6 * 4 = 21
    6
            'in': layers['c3']['d'],
            'out': 480
        }
    })
    layers.update({
        'f1': {
            'in': layers['f0']['out'],
            'out': 240
        }
    })
    layers.update({
        'f2': {
            'in': layers['f1']['out'],
            'out': 43
        }
    })
```

Next, the weight and bias objects (python dictionaries) are constructed:

```
weights = {
    'wc1': tfhe((layers['c1']['fx'], layers['c1']['fy'], n_channels, layers
['c1']['d'])),
    'wc2': tfhe((layers['c2']['fx'], layers['c2']['fy'], layers['c1']['d'],
 layers['c2']['d'])),
    'wc3': tfhe((layers['c3']['fx'], layers['c3']['fy'], layers['c2']['d'],
 layers['c3']['d'])),
    'wf0': tfhe((layers['f0']['in'], layers['f0']['out'])),
    'wf1': tfhe((layers['f1']['in'], layers['f1']['out'])),
    'wf2': tfhe((layers['f2']['in'], layers['f2']['out']))
}

biases = {
    'bc1': tf.Variable(tf.zeros(layers['c1']['d'])),
    'bc2': tf.Variable(tf.zeros(layers['c2']['d'])),
    'bc3': tf.Variable(tf.zeros(layers['c3']['d'])),
    'bf0': tf.Variable(tf.zeros(layers['f0']['out'])),
    'bf1': tf.Variable(tf.zeros(layers['f1']['out'])),
    'bf2': tf.Variable(tf.zeros(layers['f2']['out']))
}
```

where, the *tfhe* function points to the initialization routine detialed in [1].

The initial architecture chosen was LeNet's convolutional network as detailed here (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). The parameter tweaking and performance testing showed that stacking another convolutional layer is of greater benefit then increasing the number of parameters (i.e. depth vs width).

The final architecture chosen is three subsequent convolutional layers with average pooling, equal strides and equal filter widths (**w_c(0,1,2) = 5x5**), and respective filter depths (**d_c(0,1,2) = 9, 54, 220**). The following layers chosen are three subsequent fully connected layers with widths respectively (**w_fc(0,1,2) = 480, 240, 43**).

#	Layer	Description	Output
1	Input	Grayscale image	32x32x1
2	Convolution (5x5x9)	1x1 Stride, Valid Padding	28x28x9
3	ReLu		28x28x9
4	Average pooling	2x2 stride	14x14x9
5	Convolution (5x5x54)	1x1 Stride, Valid Padding	10x10x54
6	ReLu		10x10x54
7	Average pooling	2x2 stride	5x5x54
8	Convolution (5x5x216)	1x1 Stride, Valid Padding	1x1x216
9	ReLu		1x1x216
10	Average pooling	2x2 stride	1x1x216
11	Fully connected	Flattened network (1x216)	1x480
12	Dropout	val=0.85	1x480

#	Layer	Description	Output
13	Fully connected		1x240
14	Dropout	val=0.85	1x240
15	Fully connected		1x43

Train - Validate - Test

The network was trained and optimized for **50 Epochs** with a **Batch Size of 128** using: For each image, discuss what quality or qualities might be difficult to classify. | # | Layer | Description | Output |:-:|:----------:|:----------:|:----------:| | 1 | Softmax | Cross Entropy with Logits | 1x43 | 2 | Loss Operation | Reduce entropy with mean | 1x43 | 3 | Optimizer | Adam Optimizer (learning_rate = 0.0007) | 1x43

Results

Validation Accuracy

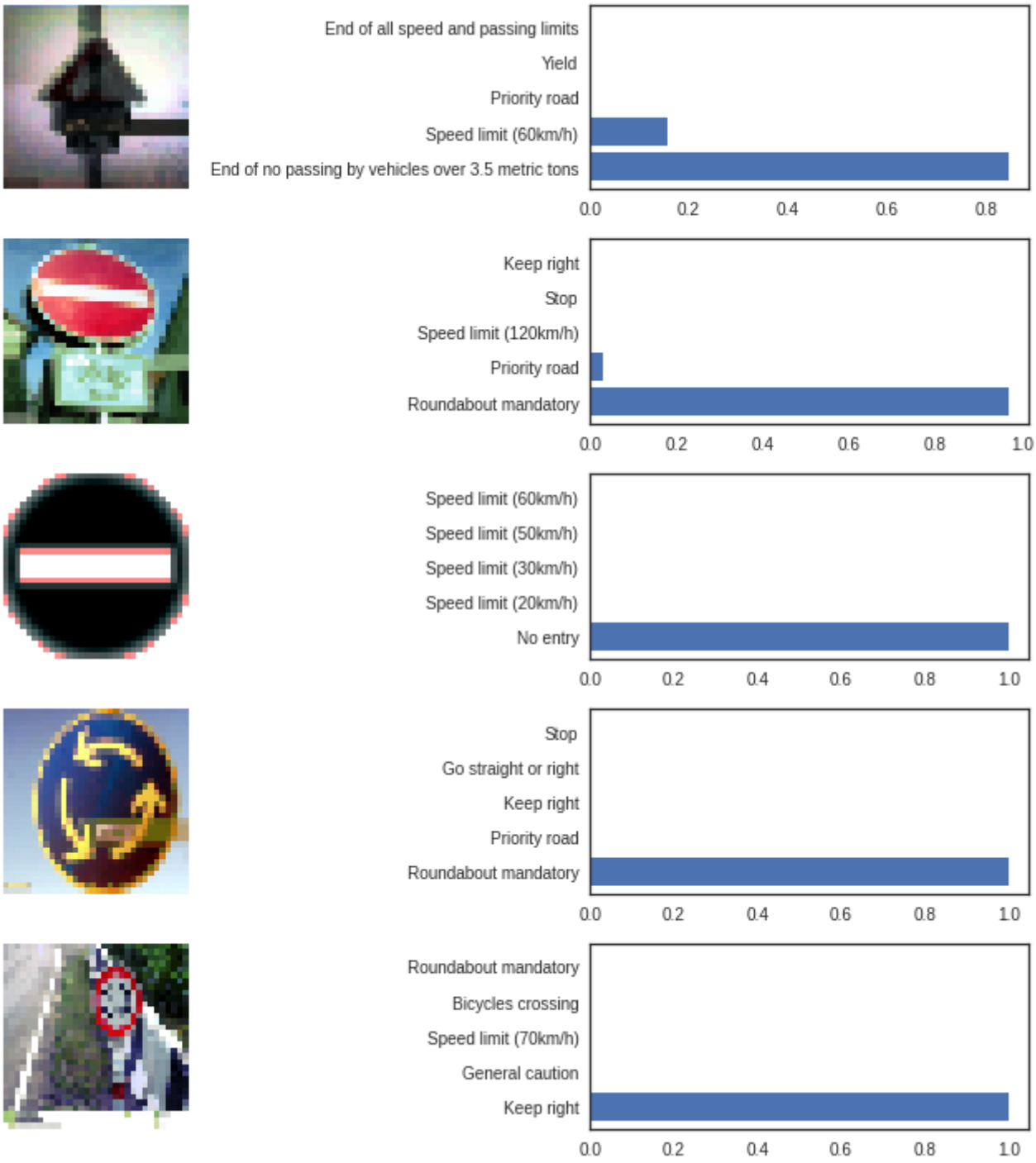
Testing Accuracy

The training accuracy achieved was in the range of 0.950-0.960

Real World Testing Accuracy

Testing with images downloaded from a google image search with key-words: "German traffic signs" resulted in accuracy of **0.30**.

The softmax probabilities 5 randomly chosen real-world images are as follows:



The individual images can below be seen in full size with their supporting discussion.

1. General Caution in Snow

The top 5 probabilities are far away from correct.

Difficulties for classification:

1. Snow! This is an image for a General Caution sign in the winter, partially covered in snow.
2. Size ratio - the sign area is much smaller than the complete image area (<< 0.5), whereas the training set had a sign to image size ratio of approx 0.5
3. Multiple Signs and overlayed text

2. No Entry under a high angle

Difficulties for classification:

1. Sign centre is shifted towards the upper edge of the image
2. The pose of the sign relative to the camera is not favorable to the algorithm
3. Size ratio

3. No Entry drawing

This image is a drawing and is as expected classified with probability of 1.0

4. Roundabout

The roundabout mandatory sign is as well classified with a high probability.

5. Small Limit 30

Problems with this image are:

1. Size ratio (sign area to image area)

Discussion