Introduction

Recognizing traffic signs from real-time video streams from smart vehicles is one of the demanding solutions in today's automobile industry. It became a demanding solution in autonomous vehicles, driver assistance systems and mobile mapping. The Traffic Sign Recognition (TSR) challenge consists two components 1) traffic sign detection and traffic sign classification. Traffic sign detection is the activity of accurate localizing the traffic sign in an image, while traffic sign classification assigns a label (symbol name/details) to the localized picture. Recent developments in Deep Learning and publically available data sets such as Belgium and German Traffic Sign Data accelerated many innovations in this field. The objective of the current project is to build a traffic sign classification system with the German Traffic Signs dataset.

Exploratory Data Analysis

The dataset is supplied as Python pickled objects. The training, validation and test data are in the same format. Each picked object contains the following information: 'labels', 'coords', 'sizes', 'features'. The 'features' contain the image pixel data, 'coords' contains localization information, 'size' contains image size and the 'labels' contains a numeric value representing the traffic sign represented in the image. The train, test and valid data consist 34799, 12630, 4410 samples respectively. There are 43 traffic signs in this image data sets, and it translates to 43 labels in the data sets.

In [1]:

```
%matplotlib inline
from matplotlib import pylab as plt
import seaborn as sn
plt.rcParams['figure.figsize'] = (9,4)
```

In [2]:

```
import glob
import pickle
import random

import numpy as np
import pandas as pd
from skimage import exposure
import cv2
import tensorflow as tf
from tensorflow.contrib.layers import flatten
from sklearn.utils import shuffle
from sklearn import metrics
```

Reading the Data

In [3]:

```
data_files = glob.glob("data/*.p")
```

In [4]:

```
train = None
test = None
valid = None

for fname in data_files:
    with open(fname,mode='rb') as pf:
        if fname.endswith("test.p"):
            test = pickle.load(pf)
        elif fname.endswith("train.p"):
            train = pickle.load(pf)
        elif fname.endswith("valid.p"):
            valid = pickle.load(pf)
```

Total records in Train Test and Valid Sets

In [5]:

```
len(train["features"]),len(test["features"]),len(valid["features"])
```

Out[5]:

```
(34799, 12630, 4410)
```

Class Distribution Analysis in the Data

An analysis of the class distribution in training data suggests that it is a highly imbalanced dataset. The well-represented class consists samples in the range of 1000 to 2500 and the under-represented classed consists instances in the range of 120 to 850. In general Machine Learning scenarios, the under-represented or imbalanced class distribution is not an ideal situation to start with any Machine Learning experiment. So it is recommended to perform either additional data collection or perform an oversampling or undersampling of the data. Oversampling of data is a typical strategy for the same.

In [6]:

```
train_df = pd.Series(train['labels'])
train_label_count = train_df.value_counts()
test_df = pd.Series(test['labels'])
test_label_count = test_df.value_counts()
valid_df = pd.Series(valid['labels'])
valid_label_count = valid_df.value_counts()
```

In [7]:

```
train_label_count_df = pd.DataFrame()
train_label_count_df["ClassId"] = train_label_count.index
train_label_count_df["Count"] = train_label_count.values
label_map = pd.read_csv("signnames.csv")
train_joined_labels = pd.merge(train_label_count_df,label_map,on='ClassId')
```

In [8]:

```
sign_label_map = dict(zip(train_joined_labels.ClassId,train_joined_labels.SignNa
me))
```

In [9]:

```
len(sign_label_map)
```

Out[9]:

```
43
```

In [10]:

```
image_samples =[np.where(train["labels"]==i)[0][0] for i, x in enumerate(np.uniq
ue(train["labels"]))]
```

In [11]:

```
samples = [train["features"][img_indx] for indx,img_indx in enumerate(image_samp
les)]
```

In [12]:

```
def plot_one_sample(samples):
    fig = plt.figure(figsize=(9, 9))
    fig.subplots_adjust(left=0, right=1, bottom=0, top=1, hspace=0.05, wspace=0.
05)
    for i in range(len(samples)):
        ax = fig.add_subplot(10, 10, i + 1, xticks=[], yticks=[])
        ax.imshow(samples[i].squeeze())
    plt.show()
```

Sample Image from all the categories

In [13]:

```
plot_one_sample(samples)
```

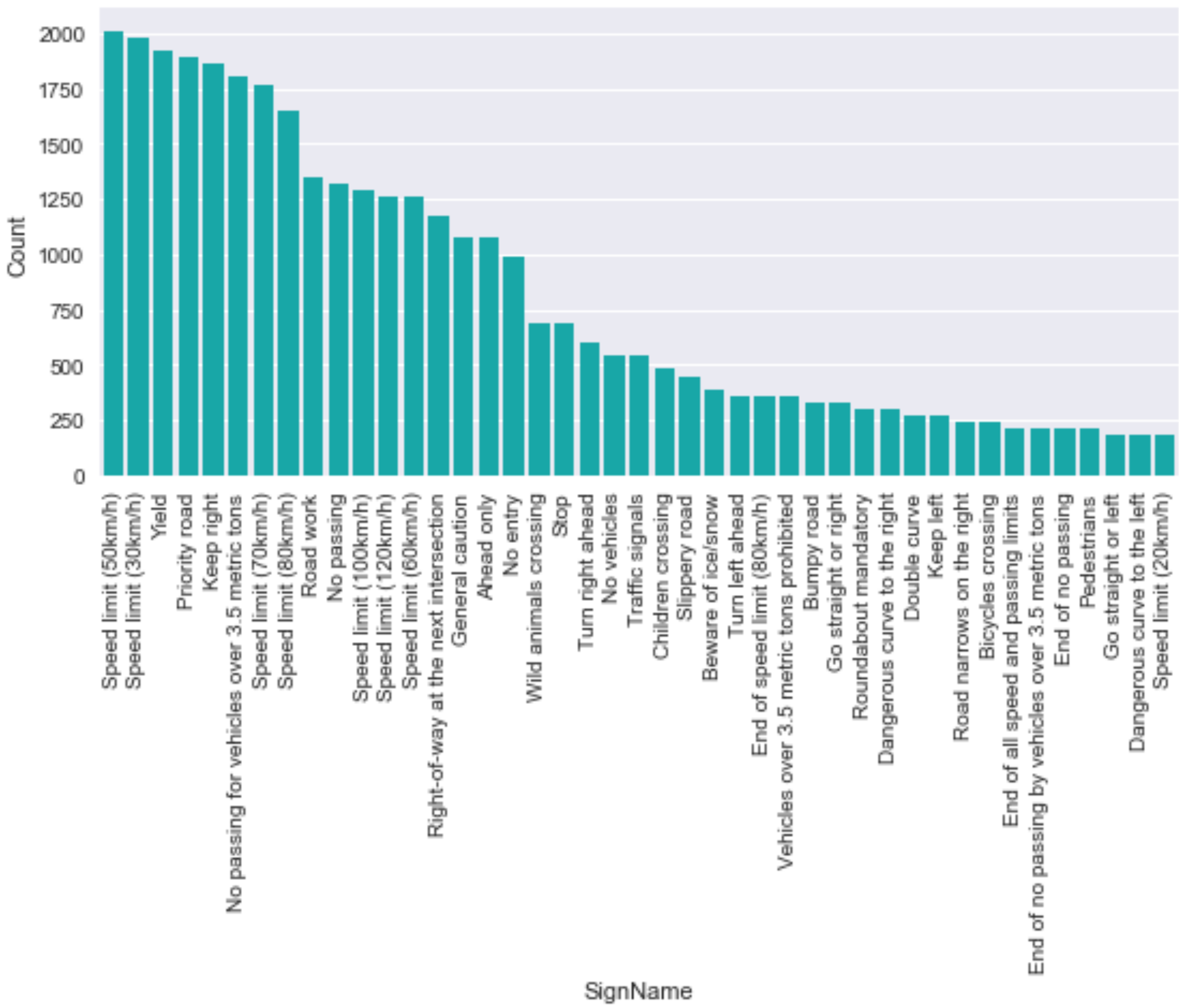
In [14]:

```
def plot_class_dict(train_label_count,color):

    train_label_count_df = pd.DataFrame()
    train_label_count_df["ClassId"] = train_label_count.index
    train_label_count_df["Count"] = train_label_count.values
    label_map = pd.read_csv("signnames.csv")
    train_joined_labels = pd.merge(train_label_count_df,label_map,on='ClassId')
    train_joined_labels.index = train_joined_labels.ClassId
    sbp = sn.barplot(x="SignName",y="Count",data=train_joined_labels,color=color
)
    d = plt.setp(sbp.get_xticklabels(), rotation=90)
    plt.ylabel("Count")
    plt.show()
```

Training Data Class Distribution

In [15]:

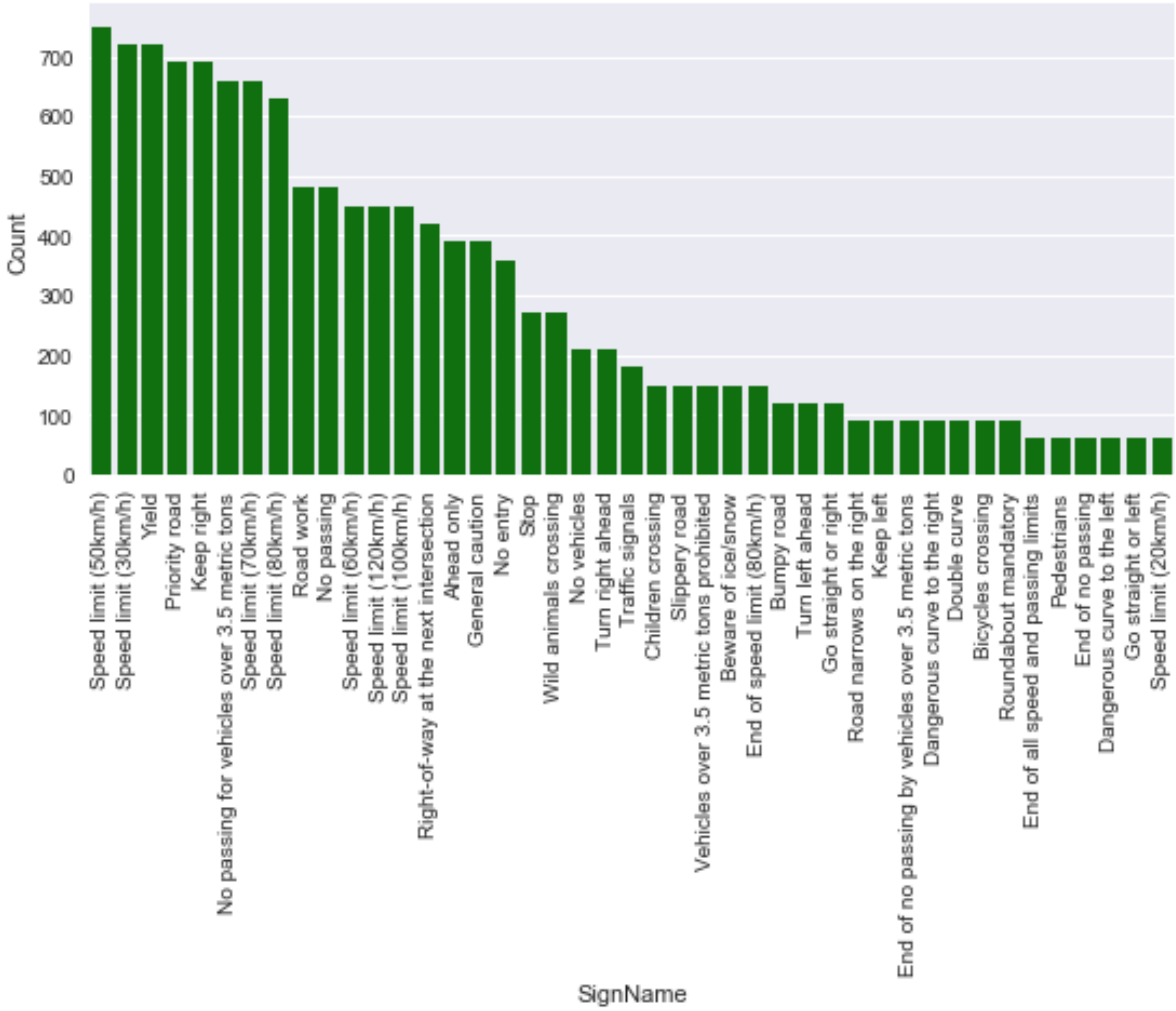
```
plot_class_dict(train_label_count,"c")
```



Test Data Class Distribution

In [16]:

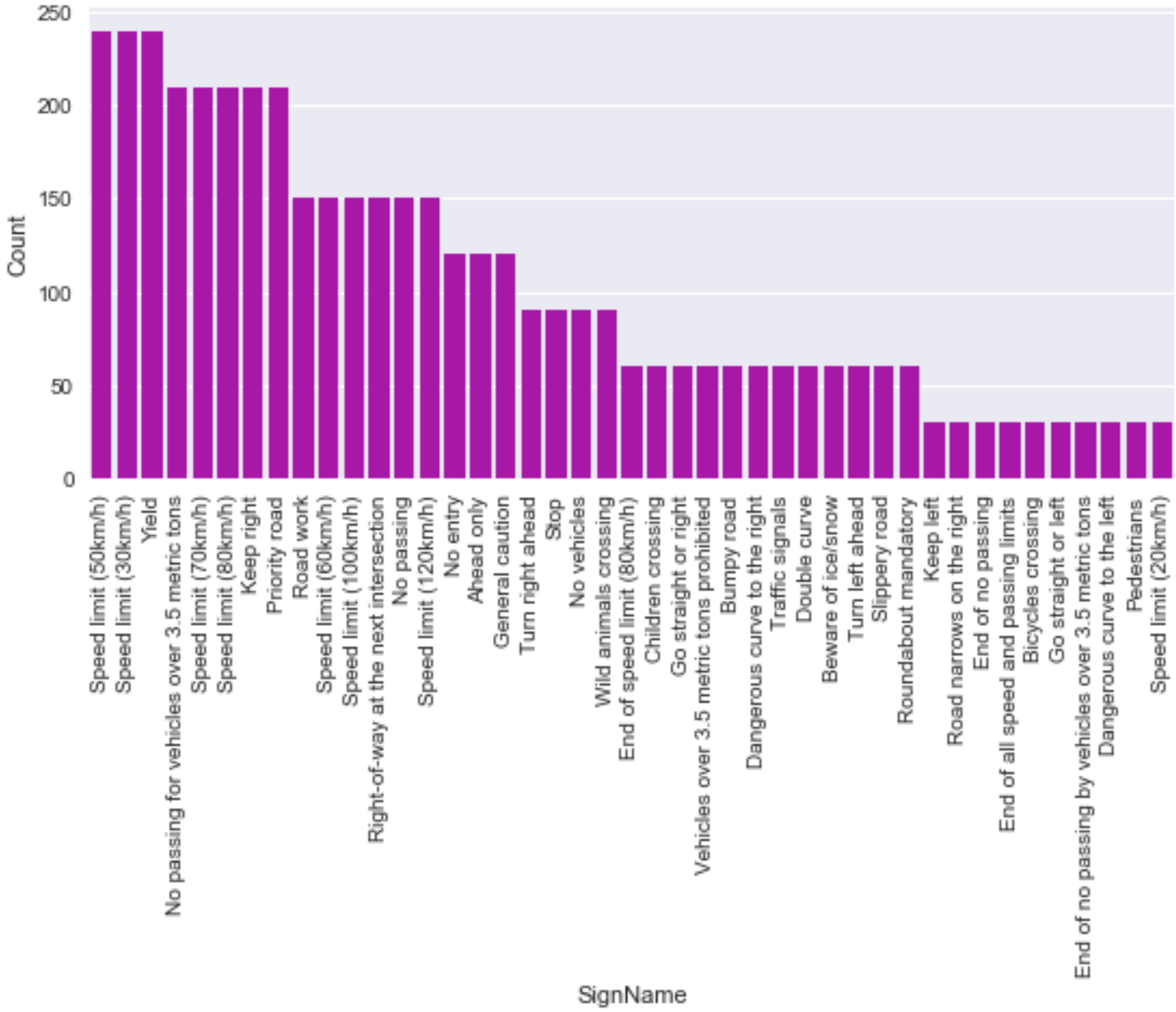
```
plot_class_dict(test_label_count,"g")
```



Validation Data Class Distribution

In [17]:

```
plot_class_dict(valid_label_count,"m")
```



Synthetic Data Generation

The additional data generation to overcome the imbalanced data is performed with Keras library. Keras provided image augmentation API with a comprehensive set of parameters to satisfy different experiment purposes. The settings used in the current projects includes

- featurewise_center: Set input mean to 0 over the dataset, feature-wise.
- rotation_range: Degree range for random rotations. The rotation range was specified as 17 for the augmentation.
- width_shift_range: Range for random horizontal shifts. Specified value 0.1
- height_shift_range: Range for random vertical shifts. Specified value 0.1
- shear_range: Shear Intensity (Shear angle in the counter-clockwise direction as radians). Specified Value: 0.3
- zoom_range: Range for random zoom. Specified Value: 0.15
- horizontal_flip: Randomly flip inputs horizontally. Not performed

In [18]:

```
from keras.preprocessing.image import ImageDataGenerator, array_to_img, img_to_a
rray, load_img



augumentar = ImageDataGenerator(rotation_range=17,width_shift_range=0.1,\
height_shift_range=0.1,shear_range=0.3,zoom_range=0.15,horizontal_flip=False,\
fill_mode='nearest',featurewise_center=True)
#fill_mode='nearest',featurewise_center=True,zca_whitening=True)

def image_aug(X,y):
    """
    Apply image Augumentation with Keras
    """
    X_aug = None
    y_aug = None
    #augumentar.fit(X)
    for X_batch, y_batch in augumentar.flow(X, y, batch_size=X.shape[0], shuffle
=False):
        X_aug = X_batch.astype('uint8')
        y_aug = y_batch
        break
    return (X_aug,y_aug)
```

```
Using TensorFlow backend.
```

In [19]:

```
augm_images = image_aug(train["features"],train["labels"])
```

```
/Users/jagan/anaconda2/envs/sdc/lib/python3.5/site-packages/keras/pr
eprocessing/image.py:500: UserWarning: This ImageDataGenerator speci
fies `featurewise_center`, but it hasn'tbeen fit on any training dat
a. Fit it first by calling `.fit(numpy_data)`.
  warnings.warn('This ImageDataGenerator specifies '
```

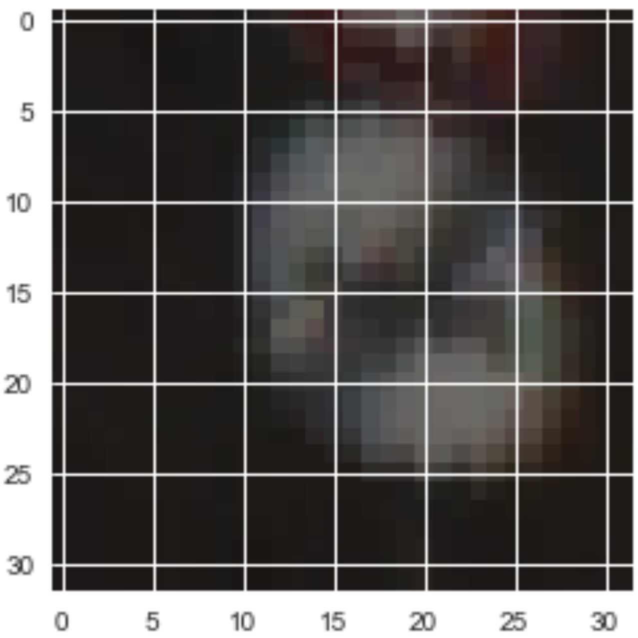
A Sample Augumented Image

In [20]:

```
plt.imshow(augm_images[0][1].squeeze())
```

Out[20]:

```
<matplotlib.image.AxesImage at 0x12ebf92b0>
```



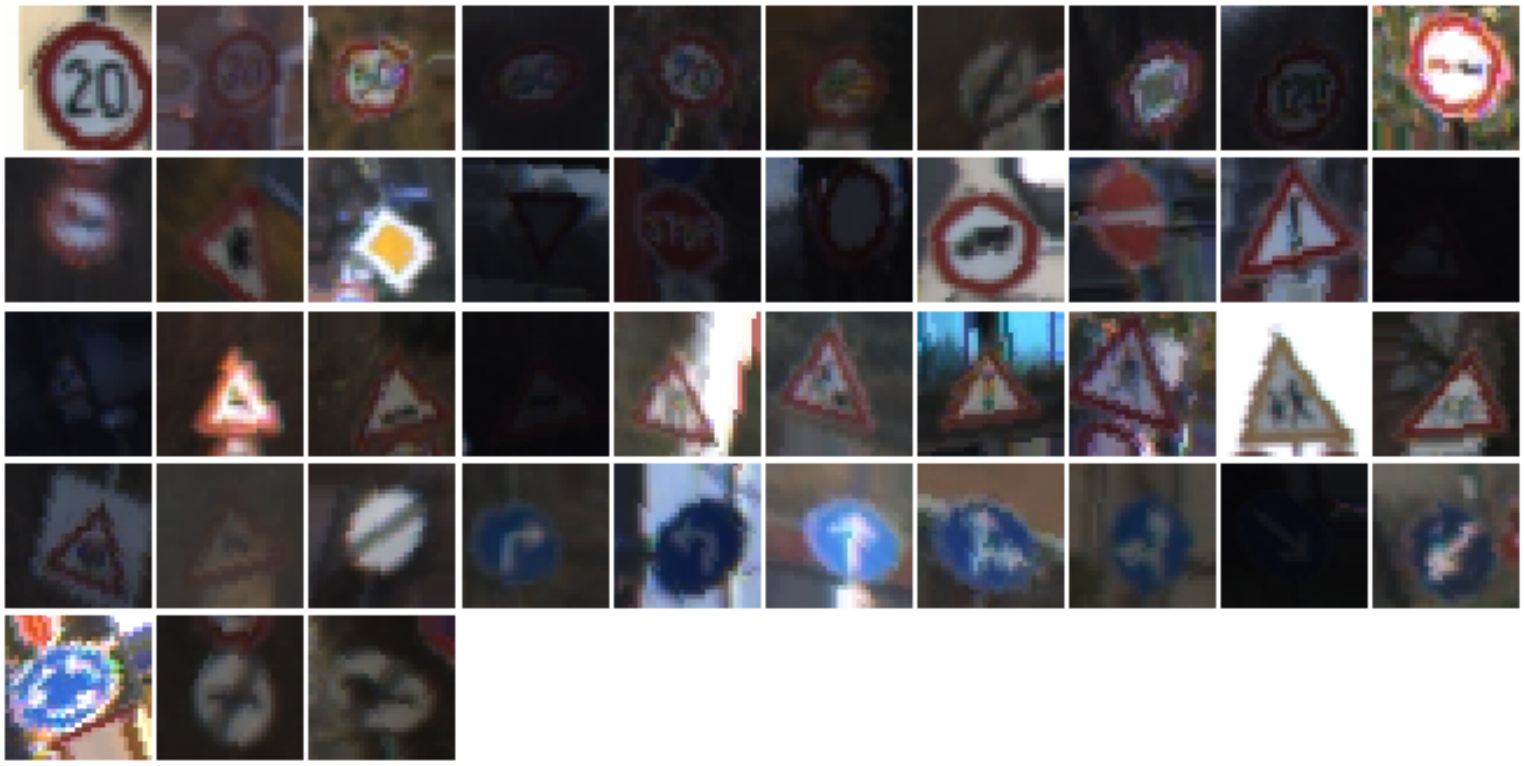
In [21]:

```
X_train_augumented = augm_images[0]
Y_train_augumented = augm_images[1]
```

Augumented Image sample from 43 categories

In [22]:

```
aug_samplees = [X_train_augumented[img_indx] for indx,img_indx in enumerate(imag
e_samples)]
plot_one_sample(aug_samplees)
```



Motion Blur

The additional image data generation step adopted in this project is Motion Blur. Motion blur is the apparent streaking of rapidly moving objects in a still image. It helps the traffic sign classifier to almost accurately classify a localized sign to the proper category. In real-time image processing, this techniques is a very useful approach.

In [23]:

```
def mblur(X):
    """
    Create a motion blur
    """
    X_out = np.empty((X.shape)).astype('uint8')
    size = 4
    kernel_motion_blur = np.zeros((size, size))
    kernel_motion_blur[int((size-1)/2), :] = np.ones(size)
    kernel_motion_blur = kernel_motion_blur / size
    for idx, img in enumerate(X):
        X_out[idx] = cv2.filter2D(img, -1, kernel_motion_blur)
    return X_out
```

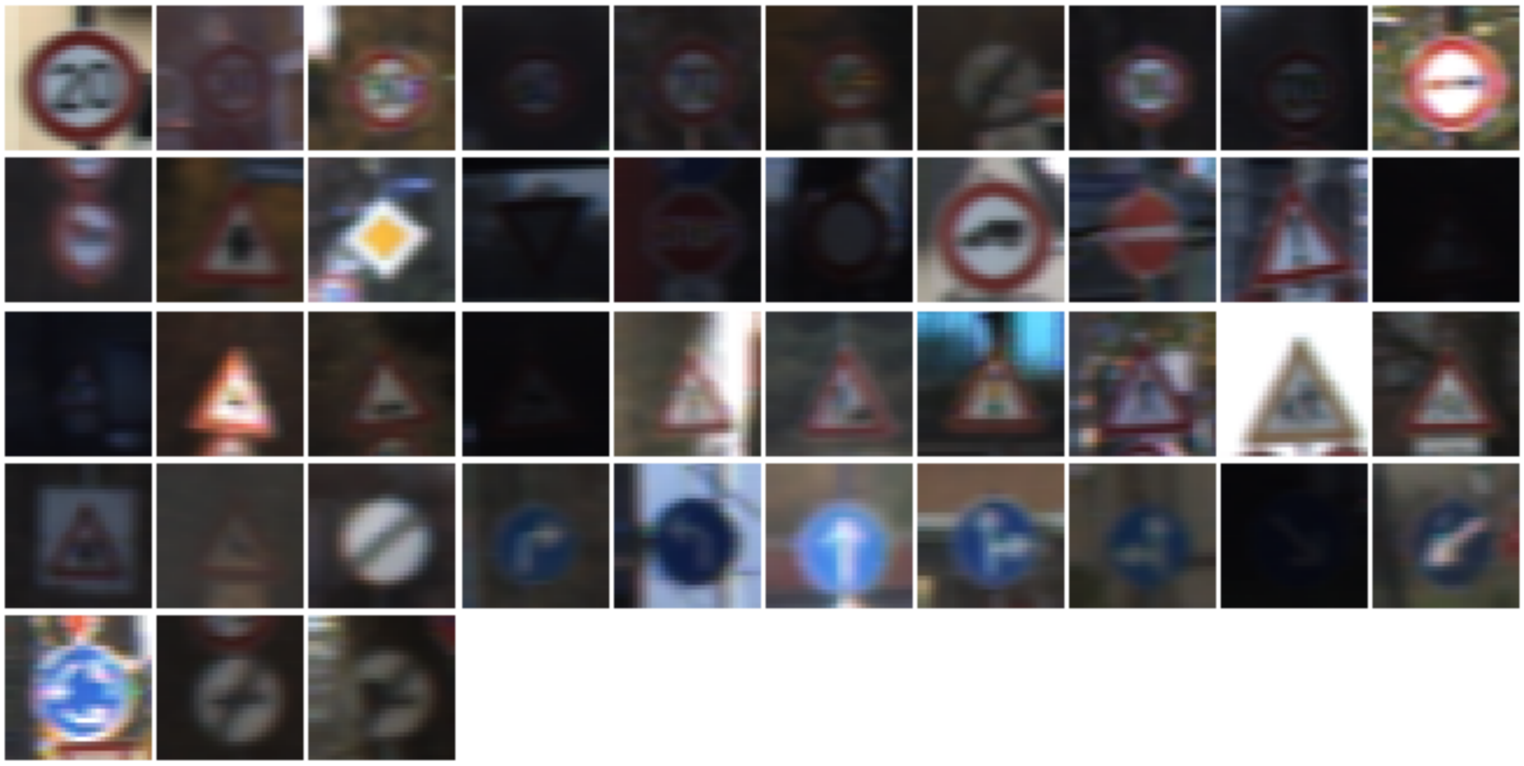
In [24]:

```
X_train_motion_blur = mblur(train["features"])
y_train_motion_blur = train["labels"]
```

Sample Results of Motion Blur

In [25]:

```
mb_samplees = [X_train_motion_blur[img_indx] for indx,img_indx in enumerate(imag
e_samples)]

plot_one_sample(mb_samplees)
```



Preprocessing

In this project, we preprocessed the images before it is being presented to the algorithm for model building. The preprocessing steps adopted in the projects are normalizing the exposure and converting the images to grayscale. This steps will help us preventing some of the adversarial scenarios, such as negative images are not getting classified correctly. Recent researched in the images processing, and Deep Learning reveals that negatives images will be a challenging one for many models.

In [26]:

```
def process_image(img):
    img_c = cv2.cvtColor(img, (cv2.COLOR_BGR2YUV))[:,:,0]
    img_c = (img_c / 255.).astype(np.float32)
    img_c = (exposure.equalize_adapthist(img_c,) - 0.5)
    img_c = img_c.reshape(img_c.shape + (1,))
    return img_c

def preprocess_data(X):
    X_processed = np.empty((X.shape[0],X.shape[1],X.shape[2],1)).astype(np.float
32)
    for idx, img in enumerate(X):
        X_processed[idx] = process_image(img)
    return X_processed
```

In [27]:

```
X_train_raw_p = preprocess_data(train["features"])
y_train_raw_p = train["labels"]
X_train_aug_p = preprocess_data(X_train_augumented)
y_train_aug_p = Y_train_augumented
X_train_mb_p = preprocess_data(X_train_motion_blur)
y_train_mb_p = y_train_motion_blur
```

```
/Users/jagan/anaconda2/envs/sdc/lib/python3.5/site-packages/skimage/
util/dtype.py:122: UserWarning: Possible precision loss when convert
ing from float32 to uint16
  .format(dtypeobj_in, dtypeobj_out))
```

In [28]:

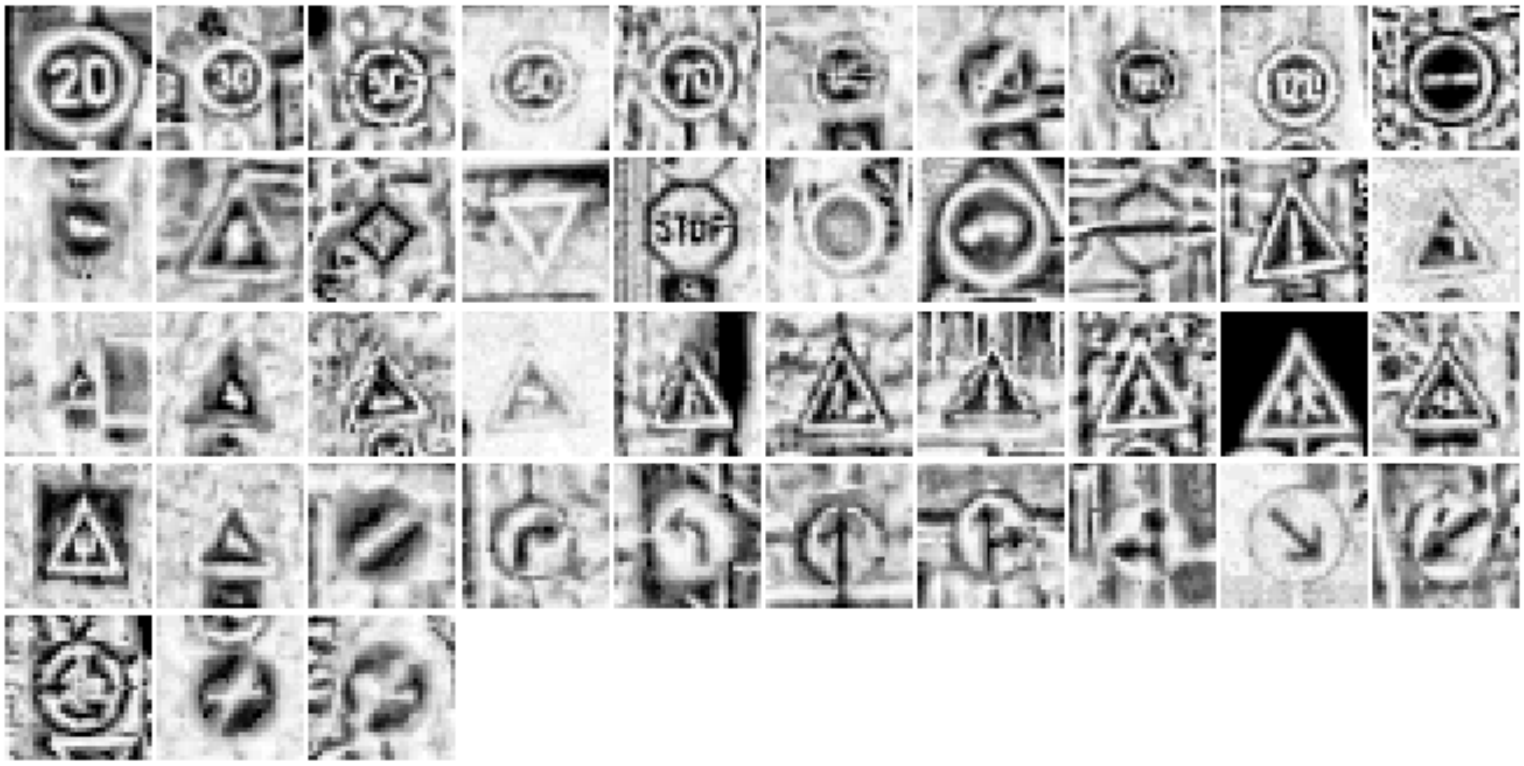
```
X_test_raw_p = preprocess_data(test["features"])
y_test_raw_p = test["labels"]

X_valid_raw_p = preprocess_data(valid["features"])
y_valid_raw_p = valid["labels"]
```

```
/Users/jagan/anaconda2/envs/sdc/lib/python3.5/site-packages/skimage/
util/dtype.py:122: UserWarning: Possible precision loss when convert
ing from float32 to uint16
  .format(dtypeobj_in, dtypeobj_out))
```

Preprocessed Raw Training Data Samples

In [29]:

```
mb_samplees = [X_train_raw_p[img_indx] for indx,img_indx in enumerate(image_samp
les)]

plot_one_sample(mb_samplees)
```



Preprocessed Augumented Data

In [30]:

```
mb_samplees = [X_train_aug_p[img_indx] for indx,img_indx in enumerate(image_samp
les)]

plot_one_sample(mb_samplees)
```

In [31]:

```
X_train = np.concatenate((X_train_raw_p,X_train_aug_p,X_train_mb_p), axis=0)
y_train = np.concatenate((y_train_raw_p,y_train_aug_p,y_train_mb_p), axis=0)
```

In [32]:

```
X_train, y_train = shuffle(X_train, y_train)
```

The Model

The current model is inspired by the LeNet and names as "ThirdEye." The Architecture has two convolution layer followed by a fully connected layer. RELU is used as activation function in all the three layers. Drop-out rate of 20,30 and 40 is specified in respective layers.

In [33]:

```
import tensorflow as tf

n_classes = len(np.unique(train["labels"]))

x = tf.placeholder(tf.float32, (None, 32, 32, 1))
y = tf.placeholder(tf.int32, (None))
one_hot_y = tf.one_hot(y, n_classes)
apply_dropout = tf.placeholder(tf.bool)
```

In [34]:

```
EPOCHS = 10
BATCH_SIZE = 128

from tensorflow.contrib.layers import flatten
```

In [35]:

```
def third_eye_net(X, w, b, dropout):
    #third_eye_net(x, weights, biases, apply_dropout):
    if dropout is not None:
        print ("Training")
    else:
        print ("Evalutation")

    layer = 0

    """
    Layer 1: Convolutional.
    Input = 32x32x1.
    Output = 28x28x12.
    """
    conv1   = tf.nn.conv2d(X, w[layer], strides=[1, 1, 1, 1], padding='VALID') +
b[layer]
```

```
    layer += 1

    """
    Activation.
    """
    conv1 = tf.nn.relu(conv1, name = 'eye1')

    """
    # Pooling.
    Input = 28x28x12.
    Output = 14x14x12.
    """

    conv1 = tf.nn.max_pool(conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padd
ing='VALID')

    """
    Dropout
    """

    conv1 = tf.cond(apply_dropout, lambda: tf.nn.dropout(conv1, keep_prob = 0.8)
, lambda: conv1)

    """
    Layer 2: Convolutional.
    Output = 10x10x24.
    """
    conv2   = tf.nn.conv2d(conv1, w[layer], strides=[1, 1, 1, 1], padding='VALID
') +  b[layer]
    layer += 1

    """
    Activation.
    """
    conv2 = tf.nn.relu(conv2, name = 'eye2')

    """
    Pooling.
    Input = 10x10x24.
    Output = 5x5x24.
    """

    conv2 = tf.nn.max_pool(conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padd
ing='VALID')

    """
    Dropout
    """

    conv2 = tf.cond(apply_dropout, lambda: tf.nn.dropout(conv2, keep_prob = 0.7)
, lambda: conv2)

    """
```

```
    Input = 14x14x12.

    Output = 7x7x12 = 588
    """
    conv1_1 = tf.nn.max_pool(conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], pa
dding='VALID')
    shape = conv1_1.get_shape().as_list()
    conv1_1 = tf.reshape(conv1_1, [-1, shape[1] * shape[2] * shape[3]])

    """
    Flatten conv2 Input = 5x5x24. Output = 600
    """
    shape = conv2.get_shape().as_list()
    conv2 = tf.reshape(conv2, [-1, shape[1] * shape[2] * shape[3]])

    fc0 = tf.concat([conv1_1, conv2],1)

    """
    Layer 3: Fully Connected. Input = 588+600 = 1188. Output = 320.
    """

    fc1   = tf.matmul(fc0, w[layer]) + b[layer]
    layer += 1

    """
    Activation.
    """

    fc1    = tf.nn.relu(fc1)

    """
    Dropout
    """

    fc1 = tf.cond(dropout, lambda: tf.nn.dropout(fc1, keep_prob = 0.6), lambda:
fc1)
    logits = tf.matmul(fc1, w[layer]) + b[layer]

    return logits
```

Model Pipeline

In [36]:

```
rate = 0.001


mu = 0
sigma = 0.1
beta = 0.001


weights = [
    tf.Variable(tf.truncated_normal(shape=(5, 5, 1, 12), mean = mu, stddev = sig
ma)),
    tf.Variable(tf.truncated_normal(shape=(5, 5, 12, 24), mean = mu, stddev = si
gma)),
    tf.Variable(tf.truncated_normal(shape=(1188, 320), mean = mu, stddev = sigma
)),
    tf.Variable(tf.truncated_normal(shape=(320, n_classes), mean = mu, stddev =
sigma))
]
biases = [
   tf.Variable(tf.zeros(12)),
   tf.Variable(tf.zeros(24)),
   tf.Variable(tf.zeros(320)),
   tf.Variable(tf.zeros(n_classes))
]


logits = third_eye_net(x, weights, biases, apply_dropout)
cross_entropy = tf.nn.softmax_cross_entropy_with_logits(logits=logits, labels=on
e_hot_y)
loss_operation = tf.reduce_mean(cross_entropy)

regularizer = tf.reduce_sum([tf.nn.l2_loss(w) for w in weights])
loss = tf.reduce_mean(loss_operation + beta * regularizer)

optimizer = tf.train.AdamOptimizer(learning_rate = rate)
training_operation = optimizer.minimize(loss)
#tf.nn.softmax_cross_entropy_with_logits(logits=prediction, labels=y)
```

Training

Model Evaluation

In [37]:

```
correct_prediction = tf.equal(tf.argmax(logits, 1), tf.argmax(one_hot_y, 1))
accuracy_operation = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
saver = tf.train.Saver()

def evaluate(X_data, y_data):
    num_examples = len(X_data)
    total_accuracy = 0
    sess = tf.get_default_session()
    for offset in range(0, num_examples, BATCH_SIZE):
        batch_x, batch_y = X_data[offset:offset+BATCH_SIZE], y_data[offset:offse
t+BATCH_SIZE]
        accuracy = sess.run(accuracy_operation, feed_dict={x: batch_x, y: batch_
y, apply_dropout: False})
        total_accuracy += (accuracy * len(batch_x))
    return total_accuracy / num_examples
```

Training the Model

In [38]:

```
best_validation_accuracy = 0.0
train_accuracy = list()
valid_accuracy = list()
```

In [39]:

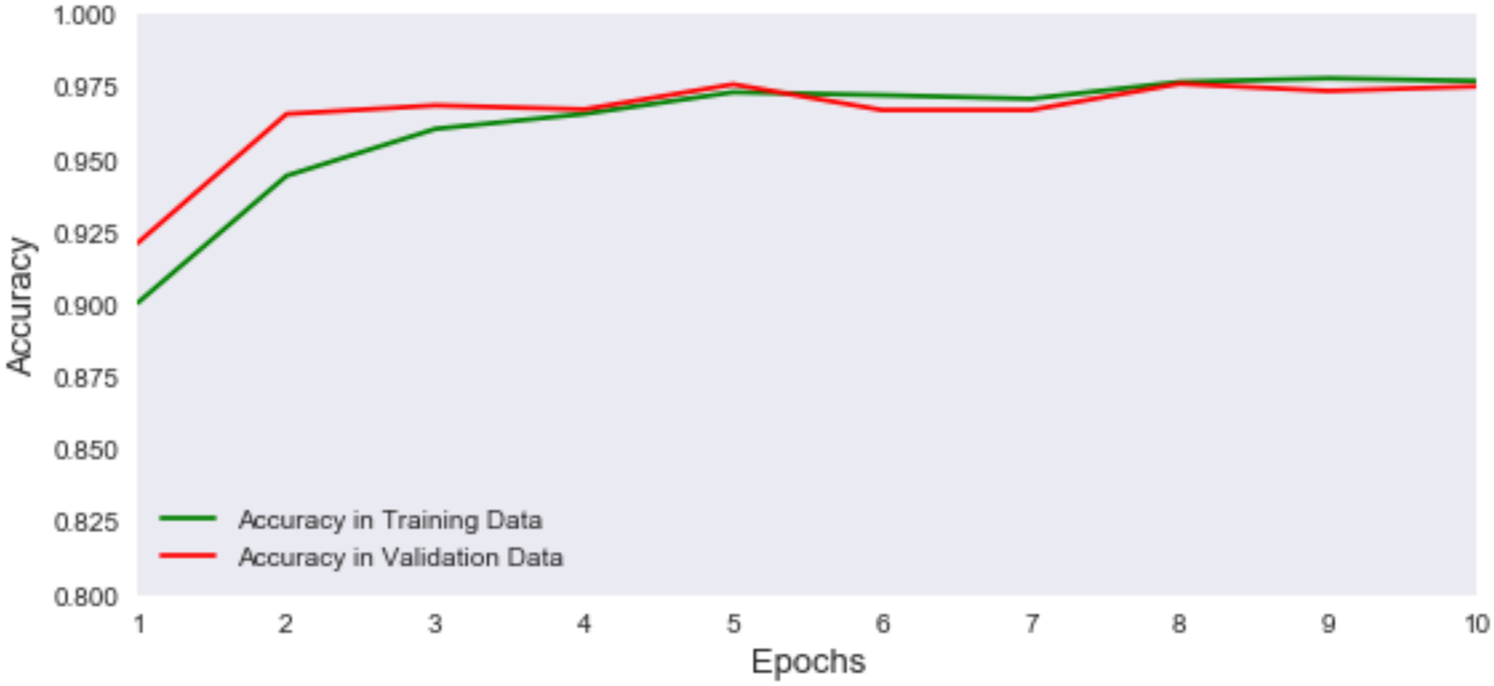
```
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    num_examples = len(X_train)

    for i in range(EPOCHS):
        X_train, y_train = shuffle(X_train, y_train)
        for offset in range(0, num_examples, BATCH_SIZE):
            end = offset + BATCH_SIZE
            batch_x, batch_y = X_train[offset:end], y_train[offset:end]
            sess.run(training_operation, feed_dict={x: batch_x, y: batch_y, appl
y_dropout: True })

        validation_accuracy = evaluate(X_valid_raw_p, y_valid_raw_p)
        valid_accuracy.append(validation_accuracy)
        training_accuracy = evaluate(X_train, y_train)
        train_accuracy.append(training_accuracy)
        if (validation_accuracy > best_validation_accuracy):
            best_validation_accuracy = validation_accuracy
            saver.save(sess, './tenet')
            print("Model saved")
```

```
Model saved
Model saved
Model saved
Model saved
Model saved
```

Model Perfromance in Validation and Training Data

In [40]:

```
px = list(range(1,11))
plt.plot(px,train_accuracy,'-g',label="Accuracy in Training Data")
plt.plot(px,valid_accuracy,'-r',label="Accuracy in Validation Data")
plt.xlabel('Epochs', fontsize=13)
plt.ylabel('Accuracy', fontsize=13)
plt.legend()
plt.xlim(1,10)
plt.ylim(0.8,1.0)
plt.grid(False)
```



Model Evaluation Results

During the training phase, the model performance was very satisfactory and resulted in about 97% accuracy in the validation data. The evaluation results in training, validation and test data are:

- Training Accuracy = 0.972
- Validation Accuracy = 0.978
- Test Accuracy = 0.965

The evaluation results in Test Data is

- test accuracy: 0.964845605625
- Precision 0.95536102367
- Recall 0.964845605701
- f1_score 0.964505652242

In [41]:

```
with tf.Session() as sess:
    #saver.restore(sess, tf.train.latest_checkpoint('.'))
    saver.restore(sess, './tenet')

    training_accuracy = evaluate(X_train, y_train)
    print("Training Accuracy = {:.3f}".format(training_accuracy))
    validation_accuracy = evaluate(X_valid_raw_p, y_valid_raw_p)
    print("Validation Accuracy = {:.3f}".format(validation_accuracy))

    test_accuracy = evaluate(X_test_raw_p, y_test_raw_p)
    print("Test Accuracy = {:.3f}".format(test_accuracy))

    #metrics
    y_p = tf.argmax(logits, 1)
    y_pred = sess.run( y_p, feed_dict={x: X_test_raw_p, y: y_test_raw_p, apply_d
ropout: False})
```

```
Training Accuracy = 0.977
Validation Accuracy = 0.976
Test Accuracy = 0.965
```

In [42]:

```
from sklearn import metrics

print ("test accuracy:", test_accuracy)
y_true = y_test_raw_p
print ("Precision", metrics.precision_score(y_true, y_pred, average='macro'))
print ("Recall", metrics.recall_score(y_true, y_pred, average='micro'))
print ("f1_score", metrics.f1_score(y_true, y_pred, average='weighted'))
print ("Confusion_matrix")
cm = metrics.confusion_matrix(y_true, y_pred)
```

```
test accuracy: 0.96468725246
Precision 0.954027285369
Recall 0.964687252573
f1_score 0.964293014987
Confusion_matrix
```

Model Results - Confusion Matrix

In [43]:

```
plt.figure(figsize = (10,7))
sn.set(font_scale=1.4)
sn.heatmap(cm,annot=False,annot_kws={"size": 10})
```

Out[43]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x12e8a0c50>
```

Test Model on New Images

A set of 38 random images of traffic signs were extracted from various web resources and used for the model evaluation. In this data, the model showed a performance of 71% accuracy.

In [44]:

```
x_test_ext = None
with open("data/gd_new_test.p","rb") as testf:
    x_test_ext = pickle.load(testf)
```

In [45]:

```
y_custom = np.array([21,39,17,17,17,39,39, 40,40,34,28,39,0,17,38,\
13,40,13,38,38,11,0,28,0, 99, 99, 99, 32, 40,28, 40,40,28,24, 0, 0, \
0,0 ])
```

In [46]:

```
len(y_custom)
```

Out[46]:

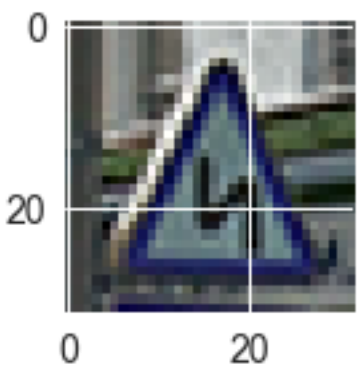
```
38
```

In [47]:

```
plt.figure(figsize=(2,2))
plt.imshow(x_test_ext["test_new"][0].squeeze())
```

Out[47]:

```
<matplotlib.image.AxesImage at 0x12f418668>
```



In [48]:

```
X_new_test = preprocess_data(np.array(x_test_ext["test_new"]))
```

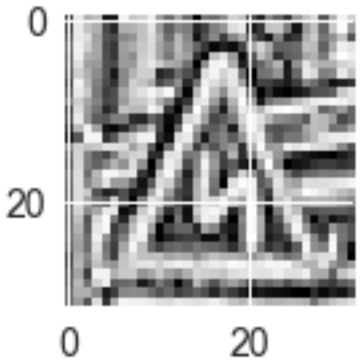
```
/Users/jagan/anaconda2/envs/sdc/lib/python3.5/site-packages/skimage/
util/dtype.py:122: UserWarning: Possible precision loss when convert
ing from float32 to uint16
  .format(dtypeobj_in, dtypeobj_out))
```

In [49]:

```
plt.figure(figsize=(2,2))
plt.imshow(X_new_test[0].squeeze())
```

Out[49]:

```
<matplotlib.image.AxesImage at 0x11bb4ba20>
```



In [50]:

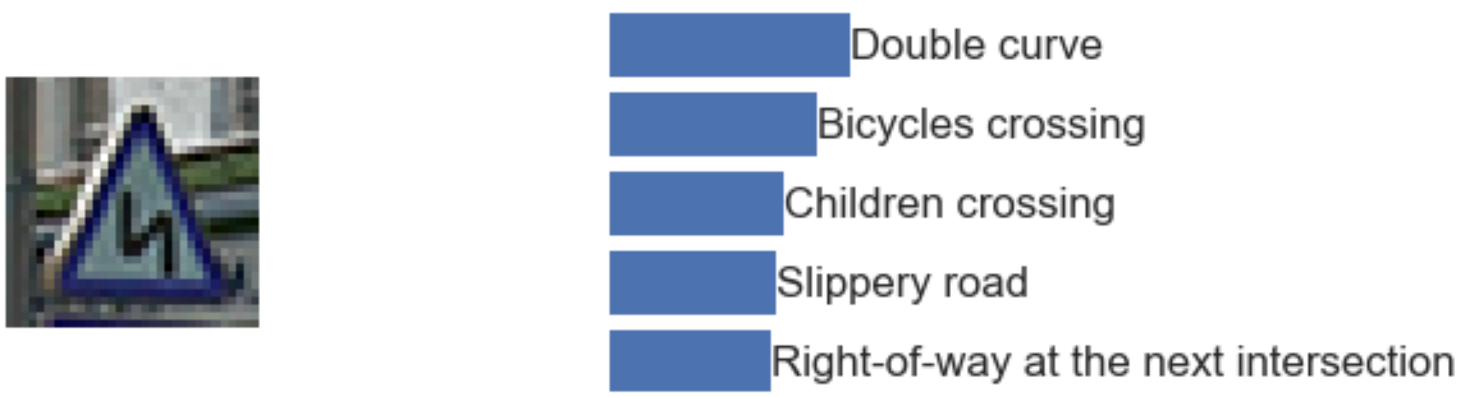
```
with tf.Session() as sess:
    saver.restore(sess, './tenet')

    test_accuracy = evaluate(X_new_test, y_custom)
    print("Test Accuracy = {:.3f}".format(test_accuracy))
```

```
Test Accuracy = 0.579
```

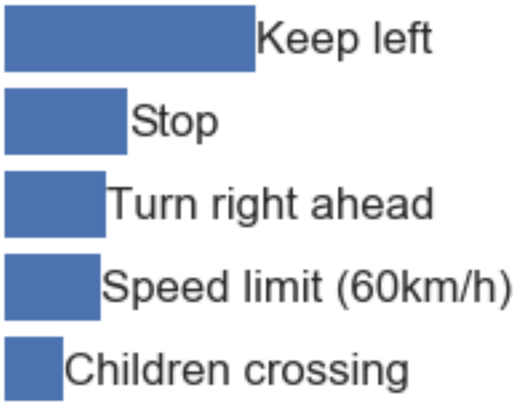
Softmax Probabilities For Each Image Found on the Web

In [51]:

```
#sign_label_map

import matplotlib.gridspec as gridspec

feed_dict_new = feed_dict={x: X_new_test, y: y_custom, apply_dropout: False}
with tf.Session() as sess:
    saver.restore(sess, './tenet')
    predictions = sess.run(logits,feed_dict = feed_dict_new)
    top5_pred = sess.run([logits, tf.nn.top_k(logits, 5)], feed_dict=feed_dict_n
ew)



for i in range(6):
    plt.figure(figsize = (6,3))
    gs = gridspec.GridSpec(1, 3)
    plt.subplot(gs[0])
    plt.axis('off')
    plt.imshow((x_test_ext["test_new"][i].squeeze()))
    plt.subplot(gs[1])
    plt.axis('off')
    plt.subplot(gs[2])
    plt.barh(6-np.arange(5),top5_pred[1][0][i], align='center')
    for i_label in range(5):
        plt.text(top5_pred[1][0][i][i_label]+.02,6-i_label-.15,
            sign_label_map[top5_pred[1][1][i][i_label]])
    plt.axis('off');

    plt.show();
```




Keep left
Turn right ahead
Stop
Speed limit (60km/h)
Go straight or left
Stop
No entry
No passing
Keep right
Speed limit (50km/h)
No entry
No passing
Stop
Keep right
Keep left
No entry
Stop
Keep right
No passing
Keep left



In [52]:

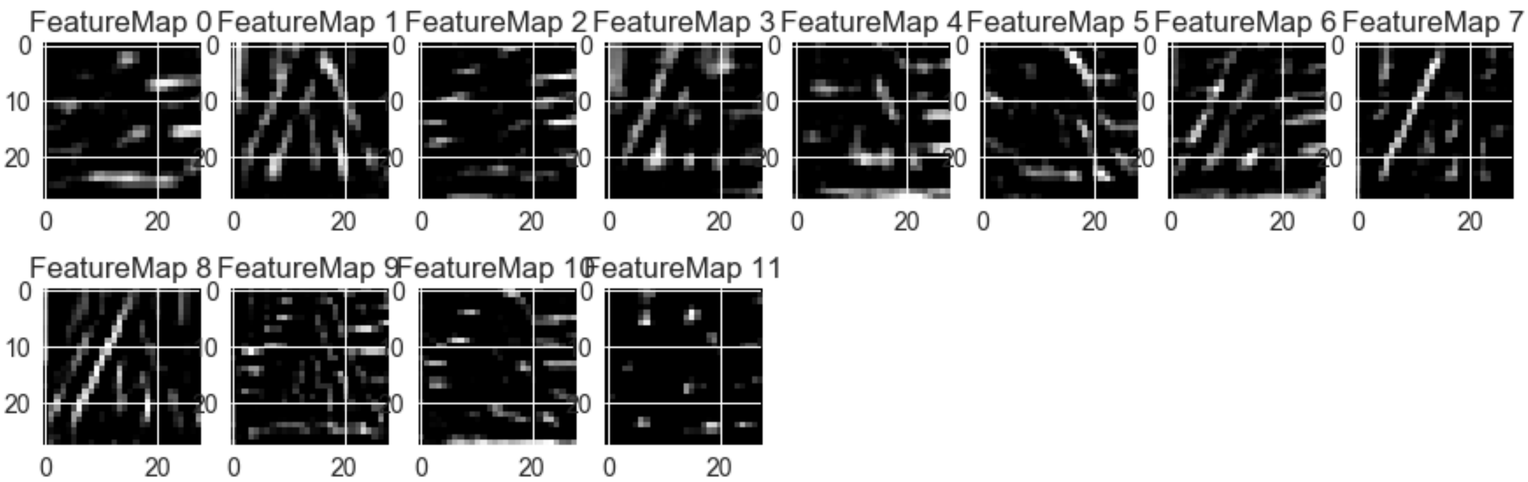
```
def outputFeatureMap(image_input, tf_activation, activation_min=-1, activation_m
ax=-1 ,plt_num=1):

    activation = tf_activation.eval(session=sess,feed_dict={x : image_input, app
ly_dropout: False})
    featuremaps = activation.shape[3]
    plt.figure(plt_num, figsize=(15,15))
    for featuremap in range(featuremaps):
        plt.subplot(6,8, featuremap+1)
        plt.title('FeatureMap ' + str(featuremap))
        if activation_min != -1 & activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", \
            vmin =activation_min, vmax=activation_max, cmap="gray")
        elif activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", \
            vmax=activation_max, cmap="gray")
        elif activation_min !=-1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", \
            vmin=activation_min, cmap="gray")
        else:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", \
            cmap="gray")
```

Visualize the Neural Network's State with Test Images

The code for the same is adapted from Udacity's training materials and the sample notebook

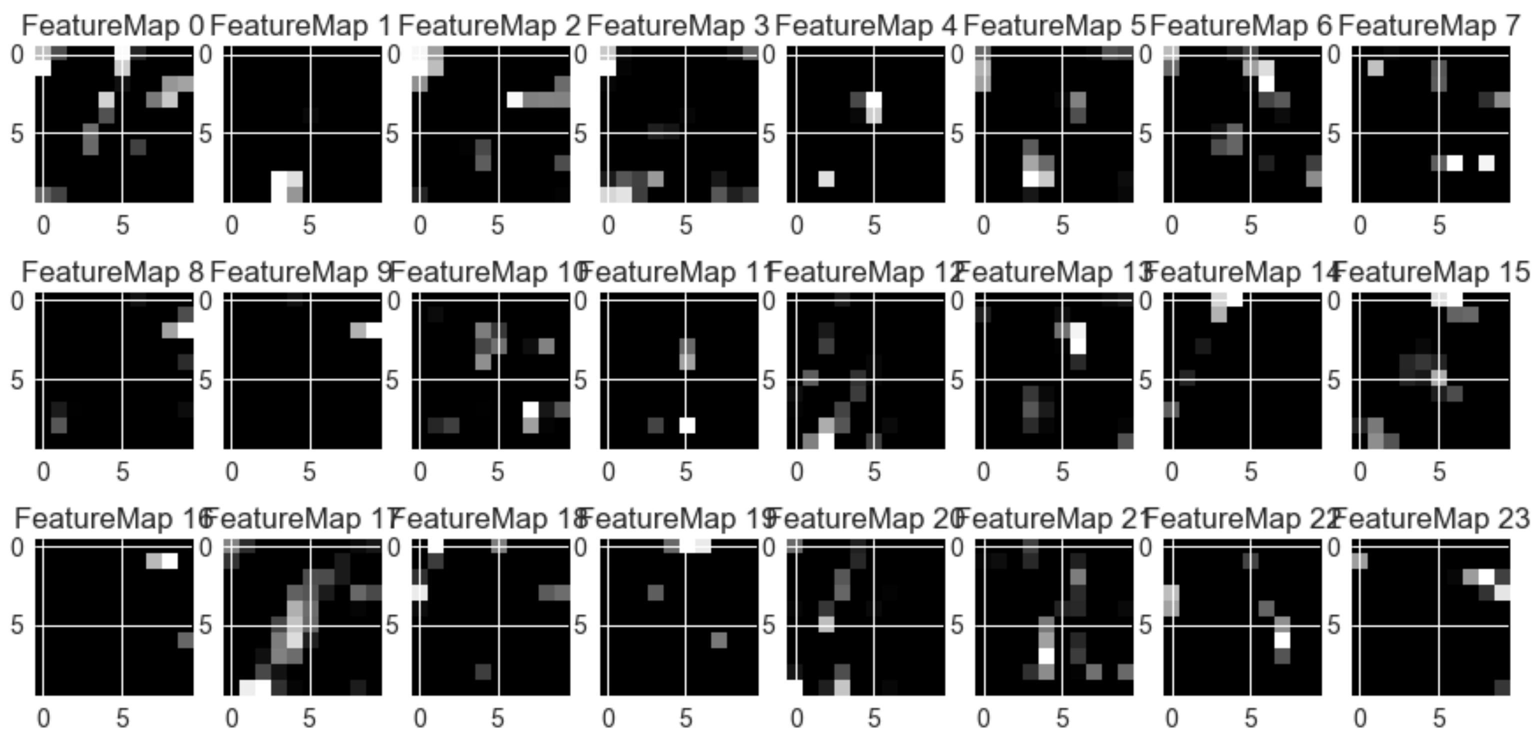
In [53]:

```
with tf.Session() as sess:
    saver.restore(sess, './tenet')
    act1 = tf.get_default_graph().get_tensor_by_name("eye1:0")
    outputFeatureMap(X_new_test, act1)
```



In [54]:

```
with tf.Session() as sess:
    saver.restore(sess, './tenet')
    act1 = tf.get_default_graph().get_tensor_by_name("eye2:0")
    outputFeatureMap(X_new_test, act1)
```



Bonus Step : Softmax Probabilities in Random Images Picked from Belgium Data

In [55]:

```
belgium_data = None
with open("data/belg_data.p","rb") as testf:
    belgium_data = pickle.load(testf)
```

In [56]:

```
X_belgium = belgium_data["belg_data"]
```

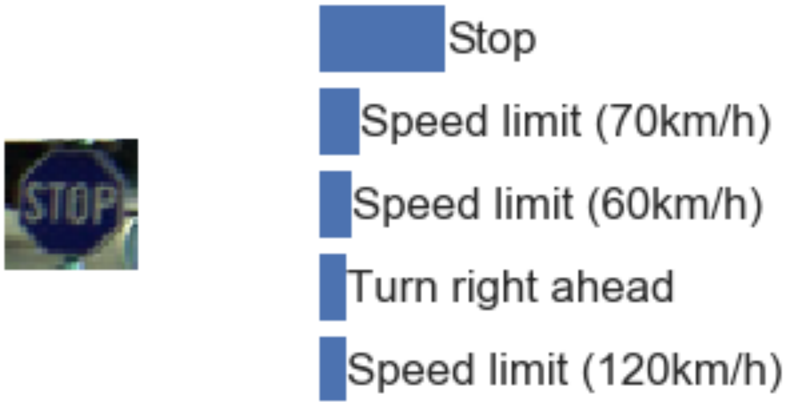
In [57]:

```
X_belg_pp = preprocess_data(np.array(X_belgium))
```

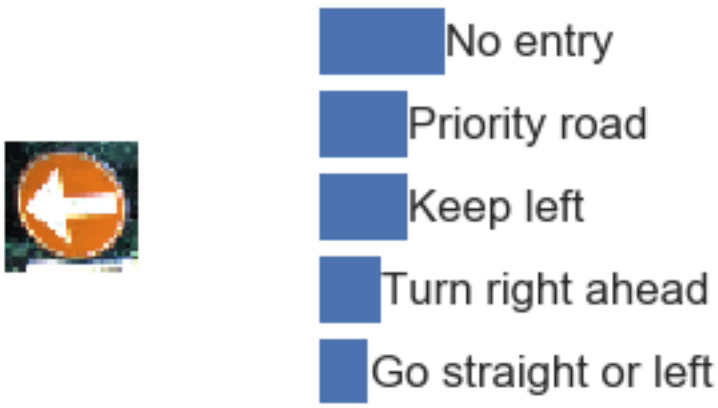
```
/Users/jagan/anaconda2/envs/sdc/lib/python3.5/site-packages/skimage/
util/dtype.py:122: UserWarning: Possible precision loss when convert
ing from float32 to uint16
  .format(dtypeobj_in, dtypeobj_out))
```

In [58]:

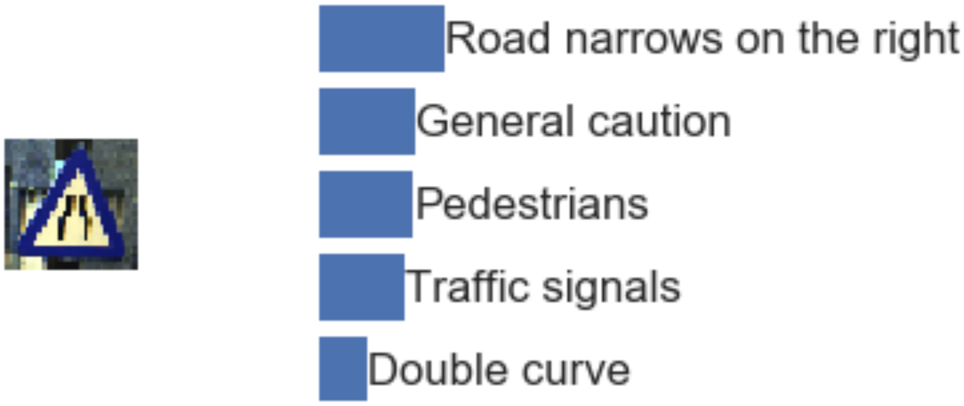
```
import matplotlib.gridspec as gridspec

feed_dict_new = feed_dict={x: X_belg_pp, apply_dropout: False}
with tf.Session() as sess:
    saver.restore(sess, './tenet')
    predictions = sess.run(logits,feed_dict = feed_dict_new)
    top5_pred = sess.run([logits, tf.nn.top_k(logits, 5)], feed_dict=feed_dict_n
ew)



for i in range(10):
    #plt.figure(figsize = (10,3))
    #plt.figure(figsize=(9, 9))
    plt.figure(figsize=(3,3))
    gs = gridspec.GridSpec(1, 3)
    plt.subplot(gs[0])
    plt.axis('off')
    plt.imshow((X_belgium[i].squeeze()))
    plt.subplot(gs[1])
    plt.axis('off')
    plt.subplot(gs[2])
    plt.barh(6-np.arange(5),top5_pred[1][0][i], align='center')
    for i_label in range(5):
        plt.text(top5_pred[1][0][i][i_label]+.02,6-i_label-.15,
            sign_label_map[top5_pred[1][1][i][i_label]])
    plt.axis('off');

    plt.show();
```

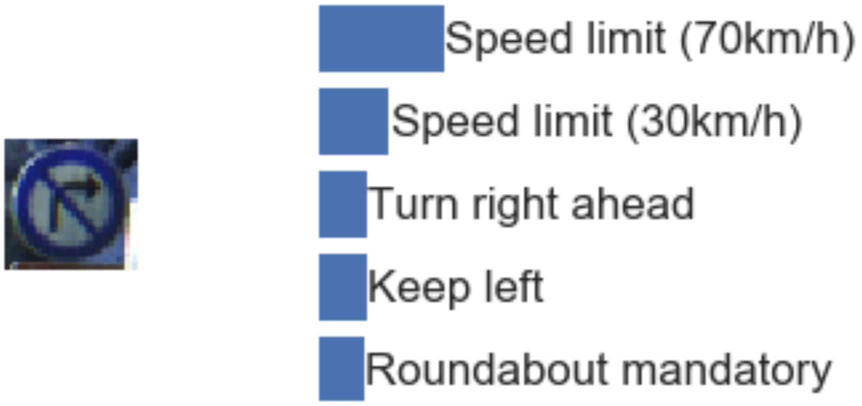

Stop
Speed limit (70km/h)
Speed limit (60km/h)
Turn right ahead
Speed limit (120km/h)

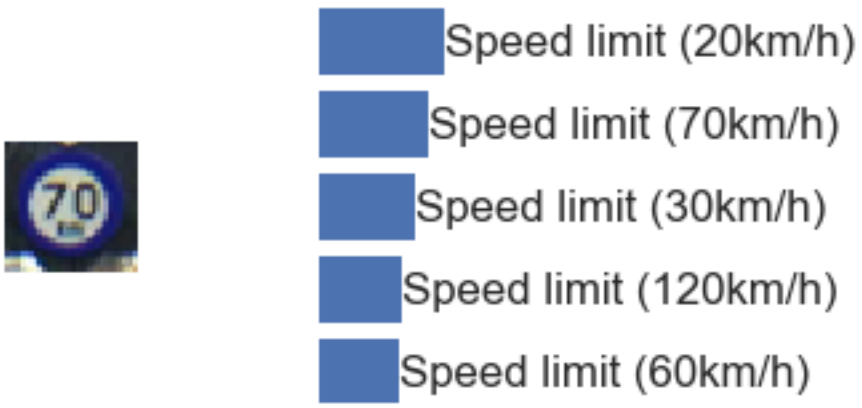

Road narrows on the right
Slippery road
Dangerous curve to the left
Children crossing
Beware of ice/snow

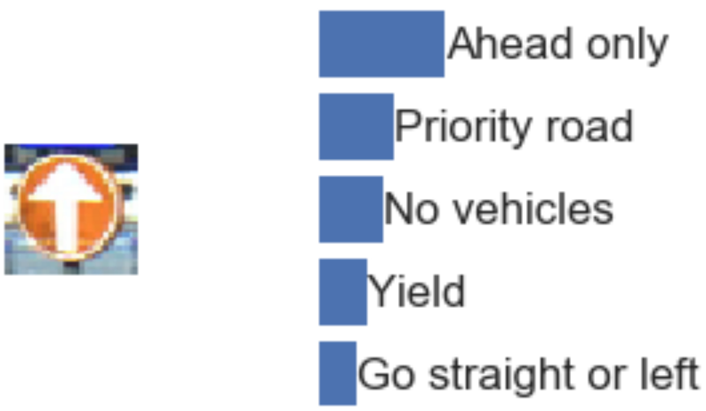

No entry
Priority road
Keep left
Turn right ahead
Go straight or left

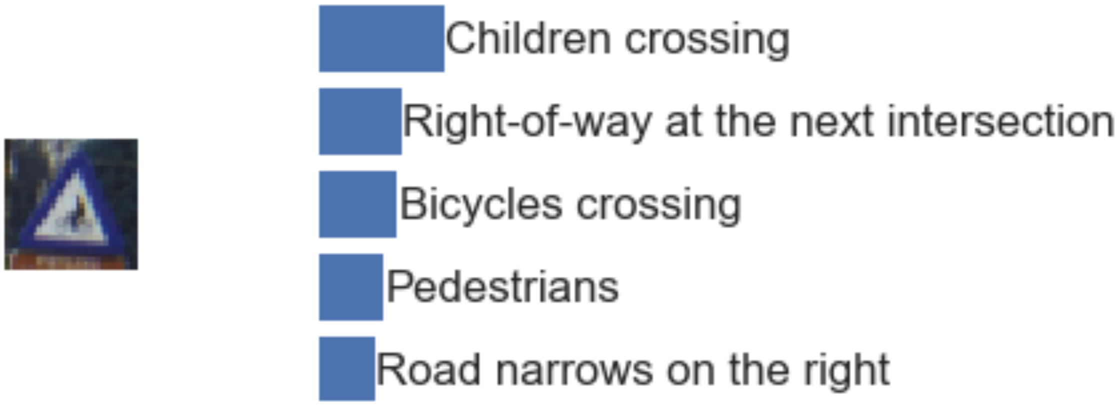

Bumpy road
Road work
Road narrows on the right
Bicycles crossing
Slippery road


Road narrows on the right
General caution
Pedestrians
Traffic signals
Double curve


Speed limit (70km/h)
Speed limit (30km/h)
Turn right ahead
Keep left
Roundabout mandatory


Speed limit (20km/h)
Speed limit (70km/h)
Speed limit (30km/h)
Speed limit (120km/h)
Speed limit (60km/h)


Ahead only
Priority road
No vehicles
Yield
Go straight or left


Children crossing
Right-of-way at the next intersection
Bicycles crossing
Pedestrians
Road narrows on the right


Priority road
Roundabout mandatory
Right-of-way at the next intersection
Keep right
Slippery road