Self-Driving Car Engineer Nanodegree

Deep Learning

Project: Build a Traffic Sign Recognition Classifier ¶

In this notebook, a template is provided for you to implement your functionality in stages which is required to successfully complete this project. If additional code is required that cannot be included in the notebook, be sure that the Python code is successfully imported and included in your submission, if necessary. Sections that begin with **'Implementation'** in the header indicate where you should begin your implementation for your project. Note that some sections of implementation are optional, and will be marked with **'Optional'** in the header.

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. In addition, Markdown cells can be edited by typically double-clicking the cell to enter edit mode.

Imports

In [1]:
```
import pickle
import time
import os
import scipy.ndimage

import numpy as np
import pandas as pd
import tensorflow as tf
from matplotlib.colors import ListedColormap
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import matplotlib.gridspec as gridspec

from sklearn import datasets
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score, f1_score
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn import decomposition
import cv2
```

Supporting Functions

In [2]:
```
#one hot coding function
def OHE_Encode(Y_tr,N_classes):
    OHC = OneHotEncoder()
    Y_ohc = OHC.fit(np.arange(N_classes).reshape(-1, 1))
    Y_labels = Y_ohc.transform(Y_tr.reshape(-1, 1)).toarray()
    return Y_labels

def OHE_Validate(cls,y):
    check = np.linalg.norm(np.argmax(cls,axis=1)-y)
    if check == 0:
        print('One hot encoding Validated')
    else:
        print('One hot encoding doesnt match the output, check code!!!')
```

Step 0: Load The Data

In [3]:
```
print('Tensor Flow version : '+tf.__version__)
training_file = 'traffic-signs-data/train.p'
testing_file = 'traffic-signs-data/test.p'

with open(training_file, mode='rb') as f:
    train = pickle.load(f)
with open(testing_file, mode='rb') as f:
    test = pickle.load(f)

X_train, y_train = train['features'], train['labels']
X_test, y_test = test['features'], test['labels']

assert(len(X_train)== len(y_train))
assert(len(X_test)== len(y_test))

#data_pd = pd.read_csv('signnames.csv')
#data_pd.head()
```

```
Tensor Flow version : 0.12.1
```

Step 1: Dataset Summary & Exploration

The pickled data is a dictionary with 4 key/value pairs:

- `'features'` is a 4D array containing raw pixel data of the traffic sign images, (num examples, width, height, channels).
- `'labels'` is a 2D array containing the label/class id of the traffic sign. The file `signnames.csv` contains id -> name mappings for each id.
- `'sizes'` is a list containing tuples, (width, height) representing the the original width and height the image.
- `'coords'` is a list containing tuples, (x1, y1, x2, y2) representing coordinates of a bounding box around the sign in the image. **THESE COORDINATES ASSUME THE ORIGINAL IMAGE. THE PICKLED DATA CONTAINS RESIZED VERSIONS (32 by 32) OF THESE IMAGES**

Complete the basic data summary below.

In [4]:
```
### Replace each question mark with the appropriate value.

# TODO: Number of training examples
n_train = len(X_train)

# TODO: Number of testing examples.
n_test = len(X_test)

# TODO: What's the shape of an traffic sign image?
image_shape = X_train[0].shape

# TODO: How many unique classes/labels there are in the dataset.
n_classes = len(set(y_train))

# Number of Channels
n_channels = X_train[0].shape[2]

print("Number of training examples =", n_train)
print("Number of testing examples =", n_test)
print("Image data shape =", image_shape)
print('Training labels shape', y_train.shape)
print("Number of classes =", n_classes)
print("Number of channels =", n_channels)
print("Number of features =", X_train.shape[1])

#One Hot Encoding
y_train_OneHot = OHE_Encode(y_train,n_classes)
y_test_OneHot = OHE_Encode(y_test,n_classes)

OHE_Validate(y_test_OneHot ,y_test)
OHE_Validate(y_train_OneHot,y_train)
```

```
Number of training examples = 39209
Number of testing examples = 12630
Image data shape = (32, 32, 3)
Training labels shape (39209,)
Number of classes = 43
Number of channels = 3
Number of features = 32
One hot encoding Validated
One hot encoding Validated
```

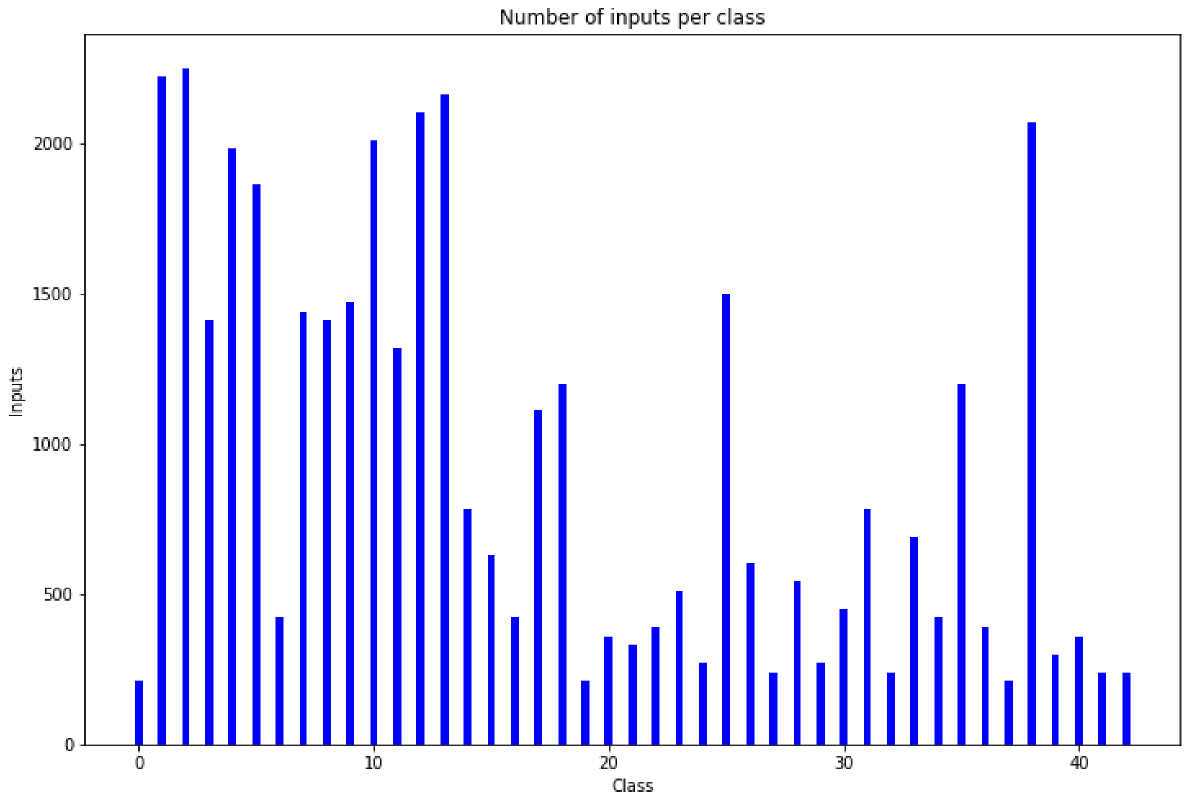
Visualize the German Traffic Signs Dataset using the pickled file(s). This is open ended, suggestions include: plotting traffic sign images, plotting the count of each sign, etc.

The [Matplotlib (http://matplotlib.org/)](http://matplotlib.org/) [examples (http://matplotlib.org/examples/index.html)](http://matplotlib.org/examples/index.html) and [gallery (http://matplotlib.org/gallery.html)](http://matplotlib.org/gallery.html) pages are a great resource for doing visualizations in Python.

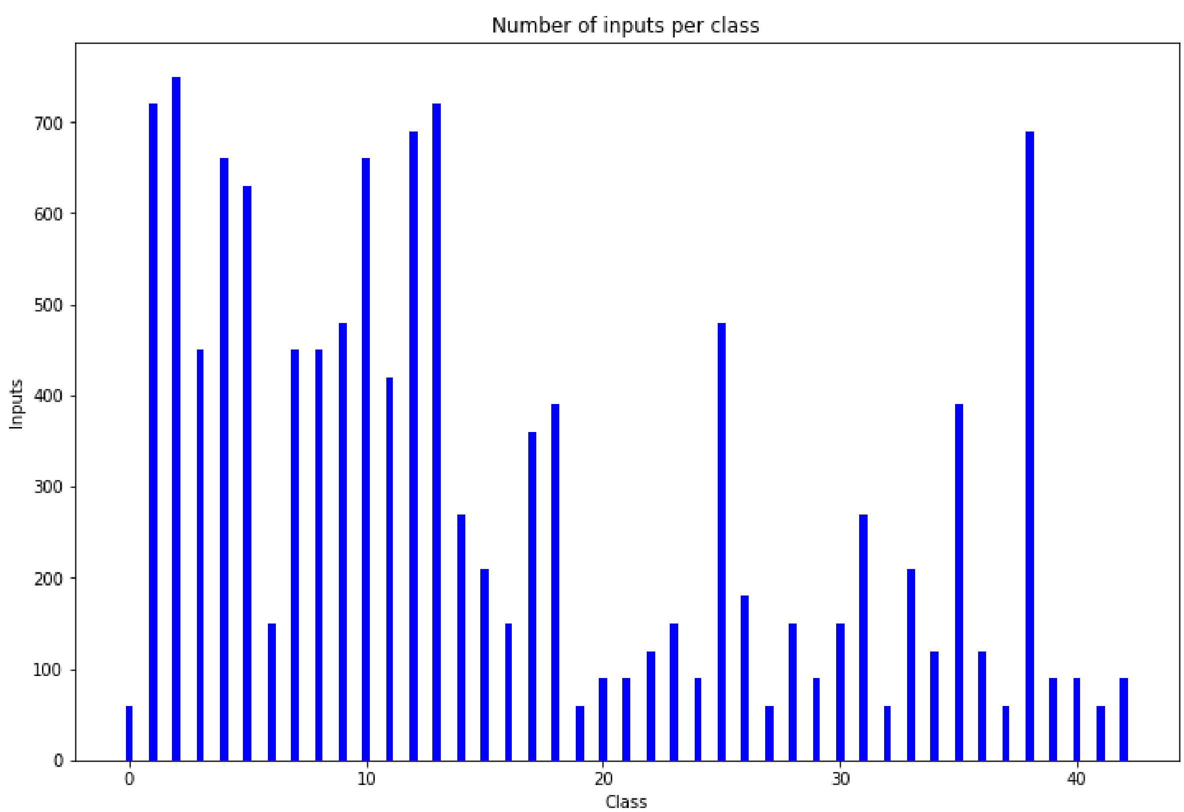
NOTE: It's recommended you start with something simple first. If you wish to do more, come back to it after you've completed the rest of the sections.

In [5]:
```
print('Training Data')
train_features = np.array(train['features'])
train_labels = np.array(train['labels'])

inputs_per_class = np.bincount(train_labels)
max_inputs = np.max(inputs_per_class)

mpl_fig = plt.figure(figsize=(12,8))
ax = mpl_fig.add_subplot(111)
ax.set_ylabel('Inputs')
ax.set_xlabel('Class')
ax.set_title('Number of inputs per class')
ax.bar(range(len(inputs_per_class)), inputs_per_class, 1/3, color='blue', labe
l='Inputs per class')
plt.show()


print('Testing Data')
test_features = np.array(test['features'])
test_labels = np.array(test['labels'])

inputs_per_class = np.bincount(test_labels)
max_inputs = np.max(inputs_per_class)

mpl_fig = plt.figure(figsize=(12,8))
ax = mpl_fig.add_subplot(111)
ax.set_ylabel('Inputs')
ax.set_xlabel('Class')
ax.set_title('Number of inputs per class')
ax.bar(range(len(inputs_per_class)), inputs_per_class, 1/3, color='blue', labe
l='Inputs per class')
plt.show()
```

Training Data



Testing Data



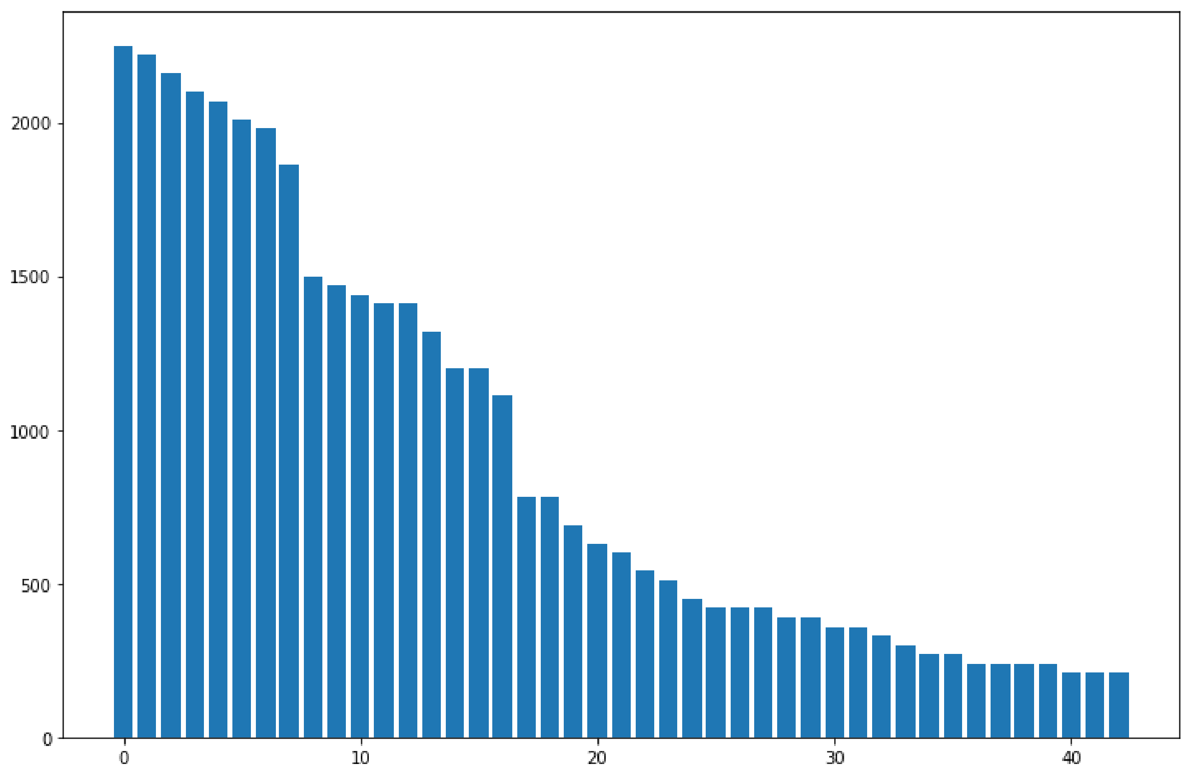
In [6]:
```
data_i = [[i,sum(y_train == i)] for i in range(len(np.unique(y_train)))]
data_i_sorted = sorted(data_i, key=lambda x: x[1])
data_pd = pd.read_csv('signnames.csv')
data_pd['Occurance'] = pd.Series(np.asarray(data_i_sorted).T[1], index=np.asar
ray(data_i_sorted).T[0])
data_pd_sorted = data_pd.sort_values(['Occurance'],ascending=
[0]).reset_index()
data_pd_sorted = data_pd_sorted.drop('index', 1)
data_pd_sorted
```

Out[6]:

	ClassId	SignName	Occurance
0	2	Speed limit (50km/h)	2250
1	1	Speed limit (30km/h)	2220
2	13	Yield	2160
3	12	Priority road	2100
4	38	Keep right	2070
5	10	No passing for vehicles over 3.5 metric tons	2010
6	4	Speed limit (70km/h)	1980
7	5	Speed limit (80km/h)	1860
8	25	Road work	1500
9	9	No passing	1470
10	7	Speed limit (100km/h)	1440
11	3	Speed limit (60km/h)	1410
12	8	Speed limit (120km/h)	1410
13	11	Right-of-way at the next intersection	1320
14	35	Ahead only	1200
15	18	General caution	1200
16	17	No entry	1110
17	31	Wild animals crossing	780
18	14	Stop	780
19	33	Turn right ahead	689
20	15	No vehicles	630
21	26	Traffic signals	600
22	28	Children crossing	540
23	23	Slippery road	510
24	30	Beware of ice/snow	450
25	16	Vehicles over 3.5 metric tons prohibited	420
26	34	Turn left ahead	420
27	6	End of speed limit (80km/h)	420
28	36	Go straight or right	390
29	22	Bumpy road	390
30	40	Roundabout mandatory	360
31	20	Dangerous curve to the right	360

	ClassId	SignName	Occurance
32	21	Double curve	330
33	39	Keep left	300
34	29	Bicycles crossing	270
35	24	Road narrows on the right	270
36	41	End of no passing	240
37	42	End of no passing by vehicles over 3.5 metric ...	240
38	32	End of all speed and passing limits	240
39	27	Pedestrians	240
40	37	Go straight or left	210
41	19	Dangerous curve to the left	210
42	0	Speed limit (20km/h)	210

In [7]:
```
plt.figure(figsize=(12,8))
plt.bar(range(n_classes),height=data_pd_sorted["Occurance"])
plt.show()
```

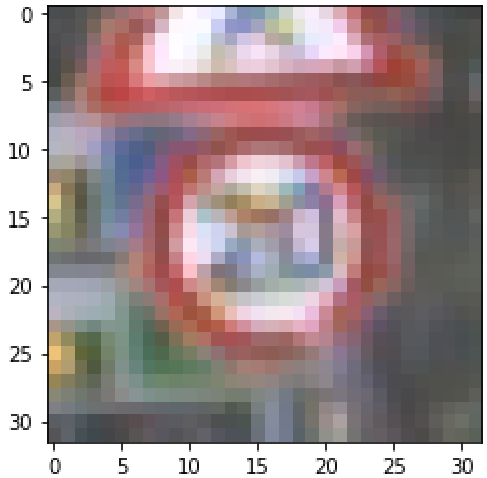


In [8]:

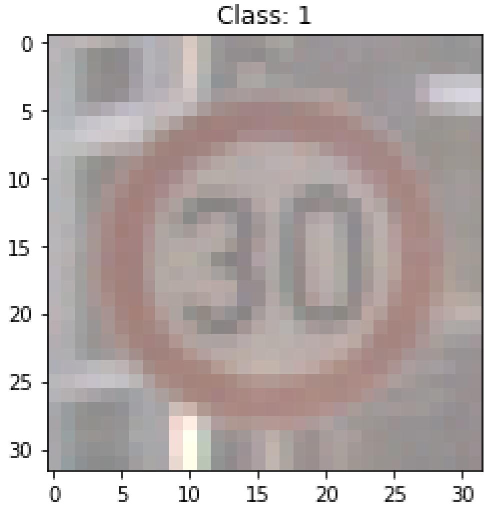
```
sign_dict = {}

print('List of Classes')
mpl_fig = plt.figure()
for i in range(n_classes):
    for j in range(len(train_labels)):
        if (i == train_labels[j]):
            sign_dict[i]=train_features[j]
            plt.title('Class: '+ str(i))
            plt.imshow(train_features[j])
            plt.show()
            break
```

List of Classes

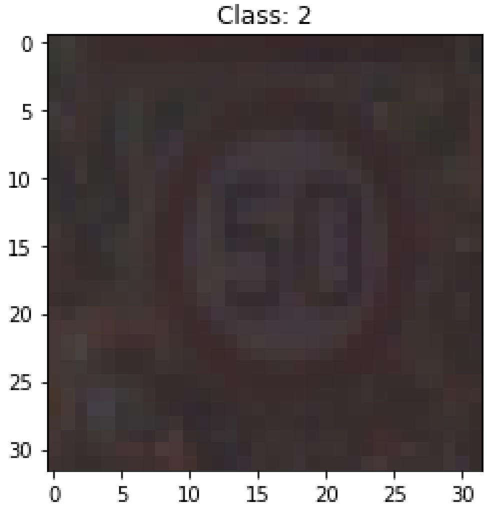
Class: 0



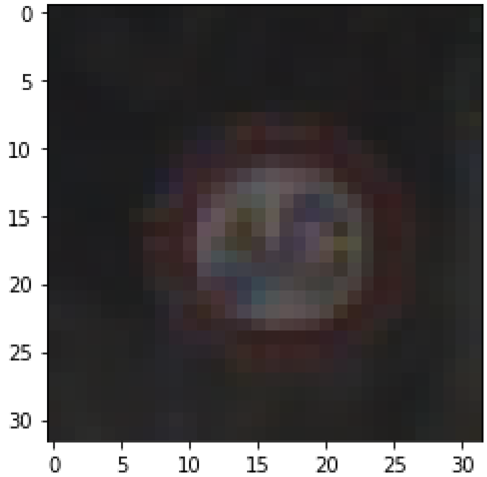
Class: 1



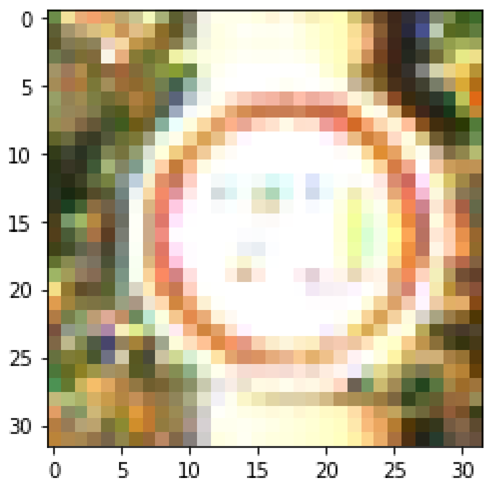
Class: 2



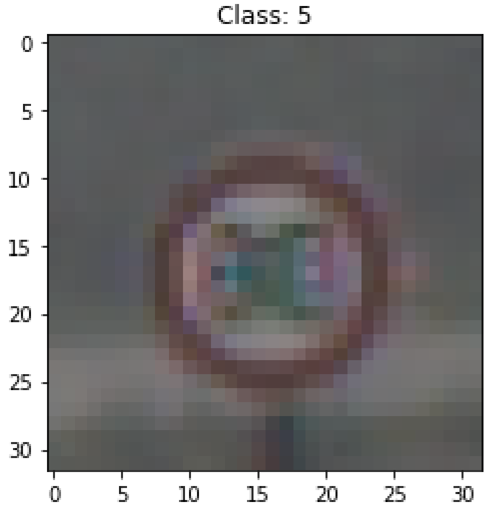
Class: 3

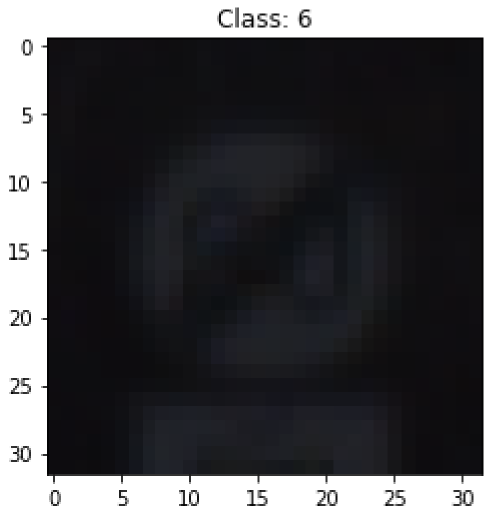


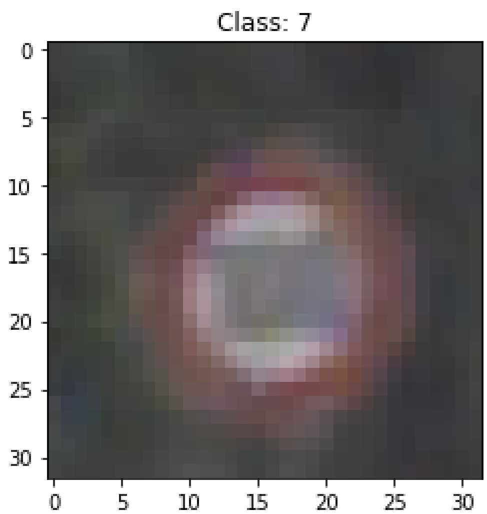
Class: 4

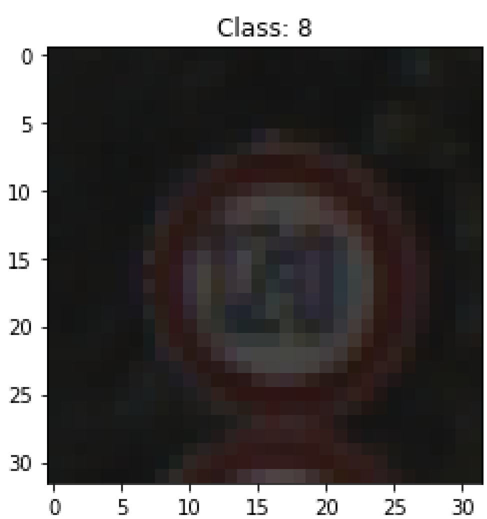


Class: 5

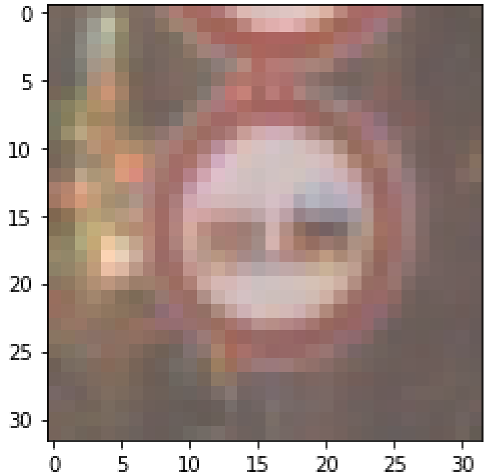



Class: 6

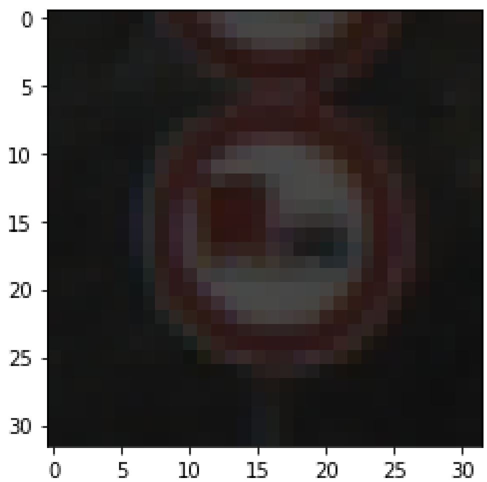

Class: 7


Class: 8

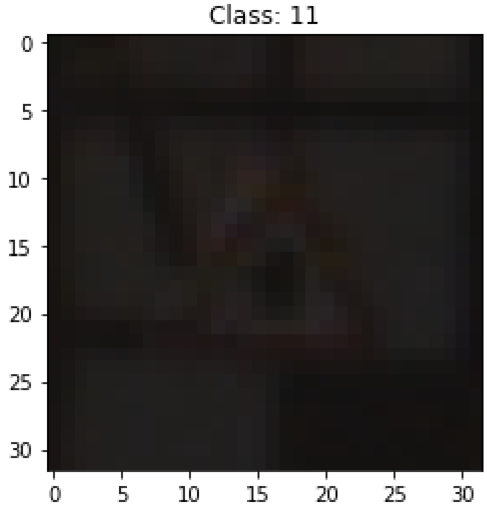
Class: 9



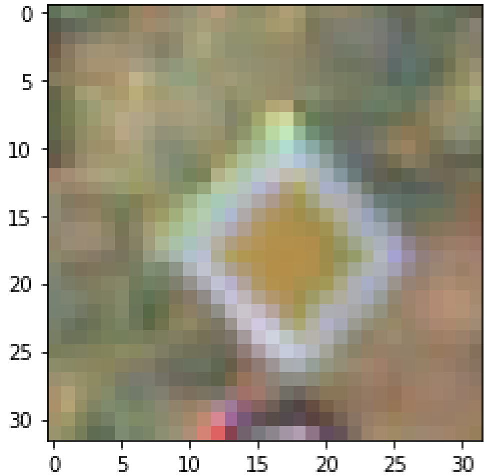
Class: 10



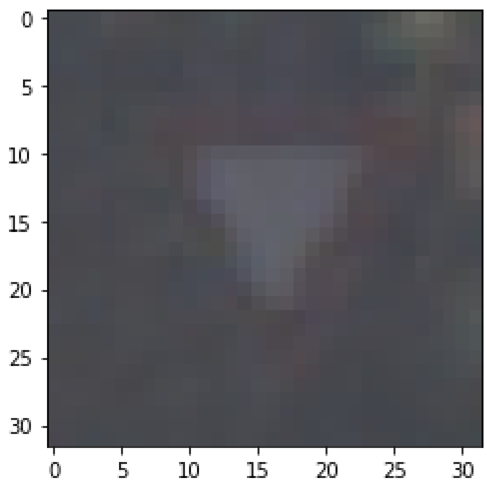
Class: 11



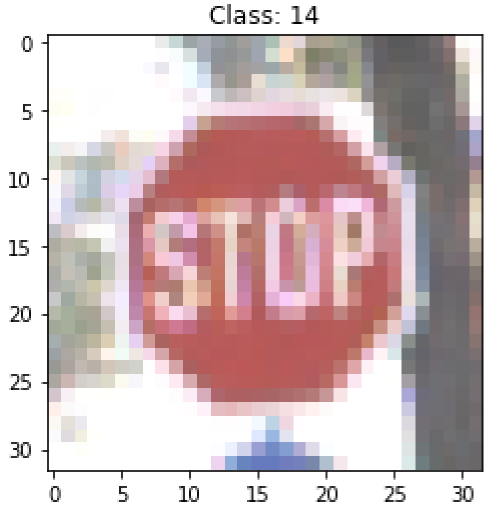
Class: 12



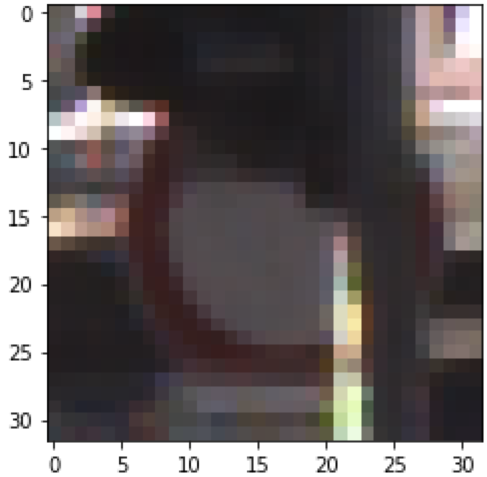
Class: 13



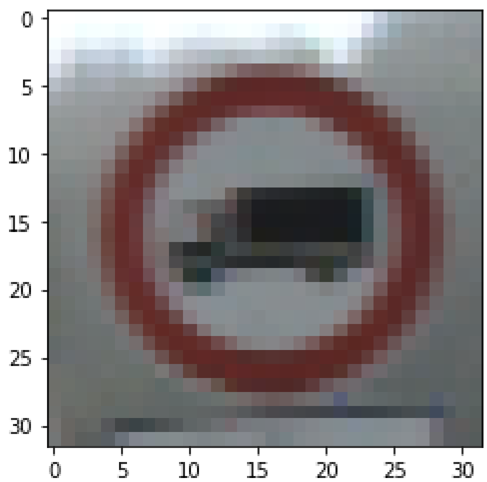
Class: 14



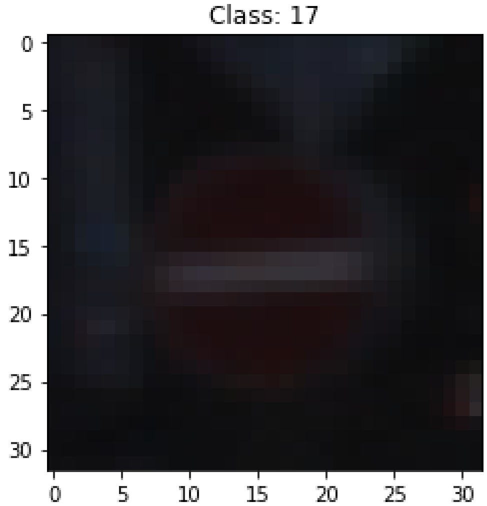
Class: 15



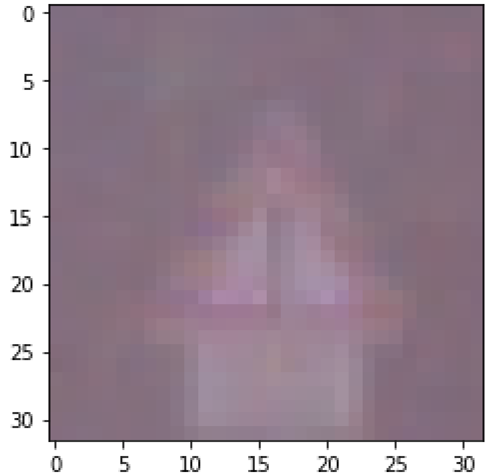
Class: 16



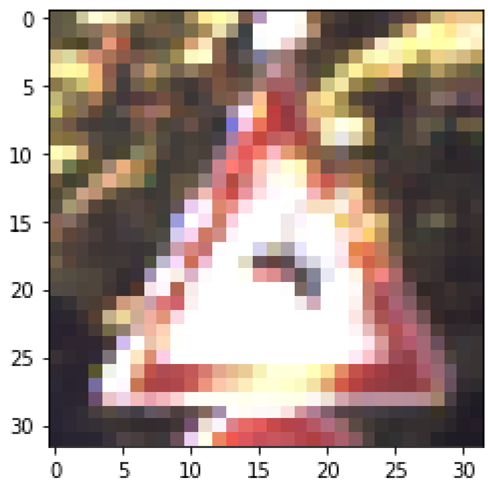
Class: 17



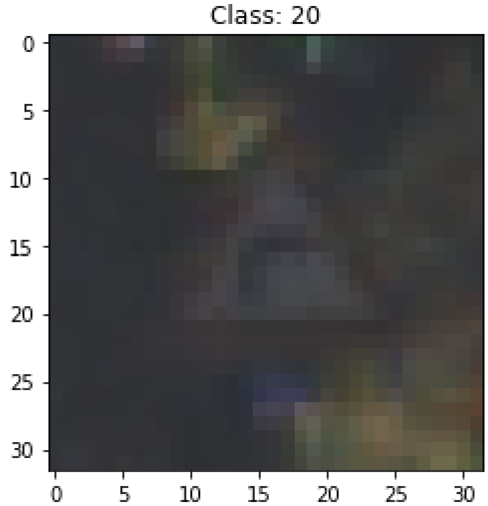
Class: 18

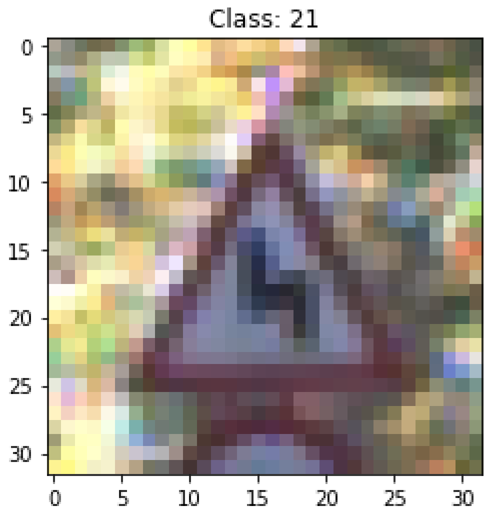


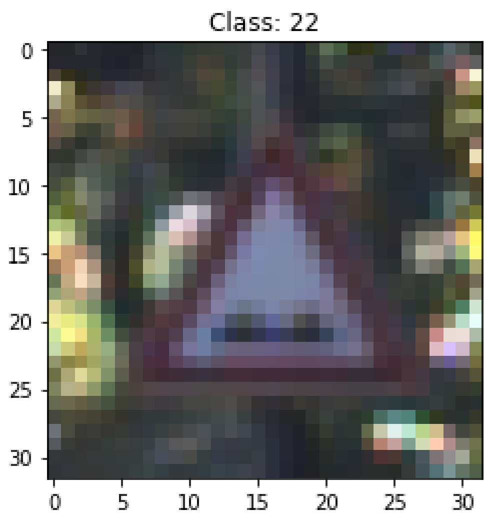
Class: 19

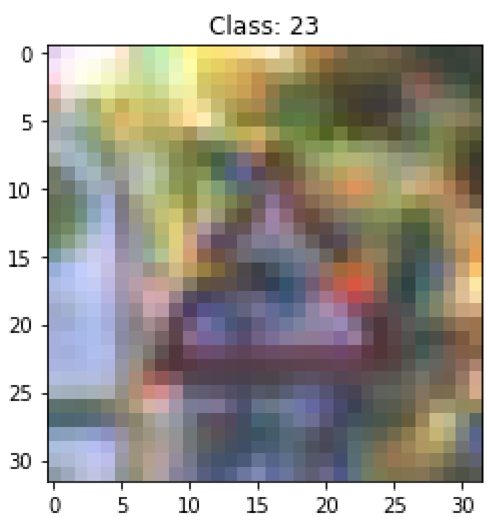


Class: 20

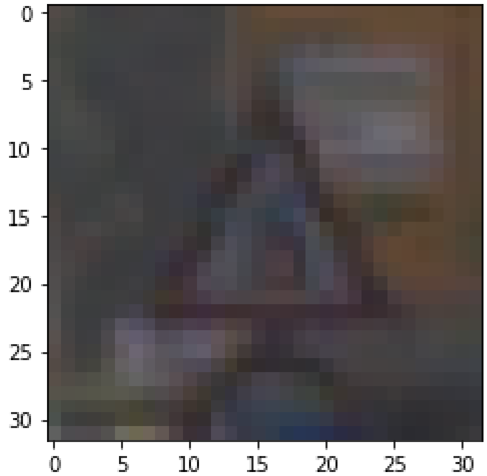



Class: 21
0
5
10
15
20
25
30

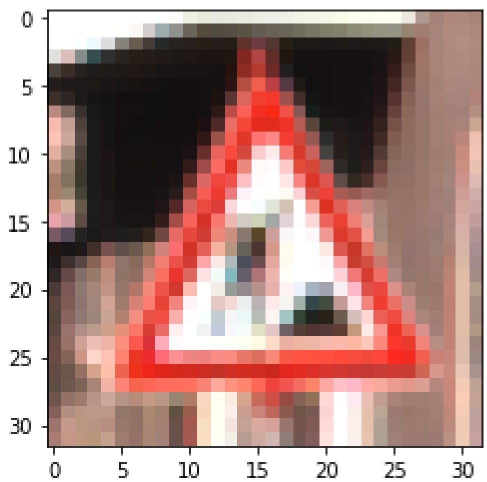

Class: 22
0
5
10
15
20
25
30


Class: 23
0
5
10
15
20
25
30

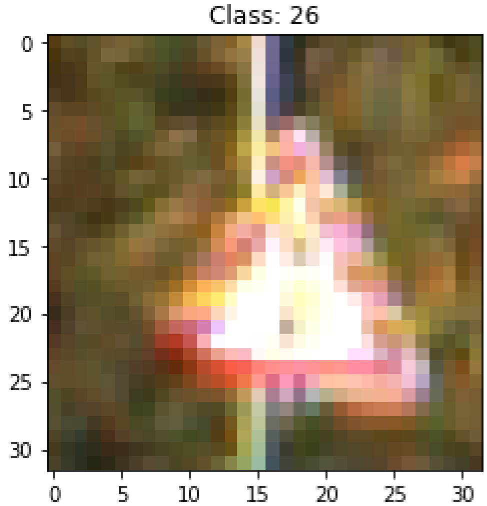
Class: 24



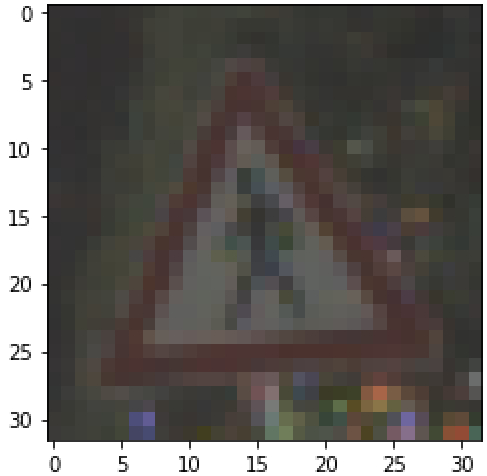
Class: 25



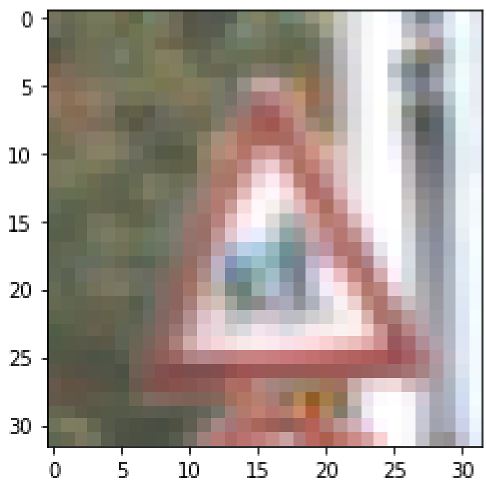
Class: 26



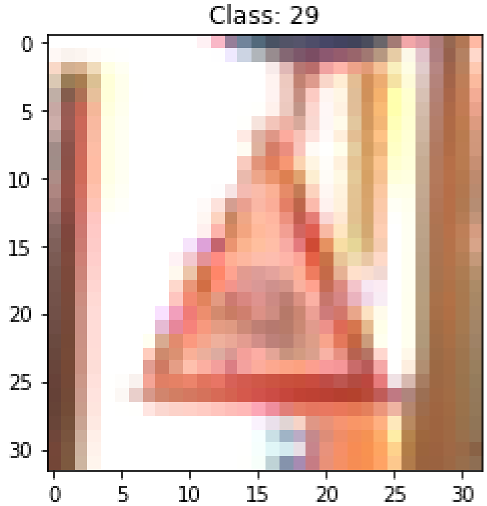
Class: 27



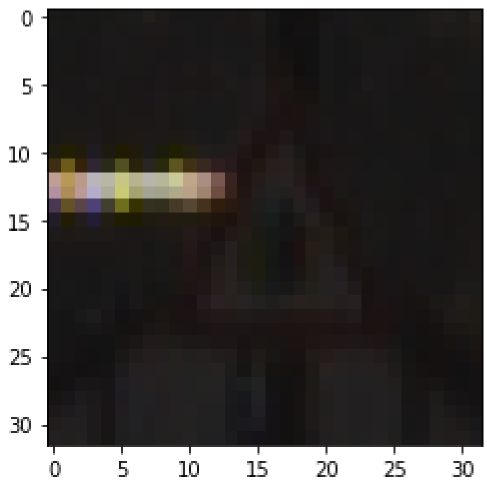
Class: 28



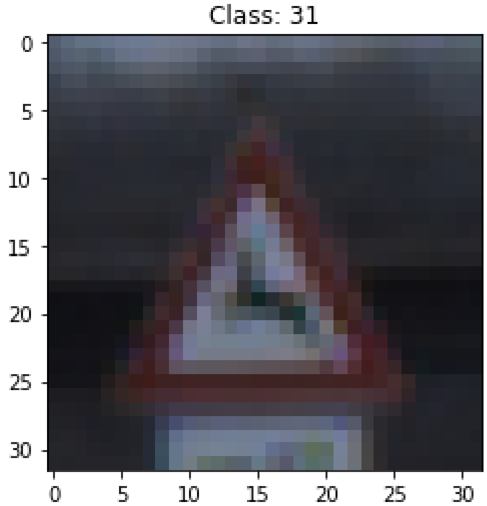
Class: 29



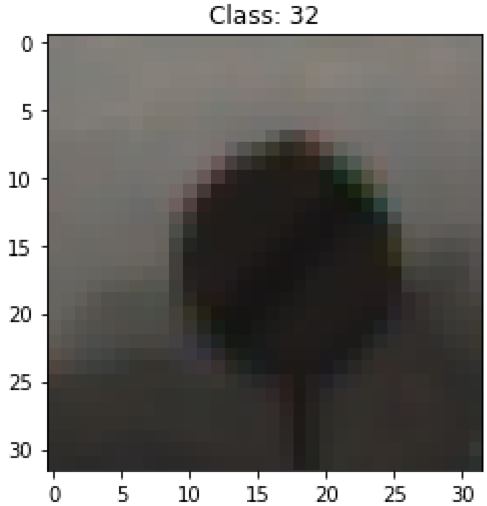
Class: 30



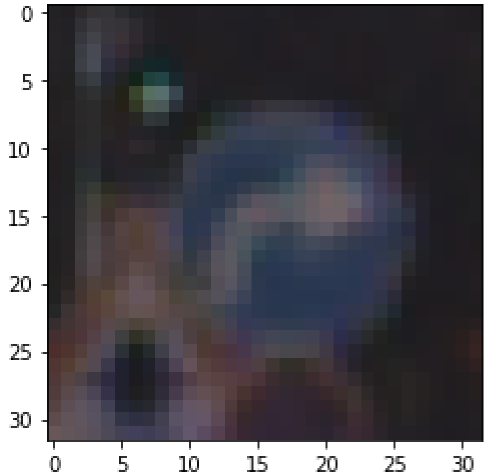
Class: 31



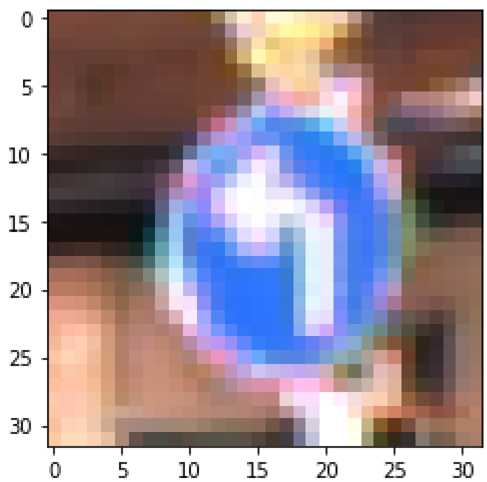
Class: 32



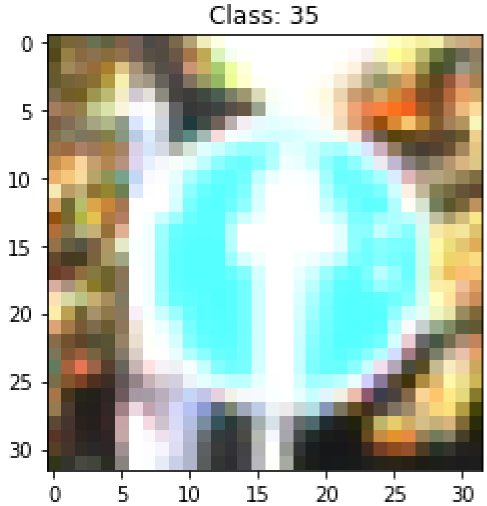
Class: 33



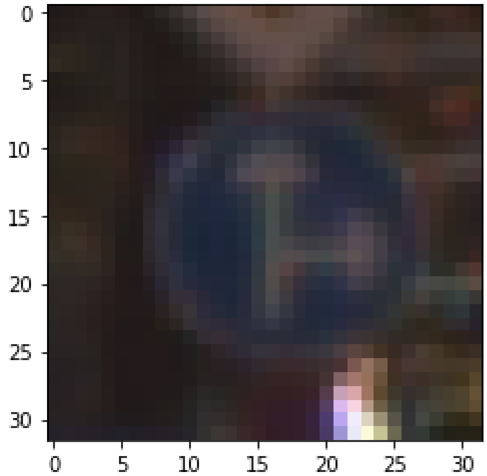
Class: 34



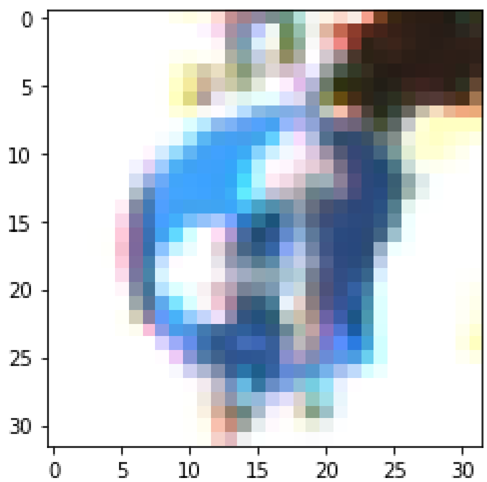
Class: 35



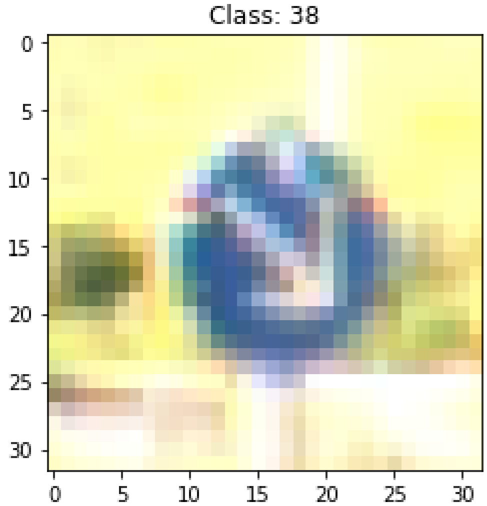
Class: 36



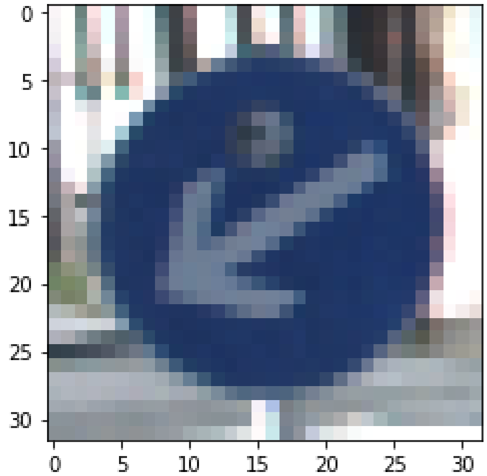
Class: 37



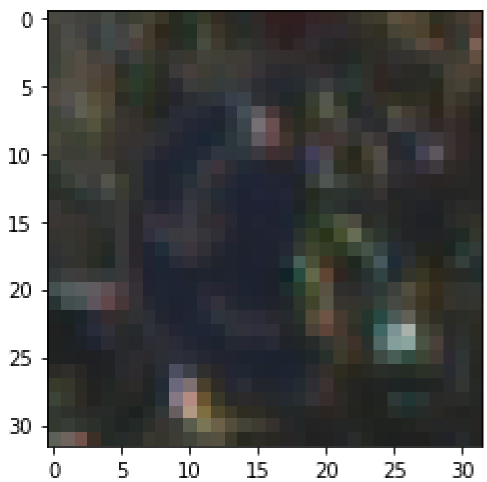
Class: 38



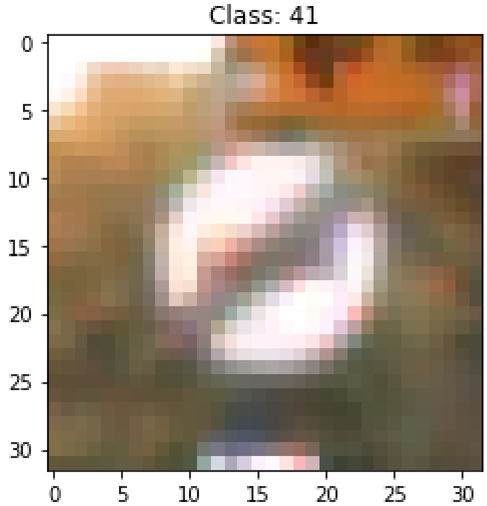
Class: 39

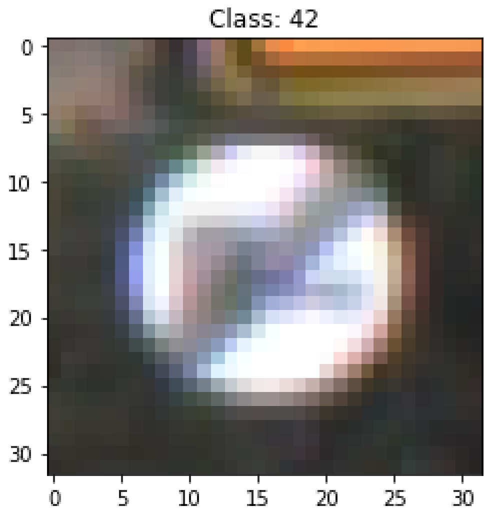


Class: 40



Class: 41





Add Extra Data to avoid OverFitting

In [9]:
```
def get_index_dict(y_train):
    # Returns indices of each label
    # Assumes that the labels are 0 to N-1
    dict_indices = {}
    ind_all = np.arange(len(y_train))

    for i in range(len(np.unique(y_train))):
        ind_i = ind_all[y_train == i]
        dict_indices[i] = ind_i
    return dict_indices

def transform_image(image,ang_range,shear_range,trans_range):

    # Rotation

    ang_rot = np.random.uniform(ang_range)-ang_range/2
    rows,cols,ch = image.shape
    Rot_M = cv2.getRotationMatrix2D((cols/2,rows/2),ang_rot,1)

    # Translation
    tr_x = trans_range*np.random.uniform()-trans_range/2
    tr_y = trans_range*np.random.uniform()-trans_range/2
    Trans_M = np.float32([[1,0,tr_x],[0,1,tr_y]])

    # Shear
    pts1 = np.float32([[5,5],[20,5],[5,20]])

    pt1 = 5+shear_range*np.random.uniform()-shear_range/2
    pt2 = 20+shear_range*np.random.uniform()-shear_range/2

    pts2 = np.float32([[pt1,5],[pt2,pt1],[5,pt2]])

    shear_M = cv2.getAffineTransform(pts1,pts2)

    image = cv2.warpAffine(image,Rot_M,(cols,rows))
```

```
    image = cv2.warpAffine(image,Trans_M,(cols,rows))
    image = cv2.warpAffine(image,shear_M,(cols,rows))

    return image

def gen_extra_data(X_train,y_train,N_classes,n_each,ang_range,shear_range,tran
s_range,randomize_Var):
    dict_indices = get_index_dict(y_train)
    n_class = len(np.unique(y_train))
    X_arr = []
    Y_arr = []
    n_train = len(X_train)
    for i in range(n_train):
        for i_n in range(n_each):
            img_trf = transform_image(X_train[i], ang_range,shear_range,trans_
range)
            X_arr.append(img_trf)
            Y_arr.append(y_train[i])

    return X_arr,Y_arr


i_train =1
ang_rot = 10*0.9**(i_train)
trans_rot = 2*0.9**(i_train)
shear_rot = 2*0.9**(i_train)

#X_train,y_train = gen_extra_data(X_train,y_train,43,5,ang_rot,trans_rot,shear
_rot,1)


#print('Training Data')
#train_features = np.array(X_train)
#train_labels = np.array(y_train)

#inputs_per_class = np.bincount(train_labels)
#max_inputs = np.max(inputs_per_class)

#mpl_fig = plt.figure(figsize=(12,8))
#ax = mpl_fig.add_subplot(111)
#ax.set_ylabel('Inputs')
#ax.set_xlabel('Class')
#ax.set_title('Number of inputs per class')
#ax.bar(range(len(inputs_per_class)), inputs_per_class, 1/3, color='blue', lab
el='Inputs per class')
#plt.show()
```

Step 2: Design and Test a Model Architecture

Design and implement a deep learning model that learns to recognize traffic signs. Train and test your model on the German Traffic Sign Dataset (http://benchmark.ini.rub.de/?section=gtsrb&subsection=dataset).

There are various aspects to consider when thinking about this problem:

- Neural network architecture
- Play around preprocessing techniques (normalization, rgb to grayscale, etc)
- Number of examples per label (some have more than others).
- Generate fake data.

Here is an example of a published baseline model on this problem (http://yann.lecun.com/exdb/publis/pdf/sermanet-ijcnn-11.pdf). It's not required to be familiar with the approach used in the paper but, it's good practice to try to read papers like these.

NOTE: The LeNet-5 implementation shown in the classroom (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) at the end of the CNN lesson is a solid starting point. You'll have to change the number of classes and possibly the preprocessing, but aside from that it's plug and play!

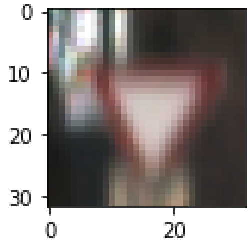
Implementation

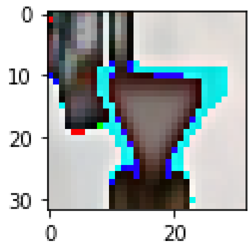
Use the code cell (or multiple code cells, if necessary) to implement the first step of your project. Once you have completed your implementation and are satisfied with the results, be sure to thoroughly answer the questions that follow.

2.1 Preprocessing

In [10]:
```
### Step 1
### Images are already resized the images to 32x32. so no padding required



### Step 2
### its important to shuffle data because order of data could effect how well
 is network gets trained
X_train, y_train = shuffle(X_train, y_train, random_state=42)



### Step 3 Normalisation (not standardising)
# The goal is to independently normalize each feature component to the [0,1] r
ange
# In image processing, normalization is a process that changes the range of pi
xel intensity values.
# In stochastic gradient descent, Normalization can sometimes improve the conv
ergence speed of the algorithm

X_train_org = X_train
X_test_org = X_test
X_train = (X_train - X_train.mean()) / (np.max(X_train) - np.min(X_train))
X_test = (X_test - X_test.mean()) / (np.max(X_test) - np.min(X_test))
print('')
print('---Before and after Normalisation Sample---')
image_index = 2
plt.subplot(2,2,1)
plt.imshow(X_train_org[image_index])
plt.show()
plt.subplot(2,2,2)
plt.imshow(X_train[image_index])
plt.show()



### Step 4 Segmenting data into training, test, and validation
X_train, X_validation, y_train, y_validation = train_test_split(X_train, y_tra
in, test_size=0.2, random_state=42)
y_validation_OneHot = OHE_Encode(y_validation,n_classes)
OHE_Validate(y_validation_OneHot,y_validation)



print('')
print('---Data shape---')
print('Validation data shape', X_validation.shape)
print('Training data shape', X_train.shape)
print('Testing data shape', X_test.shape)

print('')
print('---Label shape---')
print('Validation Label data shape', y_validation.shape)
print('Training Label data shape', y_train.shape)
print('Testing Label data shape', y_test.shape)
```

```
---Before and after Normalisation Sample---
```






```
One hot encoding Validated

---Data shape---
Validation data shape (7842, 32, 32, 3)
Training data shape (31367, 32, 32, 3)
Testing data shape (12630, 32, 32, 3)

---Label shape---
Validation Label data shape (7842,)
Training Label data shape (31367,)
Testing Label data shape (12630,)
```

Step 3: Define Network

3.1 Network parameters

In [11]:
```
n_filters = 32
kernel_size = (3, 3)
n_fc1 = 512
n_fc2 = 128
pool_size = 2 # i.e. (2,2)

dropout_conv = 0.9
dropout_fc = 0.9

weights_stddev = 0.1
weights_mean = 0.0
biases_mean = 0.0

padding = 'VALID'
if padding == 'SAME':
    conv_output_length = 6
elif padding == 'VALID':
    conv_output_length = 5
else:
    raiseException("Unknown padding.")
```

3.2 tf Graph input

In [12]:
```
x_unflattened = tf.placeholder("float", [None, image_shape[0],image_shape[1],i
mage_shape[2]])
x = x_unflattened

y_rawlabels = tf.placeholder("int32", [None])
y = tf.one_hot(y_rawlabels, depth=n_classes, on_value=1., off_value=0.,
axis=-1)
```

3.3 Model

In [13]:
```
def weight_variable(shape, weight_mean, weight_stddev):
    return tf.Variable(tf.truncated_normal(shape, stddev=weight_stddev, mean=w
eight_mean))

def bias_variable(shape, bias_mean):
    return tf.Variable(tf.constant(bias_mean, shape=shape))

def conv2d(x, W, b, strides=3):
    x = tf.nn.conv2d(x, W, strides=[1, strides, strides, 1], padding='SAME')
    x = tf.nn.bias_add(x, b)
    return tf.nn.relu(x)

def maxpool2d(x, k=2, padding_setting='SAME'):
    return tf.nn.max_pool(x, ksize=[1, k, k, 1], strides=[1, k, k, 1],
padding=padding_setting)

def plot_metric_per_epoch(accuracies):
    x_epochs = []
    y_epochs = []
    for i, val in enumerate(accuracies):
        x_epochs.append(i)
        y_epochs.append(val)

    plt.figure(figsize=(15,8))
    plt.xlabel('epoch')
    plt.ylabel('score')
    plt.title('Score per epoch')
    #plt.legend()
    plt.grid()
    plt.scatter(x_epochs, y_epochs,s=50,c='lightgreen', marker='s', label='sco
re')
    plt.show()
```

In [14]:
```
weights = {
    'conv1': weight_variable([kernel_size[0], kernel_size[1], n_channels, n_fi
lters], weights_mean, weights_stddev),
    'fc1': weight_variable([n_filters * conv_output_length**2, n_fc1], weights
_mean, weights_stddev),
    'fc2': weight_variable([n_fc1, n_fc2], weights_mean, weights_stddev),
    'out': weight_variable([n_fc2, n_classes], weights_mean, weights_stddev)
}

biases = {
    'conv1': bias_variable([n_filters], biases_mean),
    'fc1': bias_variable([n_fc1], biases_mean),
    'fc2': bias_variable([n_fc2], biases_mean),
    'out': bias_variable([n_classes], biases_mean)
}
```

In [15]:
```
def conv_net(model_x, model_weights, model_biases, model_pool_size,
             model_dropout_conv, model_dropout_fc, padding='SAME'):

    # Convolution Layer 1
    conv1 = conv2d(model_x, model_weights['conv1'], model_biases['conv1'])

    # Max Pooling (down-sampling)
    conv1 = maxpool2d(conv1, k=model_pool_size, padding_setting=padding)
    conv1 = tf.nn.dropout(conv1, model_dropout_conv)

    # Reshape conv1 output to fit fully connected layer input
    conv1_shape = conv1.get_shape().as_list()
    fc1 = tf.reshape(conv1, [-1,
conv1_shape[1]*conv1_shape[2]*conv1_shape[3]])

    # Fully connected layer 1
    fc1 = tf.add(tf.matmul(fc1, model_weights['fc1']), model_biases['fc1'])
    fc1 = tf.nn.elu(fc1)
    fc1 = tf.nn.dropout(fc1, model_dropout_fc)

    # Fully connected layer 2
    fc2 = tf.add(tf.matmul(fc1, model_weights['fc2']), model_biases['fc2'])
    fc2 = tf.nn.elu(fc2)
    fc2 = tf.nn.dropout(fc2, model_dropout_fc)

    # Output layer
    output = tf.add(tf.matmul(fc2, model_weights['out']), model_biases['out'])

    return output
```

Step 4: Train Model

4.1 Training Parameters

In [16]:
```
#Learning Rate
#It represents the step that is taken in a gradient decent algorithm to find a
n optimal solution.
#If steps is too big, algorithm can go from peak to peak, and skip lows altoge
ther.
#if steps is too small, algorithm will take lot of time to converge.
#To train a model, it is often recommended to lower the learning rate as the t
raining progresses.
#We will use exponential_decay function to do so.
#It requires 'initial learning rate' and 'global_step' value to compute the de
cayed learning rate.
learning_rate = 0.001
initial_learning_rate = learning_rate
annealing_rate = 1

#epochs number
#this represents the number of times that we will run our main "for" loop. thi
s is the loop that we will run to provide
#data to our algorithms for training and testing.
#this is not number of batches
training_epochs = 150

#Batch Size
#Deep learning algorithms are iterative in the sense that they load samples in
 batches to avoid running out of memory.
#number of batch (bin) = number of training samples / batch size.
batch_size = 100

display_step = 1
anneal_mod_frequency = 15
print_accuracy_mod_frequency = 1
```

4.2 Model/Loss/Optimizer

In [17]:
```
# Construct model
pred = conv_net(x, weights, biases, pool_size, dropout_conv, dropout_fc, paddi
ng=padding)
pred_probs = tf.nn.softmax(pred)

# Define loss and optimizer
cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(pred, y))
optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(cost)
```

4.3 Train

In [18]:
```
# Function to initialise the variables
init = tf.global_variables_initializer()

# Launch the graph
sess = tf.Session()
```

```
# Initialise variables
sess.run(init)

# Initialise time logs
init_time = time.time()
epoch_time = init_time

five_epoch_moving_average = 0.
epoch_accuracies = []
print_accuracy_mod_frequency = 1
total_batch = int(len(X_train) / batch_size)

# Training cycle
for epoch in range(training_epochs):
    if five_epoch_moving_average > 0.96:
        break

    for i in range(total_batch):
        batch_x, batch_y = np.array(X_train[i * batch_size:(i + 1) * batch_siz
e]), \
                           np.array(y_train[i * batch_size:(i + 1) * batch_siz
e])
        _, epoch_cost = sess.run([optimizer, cost], feed_dict={x_unflattened:
batch_x, y_rawlabels: batch_y})

    # Display logs per epoch step
    if epoch % display_step == 0:
        last_epoch_time = epoch_time
        epoch_time = time.time()
        print("Epoch:", '%04d' % (epoch + 1), "cost:","{:.9f}".format(epoch_co
st), "Time since last epoch: ", epoch_time - last_epoch_time)

    # Anneal learning rate
    if (epoch + 1) % anneal_mod_frequency == 0:
        learning_rate *= annealing_rate
        print("New learning rate: ", learning_rate)

    if (epoch + 1) % print_accuracy_mod_frequency == 0:
        correct_prediction = tf.equal(tf.argmax(pred, 1), tf.argmax(y, 1))
        accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
        # Line below needed only when not using `with tf.Session() as sess`
        with sess.as_default():
            epoch_accuracy = accuracy.eval({x_unflattened: X_validation, y_raw
labels: y_validation})
            epoch_accuracies.append(epoch_accuracy)

            ji = (len(epoch_accuracies), 5)[len(epoch_accuracies)>4]
            five_epoch_moving_average = np.sum(epoch_accuracies[epoch+1-ji:epo
ch+1])/ji
            print("epoch Accuracy (validation) = " + str(epoch_accuracy) + ",
 five_epoch_moving_average = " + "{:.6f}".format(five_epoch_moving_average))


print("Optimization Finished!")
plot_metric_per_epoch(epoch_accuracies)
```

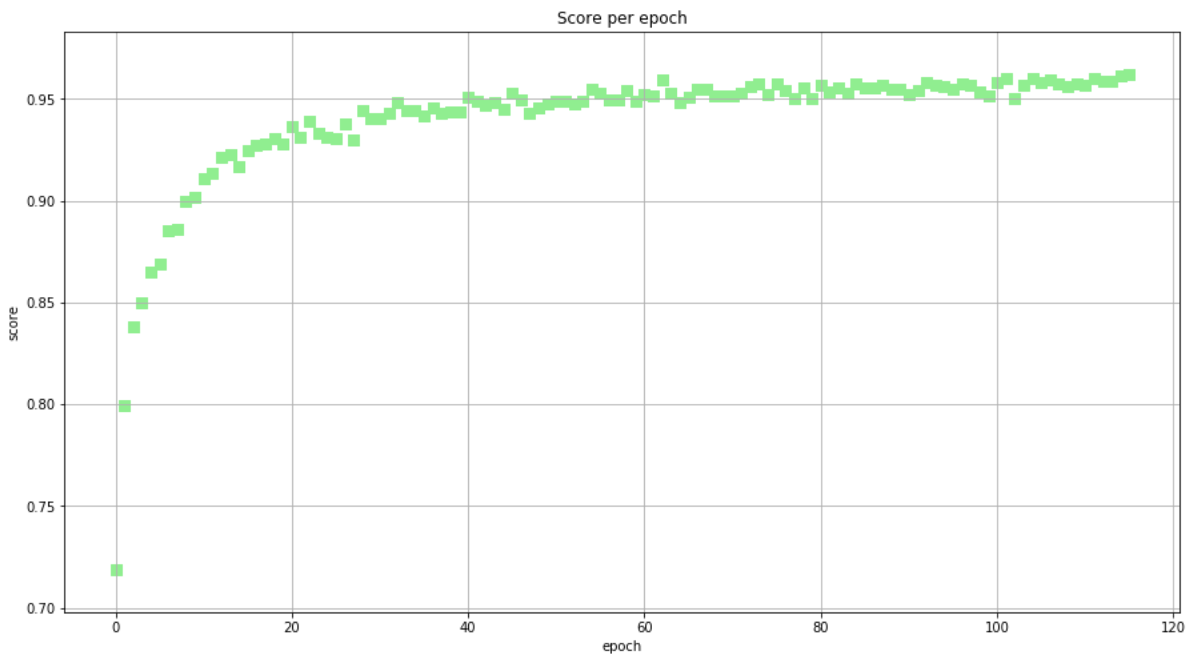
```
Epoch: 0001 cost: 0.835354030 Time since last epoch:  5.350874185562134
epoch Accuracy (validation) = 0.719077, five_epoch_moving_average = 0.719077
Epoch: 0002 cost: 0.600972295 Time since last epoch:  5.97432804107666
epoch Accuracy (validation) = 0.799413, five_epoch_moving_average = 0.759245
Epoch: 0003 cost: 0.408585429 Time since last epoch:  5.97832989692688
epoch Accuracy (validation) = 0.838307, five_epoch_moving_average = 0.785599
Epoch: 0004 cost: 0.394816637 Time since last epoch:  5.910281181335449
epoch Accuracy (validation) = 0.849911, five_epoch_moving_average = 0.801677
Epoch: 0005 cost: 0.222693145 Time since last epoch:  5.989338397979736
epoch Accuracy (validation) = 0.865085, five_epoch_moving_average = 0.814359
Epoch: 0006 cost: 0.241149440 Time since last epoch:  5.948308706283569
epoch Accuracy (validation) = 0.868783, five_epoch_moving_average = 0.844300
Epoch: 0007 cost: 0.158790365 Time since last epoch:  5.961318254470825
epoch Accuracy (validation) = 0.885106, five_epoch_moving_average = 0.861438
Epoch: 0008 cost: 0.151555955 Time since last epoch:  5.985335350036621
epoch Accuracy (validation) = 0.885871, five_epoch_moving_average = 0.870951
Epoch: 0009 cost: 0.166201204 Time since last epoch:  5.971325397491455
epoch Accuracy (validation) = 0.900025, five_epoch_moving_average = 0.880974
Epoch: 0010 cost: 0.159873873 Time since last epoch:  5.992340803146362
epoch Accuracy (validation) = 0.901556, five_epoch_moving_average = 0.888268
Epoch: 0011 cost: 0.203673854 Time since last epoch:  5.974327325820923
epoch Accuracy (validation) = 0.910865, five_epoch_moving_average = 0.896685
Epoch: 0012 cost: 0.091472618 Time since last epoch:  5.9483091831207275
epoch Accuracy (validation) = 0.913797, five_epoch_moving_average = 0.902423
Epoch: 0013 cost: 0.156288356 Time since last epoch:  5.9663214683532715
epoch Accuracy (validation) = 0.921194, five_epoch_moving_average = 0.909487
Epoch: 0014 cost: 0.122915223 Time since last epoch:  5.96732234954834
epoch Accuracy (validation) = 0.922724, five_epoch_moving_average = 0.914027
Epoch: 0015 cost: 0.100420021 Time since last epoch:  6.0033485889434814
New learning rate:  0.001
epoch Accuracy (validation) = 0.91673, five_epoch_moving_average = 0.917062
Epoch: 0016 cost: 0.110888556 Time since last epoch:  6.00434947013855
epoch Accuracy (validation) = 0.924637, five_epoch_moving_average = 0.919816
Epoch: 0017 cost: 0.066086076 Time since last epoch:  6.013355731964111
epoch Accuracy (validation) = 0.927442, five_epoch_moving_average = 0.922545
Epoch: 0018 cost: 0.085709855 Time since last epoch:  5.984334707260132
epoch Accuracy (validation) = 0.927825, five_epoch_moving_average = 0.923871
Epoch: 0019 cost: 0.131604791 Time since last epoch:  6.001347064971924
epoch Accuracy (validation) = 0.930885, five_epoch_moving_average = 0.925504
Epoch: 0020 cost: 0.109586865 Time since last epoch:  6.029367208480835
epoch Accuracy (validation) = 0.927697, five_epoch_moving_average = 0.927697
Epoch: 0021 cost: 0.079925150 Time since last epoch:  6.027366399765015
epoch Accuracy (validation) = 0.936241, five_epoch_moving_average = 0.930018
Epoch: 0022 cost: 0.084870398 Time since last epoch:  5.894269943237305
epoch Accuracy (validation) = 0.931523, five_epoch_moving_average = 0.930834
Epoch: 0023 cost: 0.086388804 Time since last epoch:  5.9673216342926025
epoch Accuracy (validation) = 0.938791, five_epoch_moving_average = 0.933027
Epoch: 0024 cost: 0.079331897 Time since last epoch:  5.944306135177612
epoch Accuracy (validation) = 0.933053, five_epoch_moving_average = 0.933461
Epoch: 0025 cost: 0.095811225 Time since last epoch:  5.960317134857178
epoch Accuracy (validation) = 0.931013, five_epoch_moving_average = 0.934124
Epoch: 0026 cost: 0.038326349 Time since last epoch:  5.953312635421753
epoch Accuracy (validation) = 0.930502, five_epoch_moving_average = 0.932976
Epoch: 0027 cost: 0.063909359 Time since last epoch:  5.984334945678711
epoch Accuracy (validation) = 0.937899, five_epoch_moving_average = 0.934251
Epoch: 0028 cost: 0.060087390 Time since last epoch:  5.980331897735596
epoch Accuracy (validation) = 0.930247, five_epoch_moving_average = 0.932543
```

```
Epoch: 0029 cost: 0.068583719 Time since last epoch:  6.011354207992554
epoch Accuracy (validation) = 0.944147, five_epoch_moving_average = 0.934762
Epoch: 0030 cost: 0.043039475 Time since last epoch:  6.050382852554321
New learning rate:  0.001
epoch Accuracy (validation) = 0.940194, five_epoch_moving_average = 0.936598
Epoch: 0031 cost: 0.121078894 Time since last epoch:  6.043377637863159
epoch Accuracy (validation) = 0.940576, five_epoch_moving_average = 0.938613
Epoch: 0032 cost: 0.044603173 Time since last epoch:  6.070396900177002
epoch Accuracy (validation) = 0.943254, five_epoch_moving_average = 0.939684
Epoch: 0033 cost: 0.012664272 Time since last epoch:  6.062391519546509
epoch Accuracy (validation) = 0.947972, five_epoch_moving_average = 0.943229
Epoch: 0034 cost: 0.058574189 Time since last epoch:  6.096415758132935
epoch Accuracy (validation) = 0.944402, five_epoch_moving_average = 0.943280
Epoch: 0035 cost: 0.041081220 Time since last epoch:  6.079403877258301
epoch Accuracy (validation) = 0.944274, five_epoch_moving_average = 0.944096
Epoch: 0036 cost: 0.016299020 Time since last epoch:  6.0313684940338135
epoch Accuracy (validation) = 0.941724, five_epoch_moving_average = 0.944325
Epoch: 0037 cost: 0.050895378 Time since last epoch:  6.139447450637817
epoch Accuracy (validation) = 0.94555, five_epoch_moving_average = 0.944785
Epoch: 0038 cost: 0.070183635 Time since last epoch:  6.054385662078857
epoch Accuracy (validation) = 0.942999, five_epoch_moving_average = 0.943790
Epoch: 0039 cost: 0.187935829 Time since last epoch:  6.092412948608398
epoch Accuracy (validation) = 0.943892, five_epoch_moving_average = 0.943688
Epoch: 0040 cost: 0.056463469 Time since last epoch:  6.081405162811279
epoch Accuracy (validation) = 0.943764, five_epoch_moving_average = 0.943586
Epoch: 0041 cost: 0.026422201 Time since last epoch:  6.097416639328003
epoch Accuracy (validation) = 0.95065, five_epoch_moving_average = 0.945371
Epoch: 0042 cost: 0.024405001 Time since last epoch:  6.1334428787231445
epoch Accuracy (validation) = 0.948738, five_epoch_moving_average = 0.946009
Epoch: 0043 cost: 0.037014674 Time since last epoch:  6.145451545715332
epoch Accuracy (validation) = 0.94708, five_epoch_moving_average = 0.946825
Epoch: 0044 cost: 0.049144726 Time since last epoch:  6.135444164276123
epoch Accuracy (validation) = 0.948227, five_epoch_moving_average = 0.947692
Epoch: 0045 cost: 0.013649072 Time since last epoch:  6.130427837371826
New learning rate:  0.001
epoch Accuracy (validation) = 0.94504, five_epoch_moving_average = 0.947947
Epoch: 0046 cost: 0.039474308 Time since last epoch:  6.152416944503784
epoch Accuracy (validation) = 0.953073, five_epoch_moving_average = 0.948431
Epoch: 0047 cost: 0.004283312 Time since last epoch:  6.117392063140869
epoch Accuracy (validation) = 0.949503, five_epoch_moving_average = 0.948585
Epoch: 0048 cost: 0.053008489 Time since last epoch:  6.190444469451904
epoch Accuracy (validation) = 0.943254, five_epoch_moving_average = 0.947819
Epoch: 0049 cost: 0.013232770 Time since last epoch:  6.1774351596832275
epoch Accuracy (validation) = 0.945805, five_epoch_moving_average = 0.947335
Epoch: 0050 cost: 0.014396756 Time since last epoch:  6.202452898025513
epoch Accuracy (validation) = 0.947717, five_epoch_moving_average = 0.947870
Epoch: 0051 cost: 0.019178521 Time since last epoch:  6.192445993423462
epoch Accuracy (validation) = 0.948993, five_epoch_moving_average = 0.947054
Epoch: 0052 cost: 0.070833355 Time since last epoch:  6.177434921264648
epoch Accuracy (validation) = 0.949248, five_epoch_moving_average = 0.947003
Epoch: 0053 cost: 0.005360267 Time since last epoch:  6.196448802947998
epoch Accuracy (validation) = 0.947845, five_epoch_moving_average = 0.947921
Epoch: 0054 cost: 0.016064167 Time since last epoch:  6.2395102977752686
epoch Accuracy (validation) = 0.949248, five_epoch_moving_average = 0.948610
Epoch: 0055 cost: 0.003761522 Time since last epoch:  6.292487144470215
epoch Accuracy (validation) = 0.954731, five_epoch_moving_average = 0.950013
Epoch: 0056 cost: 0.007220398 Time since last epoch:  6.268500328063965
```

```
epoch Accuracy (validation) = 0.953073, five_epoch_moving_average = 0.950829
Epoch: 0057 cost: 0.072295405 Time since last epoch:  6.269501209259033
epoch Accuracy (validation) = 0.949885, five_epoch_moving_average = 0.950956
Epoch: 0058 cost: 0.004718235 Time since last epoch:  6.334547996520996
epoch Accuracy (validation) = 0.94963, five_epoch_moving_average = 0.951313
Epoch: 0059 cost: 0.110409088 Time since last epoch:  6.3015241622924805
epoch Accuracy (validation) = 0.954221, five_epoch_moving_average = 0.952308
Epoch: 0060 cost: 0.083273195 Time since last epoch:  6.325541257858276
New learning rate:  0.001
epoch Accuracy (validation) = 0.948865, five_epoch_moving_average = 0.951135
Epoch: 0061 cost: 0.020478291 Time since last epoch:  6.246484756469727
epoch Accuracy (validation) = 0.952181, five_epoch_moving_average = 0.950956
Epoch: 0062 cost: 0.007613658 Time since last epoch:  6.289515018463135
epoch Accuracy (validation) = 0.95167, five_epoch_moving_average = 0.951313
Epoch: 0063 cost: 0.055680636 Time since last epoch:  6.239480018615723
epoch Accuracy (validation) = 0.959194, five_epoch_moving_average = 0.953226
Epoch: 0064 cost: 0.005754110 Time since last epoch:  6.282510280609131
epoch Accuracy (validation) = 0.953201, five_epoch_moving_average = 0.953022
Epoch: 0065 cost: 0.007944511 Time since last epoch:  6.277507305145264
epoch Accuracy (validation) = 0.9481, five_epoch_moving_average = 0.952869
Epoch: 0066 cost: 0.013578608 Time since last epoch:  6.311530828475952
epoch Accuracy (validation) = 0.951033, five_epoch_moving_average = 0.952640
Epoch: 0067 cost: 0.003912454 Time since last epoch:  6.265498876571655
epoch Accuracy (validation) = 0.955113, five_epoch_moving_average = 0.953328
Epoch: 0068 cost: 0.024532700 Time since last epoch:  6.3325464725494385
epoch Accuracy (validation) = 0.954731, five_epoch_moving_average = 0.952436
Epoch: 0069 cost: 0.023792870 Time since last epoch:  6.356595993041992
epoch Accuracy (validation) = 0.95167, five_epoch_moving_average = 0.952130
Epoch: 0070 cost: 0.003479885 Time since last epoch:  6.378546953201294
epoch Accuracy (validation) = 0.951415, five_epoch_moving_average = 0.952793
Epoch: 0071 cost: 0.016517812 Time since last epoch:  6.3875861167907715
epoch Accuracy (validation) = 0.951288, five_epoch_moving_average = 0.952844
Epoch: 0072 cost: 0.039033893 Time since last epoch:  6.411603212356567
epoch Accuracy (validation) = 0.952818, five_epoch_moving_average = 0.952385
Epoch: 0073 cost: 0.010777423 Time since last epoch:  6.352560758590698
epoch Accuracy (validation) = 0.956006, five_epoch_moving_average = 0.952640
Epoch: 0074 cost: 0.093356892 Time since last epoch:  6.407600402832031
epoch Accuracy (validation) = 0.957664, five_epoch_moving_average = 0.953838
Epoch: 0075 cost: 0.064308852 Time since last epoch:  6.376578092575073
New learning rate:  0.001
epoch Accuracy (validation) = 0.952053, five_epoch_moving_average = 0.953966
Epoch: 0076 cost: 0.073636942 Time since last epoch:  6.464641094207764
epoch Accuracy (validation) = 0.957281, five_epoch_moving_average = 0.955164
Epoch: 0077 cost: 0.115127563 Time since last epoch:  6.392589569091797
epoch Accuracy (validation) = 0.954221, five_epoch_moving_average = 0.955445
Epoch: 0078 cost: 0.052979246 Time since last epoch:  6.474648475646973
epoch Accuracy (validation) = 0.95014, five_epoch_moving_average = 0.954272
Epoch: 0079 cost: 0.038093597 Time since last epoch:  6.385584115982056
epoch Accuracy (validation) = 0.955241, five_epoch_moving_average = 0.953787
Epoch: 0080 cost: 0.041793946 Time since last epoch:  6.468644618988037
epoch Accuracy (validation) = 0.950013, five_epoch_moving_average = 0.953379
Epoch: 0081 cost: 0.059610769 Time since last epoch:  6.468644142150879
epoch Accuracy (validation) = 0.957026, five_epoch_moving_average = 0.953328
Epoch: 0082 cost: 0.008477603 Time since last epoch:  6.473647832870483
epoch Accuracy (validation) = 0.953328, five_epoch_moving_average = 0.953150
Epoch: 0083 cost: 0.070866391 Time since last epoch:  6.517679214477539
epoch Accuracy (validation) = 0.955751, five_epoch_moving_average = 0.954272
```

```
Epoch: 0084 cost: 0.057302065 Time since last epoch:  6.459637403488159
epoch Accuracy (validation) = 0.952691, five_epoch_moving_average = 0.953762
Epoch: 0085 cost: 0.067126825 Time since last epoch:  6.455635070800781
epoch Accuracy (validation) = 0.957409, five_epoch_moving_average = 0.955241
Epoch: 0086 cost: 0.001766566 Time since last epoch:  6.489658832550049
epoch Accuracy (validation) = 0.955241, five_epoch_moving_average = 0.954884
Epoch: 0087 cost: 0.004638392 Time since last epoch:  6.534748554229736
epoch Accuracy (validation) = 0.955369, five_epoch_moving_average = 0.955292
Epoch: 0088 cost: 0.005679436 Time since last epoch:  6.519680738449097
epoch Accuracy (validation) = 0.956899, five_epoch_moving_average = 0.955522
Epoch: 0089 cost: 0.005729181 Time since last epoch:  6.533705472946167
epoch Accuracy (validation) = 0.954858, five_epoch_moving_average = 0.955955
Epoch: 0090 cost: 0.010331319 Time since last epoch:  6.542698621749878
New learning rate:  0.001
epoch Accuracy (validation) = 0.954858, five_epoch_moving_average = 0.955445
Epoch: 0091 cost: 0.007515794 Time since last epoch:  6.452662229537964
epoch Accuracy (validation) = 0.952181, five_epoch_moving_average = 0.954833
Epoch: 0092 cost: 0.005800207 Time since last epoch:  6.536692142486572
epoch Accuracy (validation) = 0.954348, five_epoch_moving_average = 0.954629
Epoch: 0093 cost: 0.062640086 Time since last epoch:  6.556677341461182
epoch Accuracy (validation) = 0.958174, five_epoch_moving_average = 0.954884
Epoch: 0094 cost: 0.034962095 Time since last epoch:  6.508673429489136
epoch Accuracy (validation) = 0.956899, five_epoch_moving_average = 0.955292
Epoch: 0095 cost: 0.003305486 Time since last epoch:  6.5687150955200195
epoch Accuracy (validation) = 0.956389, five_epoch_moving_average = 0.955598
Epoch: 0096 cost: 0.046248607 Time since last epoch:  6.661783933639526
epoch Accuracy (validation) = 0.954986, five_epoch_moving_average = 0.956159
Epoch: 0097 cost: 0.003345174 Time since last epoch:  6.62578821182251
epoch Accuracy (validation) = 0.957664, five_epoch_moving_average = 0.956822
Epoch: 0098 cost: 0.015654625 Time since last epoch:  6.5707175731658936
epoch Accuracy (validation) = 0.957026, five_epoch_moving_average = 0.956593
Epoch: 0099 cost: 0.016251313 Time since last epoch:  6.519681215286255
epoch Accuracy (validation) = 0.953838, five_epoch_moving_average = 0.955981
Epoch: 0100 cost: 0.051637076 Time since last epoch:  6.615718126296997
epoch Accuracy (validation) = 0.95167, five_epoch_moving_average = 0.955037
Epoch: 0101 cost: 0.016700024 Time since last epoch:  6.605775356292725
epoch Accuracy (validation) = 0.958174, five_epoch_moving_average = 0.955675
Epoch: 0102 cost: 0.024302680 Time since last epoch:  6.539692640304565
epoch Accuracy (validation) = 0.959959, five_epoch_moving_average = 0.956134
Epoch: 0103 cost: 0.007559350 Time since last epoch:  6.637734889984131
epoch Accuracy (validation) = 0.950268, five_epoch_moving_average = 0.954782
Epoch: 0104 cost: 0.006651680 Time since last epoch:  6.662298917770386
epoch Accuracy (validation) = 0.956516, five_epoch_moving_average = 0.955317
Epoch: 0105 cost: 0.016676918 Time since last epoch:  6.683793544769287
New learning rate:  0.001
epoch Accuracy (validation) = 0.960214, five_epoch_moving_average = 0.957026
Epoch: 0106 cost: 0.003506209 Time since last epoch:  6.6568920612335205
epoch Accuracy (validation) = 0.958301, five_epoch_moving_average = 0.957052
Epoch: 0107 cost: 0.011197917 Time since last epoch:  6.675769329071045
epoch Accuracy (validation) = 0.959194, five_epoch_moving_average = 0.956899
Epoch: 0108 cost: 0.007262496 Time since last epoch:  6.699810981750488
epoch Accuracy (validation) = 0.957664, five_epoch_moving_average = 0.958378
Epoch: 0109 cost: 0.008470118 Time since last epoch:  6.738868474960327
epoch Accuracy (validation) = 0.956006, five_epoch_moving_average = 0.958276
Epoch: 0110 cost: 0.002060802 Time since last epoch:  6.6337316036224365
epoch Accuracy (validation) = 0.957281, five_epoch_moving_average = 0.957689
Epoch: 0111 cost: 0.108816624 Time since last epoch:  6.636765241622925
```

```
epoch Accuracy (validation) = 0.956771, five_epoch_moving_average = 0.957383
Epoch: 0112 cost: 0.026132941 Time since last epoch:  6.74183988571167
epoch Accuracy (validation) = 0.959959, five_epoch_moving_average = 0.957536
Epoch: 0113 cost: 0.093736030 Time since last epoch:  6.73883843421936
epoch Accuracy (validation) = 0.958684, five_epoch_moving_average = 0.957740
Epoch: 0114 cost: 0.001585683 Time since last epoch:  6.722826719284058
epoch Accuracy (validation) = 0.958684, five_epoch_moving_average = 0.958276
Epoch: 0115 cost: 0.002818441 Time since last epoch:  6.809889078140259
epoch Accuracy (validation) = 0.961107, five_epoch_moving_average = 0.959041
Epoch: 0116 cost: 0.061915379 Time since last epoch:  6.718854188919067
epoch Accuracy (validation) = 0.961999, five_epoch_moving_average = 0.960087
Optimization Finished!
```



4.4 Test Model

In [19]:
```
# Test model
correct_prediction = tf.equal(tf.argmax(pred, 1), tf.argmax(y, 1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))

with sess.as_default():
    print("Accuracy (test):", accuracy.eval({x_unflattened: X_test, y_rawlabel
s: y_test}))

# Print parameters for reference
print("\nParameters:")
print("Learning rate (initial): ", initial_learning_rate)
print("Anneal learning rate every ", anneal_mod_frequency, " epochs by ", 1 -
annealing_rate)
print("Learning rate (final): ", learning_rate)
print("Training epochs: ", training_epochs)
print("Batch size: ", batch_size)
print("Dropout (conv): ", dropout_conv)
print("Dropout (fc): ", dropout_fc)
print("Padding: ", padding)
print("weights_mean: ", weights_mean)
print("weights_stddev: ", weights_stddev)
print("biases_mean: ", biases_mean)
```

```
Accuracy (test): 0.793508

Parameters:
Learning rate (initial):  0.001
Anneal learning rate every  15  epochs by  0
Learning rate (final):  0.001
Training epochs:  150
Batch size:  100
Dropout (conv):  0.9
Dropout (fc):  0.9
Padding:  VALID
weights_mean:  0.0
weights_stddev:  0.1
biases_mean:  0.0
```

Question 1

Describe how you preprocessed the data. Why did you choose that technique?

Answer:

See Section 2.1 for Preprocessing steps

1. As image was 32x32 no Padding done
2. avoid overfitting by features randomization
3. data normallized to avoid high variance and improve classifier performance
4. labels one hot encoded
5. Added Extra data for low frequency Sign classes

Question 2

Describe how you set up the training, validation and testing data for your model. ***Optional****: If you generated additional data, how did you generate the data? Why did you generate the data? What are the differences in the new dataset (with generated data) from the original dataset?*

Answer:

See Section 2.1 for Splitting Data

1. Training and test data were already separated (downloaded pickled files train.p and test.p).
2. shuffled the training data because they were arranged in ascending order by label. If I don't shuffle the training data, the first series of batches will all be the first type of sign followed by the second type and so on. This will distort the learning process.
3. I further split the training data into test and valdiation sets so the model wouldn't be cheating when we optimised it.
4. Improvement: Generate additional data. The number of examples in the training data for each class is uneven, so the model may be biased towards predicting an unknown sign belongs to a class where there is abundant training data since we are minimising the training loss.

Question 3

What does your final architecture look like? (Type of model, layers, sizes, connectivity, etc.) For reference on how to build a deep neural network using TensorFlow, see [Deep Neural Network in TensorFlow (https://classroom.udacity.com/nanodegrees/nd013/parts/fbf77062-5703-404e-b60c-95b78b2f3f9e/modules/6df7ae49-c61c-4bb2-a23e-6527e69209ec/lessons/b516a270-8600-4f93-a0a3-20dfeabe5da6/concepts/83a3a2a2-a9bd-4b7b-95b0-eb924ab14432)](https://classroom.udacity.com/nanodegrees/nd013/parts/fbf77062-5703-404e-b60c-95b78b2f3f9e/modules/6df7ae49-c61c-4bb2-a23e-6527e69209ec/lessons/b516a270-8600-4f93-a0a3-20dfeabe5da6/concepts/83a3a2a2-a9bd-4b7b-95b0-eb924ab14432) from the classroom.

Answer:

See 3.3 for Model / Network Defination

- 3-layer Convolutional Neural Network.
- It consists of one convolution layer (feature extraction) followed by two fully connected layers (ReLU activation) and a single fully connected linear classifier.

  1 : Convolution layer Input: (32, 32, 3)
  Output: (5, 5, 32) 'VALID' padding Filters: 32 Stride: 3 ReLU Activation 2D Max Pooling (down-sampling) layer Dropout: 0.9

  2 : Reshape Layer Input: (5, 5, 32) Output: 800

  3 : Fully connected layer
  Input: 800 Output: 512 ReLU Activation Dropout: 0.9

  4 : Fully connected layer
  Input: 512 Output: 128 ReLU Activation Dropout: 0.9

  5 : output layer
  Input: 128 Output: 43
- The network uses full colour information (all three channels) and normalised data.

Question 4

How did you train your model? (Type of optimizer, batch size, epochs, hyperparameters, etc.)

See Section 4.3

- Type of optimiser: AdamOptimizer
- Batch size: 100
- Training Epochs: 105(with ELU)
- Learning rate: 0.001

Network Parameters:

- Dropout (conv layer): 0.9
- Dropout (fully connected layers): 0.9
- Padding: VALID

tf.train.AdamOptimizer ref http://stats.stackexchange.com/questions/184448/difference-between-gradientdescentoptimizer-and-adamoptimizer-tensorflow (http://stats.stackexchange.com/questions/184448/difference-between-gradientdescentoptimizer-and-adamoptimizer-tensorflow)

•Main advantage of Adam over the simple tf.train.GradientDescentOptimizer: Uses moving averages of the parameters (momentum) -> enables Adam to use a larger effective step size, and the algorithm will converge to this step size without fine tuning. A simple tf.train.GradientDescentOptimizer would require more hyperparameter tuning before it would converge as quickly.

•Disadvantage: Adam requires more computation to be performed for each parameter in each training step (to maintain the moving averages and variance, and calculate the scaled gradient) and more state to be retained for each parameter (approximately tripling the size of the model to store the average and variance for each parameter).

Question 5

What approach did you take in coming up with a solution to this problem? It may have been a process of trial and error, 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 this is suitable for the current problem.

Answer:

1. First attempt: building a minimum viable model and debugging

- I wanted to get a working model first. I started with a basic multilayer perceptron which I adapted from `TensorFlow-Examples`. I trained it for 15 epochs, which had an accuracy of 6% on the training and test sets. I then trained a two-layer convolutional neural network for 15 epochs which had an accuracy of 5-6% on the training and test sets.
    - The accuracy was lower than I expected and the cost seemed high (of order 10^6 in the first epoch, 10^5 in the second and third and in the hundreds in the tenth epoch), so I adjusted parameters hoping to improve it before training for longer.
    - The cost reduced significantly (to single digits by the second epoch as opposed to order 10^5) after I added a small positive bias to the initial weights and biases. Strangely, the accuracy did not increase, but remained at 5-6%. The cost did not decrease significantly over the next 10 epochs either.
    - I went on Slack to see what results people were getting to get a feel for how wrong I was. I saw that people often trained their networks for hundreds of epochs so I thought it would be good to train my network for e.g. 100 epochs.
- I rewrote the multilayer perceptron in a Python Script and it worked fine, returning an accuracy of over 70% accuracy within 2 epochs.

2. Improvements to the model

- I then added a convolution layer before the two fully connected layers and the output layer.
- This new model produced a validation accuracy of above 90% after 15 epochs (parameters not tuned), which was higher than that for the two-layer feedforward network. So I chose this model with a convolution layer.

3. Tuning Parameters

- I altered the model code (replaced hard-coded numbers with variables) so I could tweak parameters easily.
- I tested models with different values or settings for
    - dropout for the fully connected layers,
    - dropout for the convolution layer,
    - padding (SAME vs VALID),
    - weight and bias initialisation
    - maxpool vs no max pool
- I used Keras to implement comparisons so I could get full figures on training and validation loss and accuracy easily.
- I stopped when the model reached a validation accuracy of over 95% within 100 epochs.
    - This figure is strange because my models implemented in Keras reach validation accuracy of over 99% within 15 epochs.

Step 3: Test a Model on New Images

Take several pictures of traffic signs that you find on the web or around you (at least five), and run them through your classifier on your computer to produce example results. The classifier might not recognize some local signs but it could prove interesting nonetheless.

You may find `signnames.csv` useful as it contains mappings from the class id (integer) to the actual sign name.

Implementation

Use the code cell (or multiple code cells, if necessary) to implement the first step of your project. Once you have completed your implementation and are satisfied with the results, be sure to thoroughly answer the questions that follow.

In [20]:
```
def read_image_and_print_dims(image_path):
    image = mpimg.imread(image_path)
    print('This image is:', type(image), 'with dimensions:', image.shape)
    plt.imshow(image)
    return image

def process_image_file(name):
    image = cv2.imread(name)
    image = cv2.resize(image,(32,32))
    image = cv2.cvtColor(image,cv2.COLOR_BGR2RGB)
    image = image/255.-.5
    return image

def plot_image_grid(n_row,n_col,X):
    plt.figure(figsize = (8,6))
    gs1 = gridspec.GridSpec(n_row,n_row)
    gs1.update(wspace=0.01, hspace=0.02) # set the spacing between axes.

    for i in range(n_row*n_col):
        # i = i + 1 # grid spec indexes from 0
        ax1 = plt.subplot(gs1[i])
        plt.axis('on')
        ax1.set_xticklabels([])
        ax1.set_yticklabels([])
        ax1.set_aspect('equal')
        #plt.subplot(4,11,i+1)
        ind_plot = i
        plt.imshow(X[ind_plot])
        plt.axis('off')
    plt.show()

def predict(img):
    classification = sess.run(tf.argmax(pred, 1), feed_dict={x_unflattened: [i
mg]})
    print('NN predicted', classification[0])
```

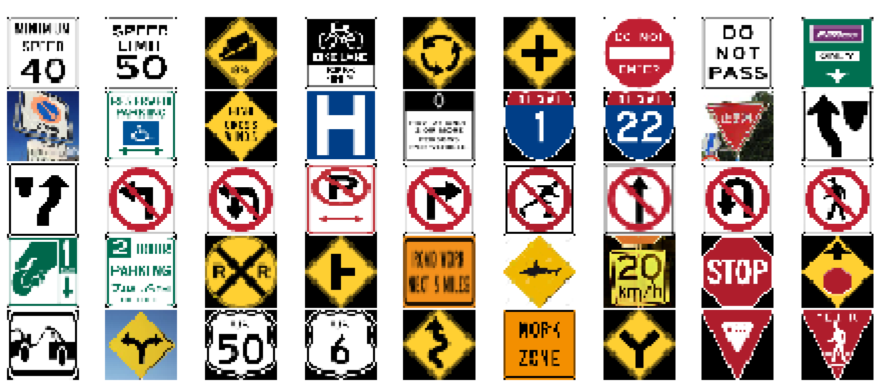
```
    plt.imshow(sign_dict[classification[0]])
    plt.show()

def top_5_predictions(img):
    #Return model's top five choices for what traffic sign this image is and i
ts confidence in its predictions.
    top_five_certainties = sess.run(tf.nn.top_k(tf.nn.softmax(pred), k=5), fee
d_dict={x_unflattened: [img]})
    print("Top five: ", top_five_certainties)
    plot_certainty_arrays(top_five_certainties[0][0], top_five_certainties[1]
[0])
    return top_five_certainties

def plot_certainty_arrays(probabilities, labels):
    # Plot model's probabilities (y) and traffic sign labels (x) in a bar char
t.
    y_pos = np.arange(len(labels))
    plt.bar(y_pos, probabilities, align='center', alpha=0.5)
    plt.xticks(y_pos, labels)
    plt.ylabel('Probability')
    plt.xlabel('Traffic sign')
    plt.title('Model\'s certainty of its predictions')
    plt.show()
    print("Traffic Sign Key")
    for label in labels:
        print(label, ": ", data_pd.loc[label]['SignName'])
```

Question 6

Choose five candidate images of traffic signs and provide them in the report. Are there any particular qualities of the image(s) that might make classification difficult? It could be helpful to plot the images in the notebook.

Answer:

In [21]:
```
newdata = [process_image_file("./new_signs/"+name) for name in os.listdir("./n
ew_signs/")]
namenewdata = [name for name in os.listdir("./new_signs/")]
newdata = np.array(newdata ,dtype = np.float32)
plot_image_grid(9,5,newdata+.5)
```



Question 7

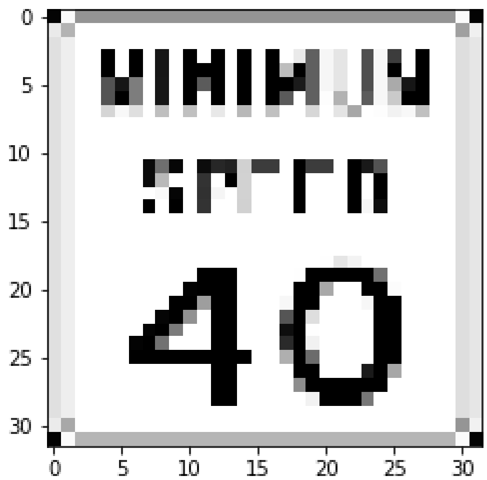
Is your model able to perform equally well on captured pictures when compared to testing on the dataset? The simplest way to do this check the accuracy of the predictions. For example, if the model predicted 1 out of 5 signs correctly, it's 20% accurate.

NOTE: *You could check the accuracy manually by using `signnames.csv` (same directory). This file has a mapping from the class id (0-42) to the corresponding sign name. So, you could take the class id the model outputs, lookup the name in `signnames.csv` and see if it matches the sign from the image.*

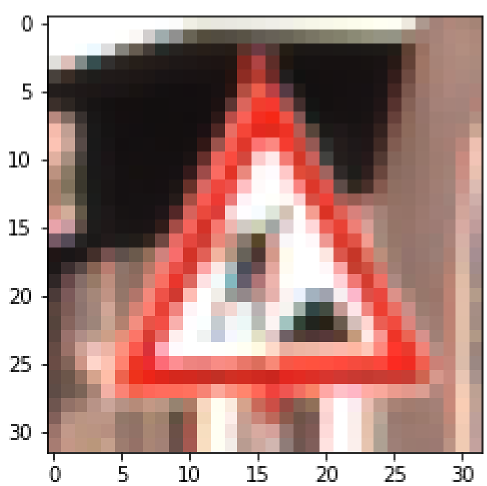
Answer:

In [22]:
```
for i in range(len(namenewdata)):
    print('\n\n\n\n')
    print(namenewdata[i])
    plt.imshow(newdata[i]+.5)
    plt.show()
    predict(newdata[i])
```

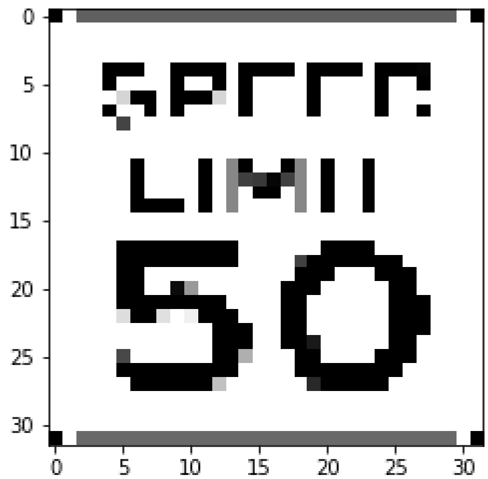
40mph.png



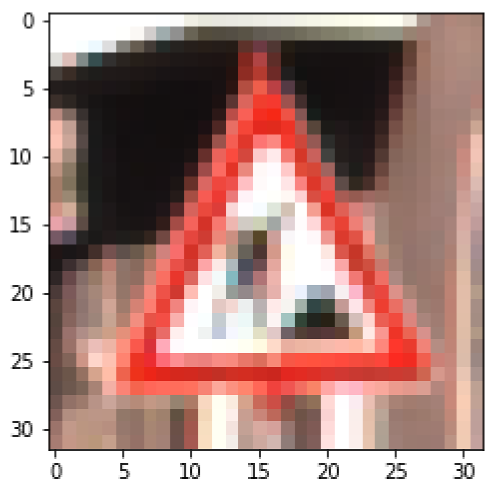
NN predicted 25



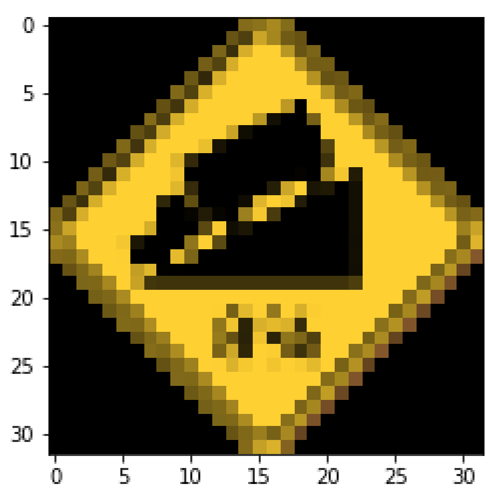
50mph.png



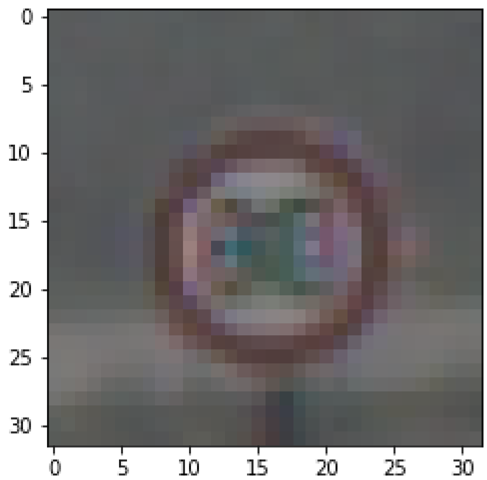
NN predicted 25



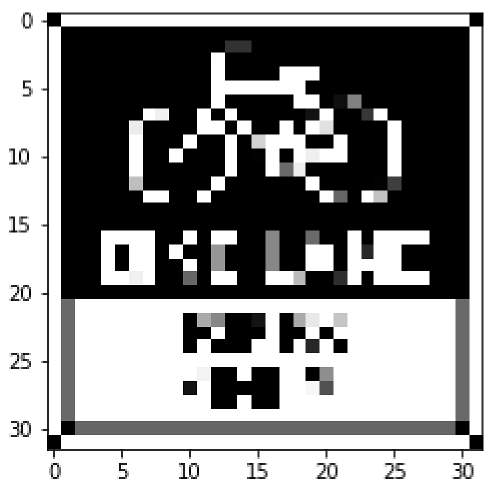
8pcGrade.png



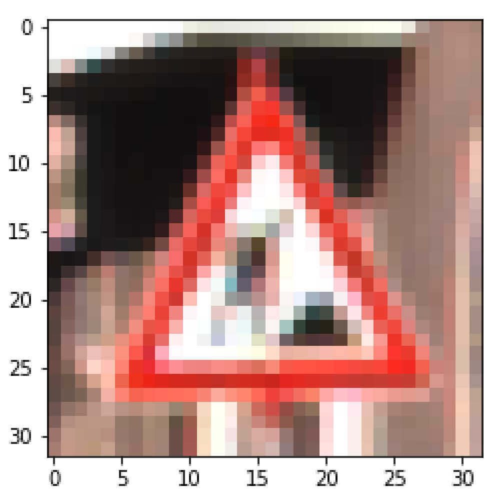
NN predicted 5



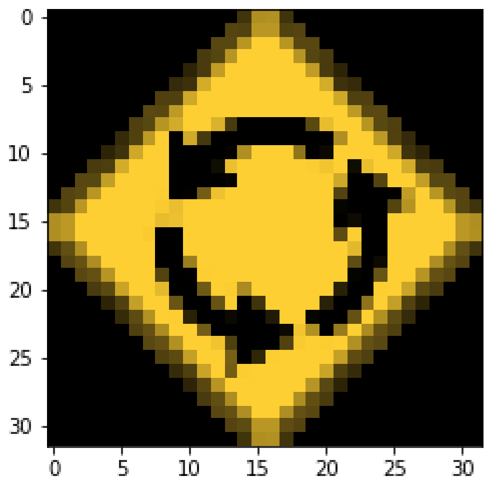
bikelane.png



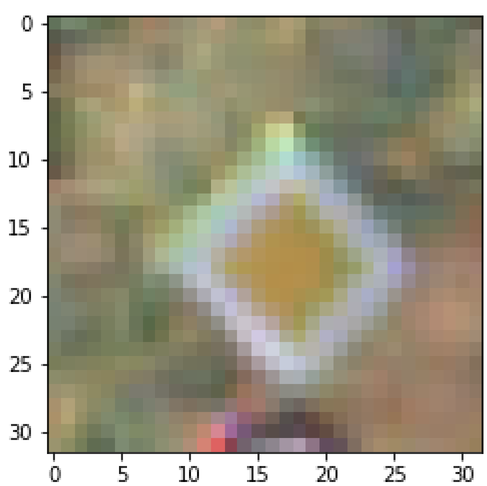
NN predicted 25



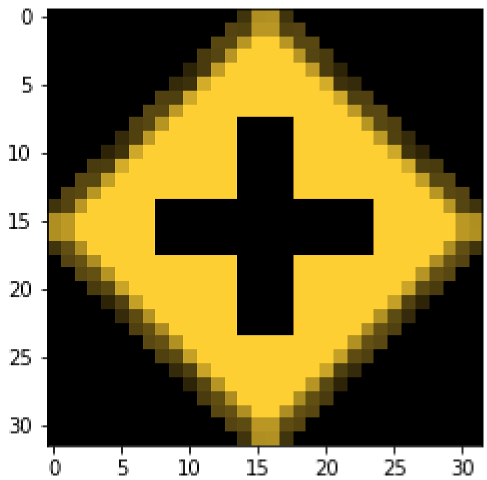
circle.png



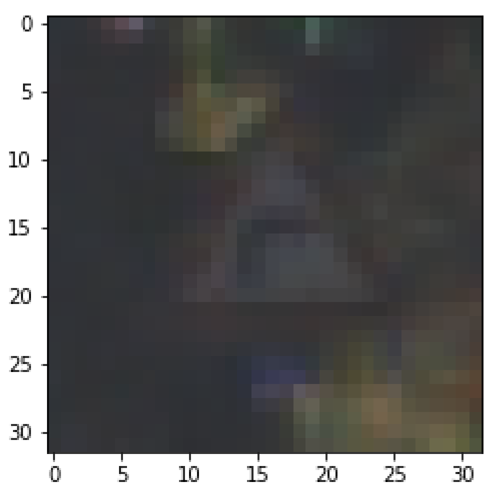
NN predicted 12



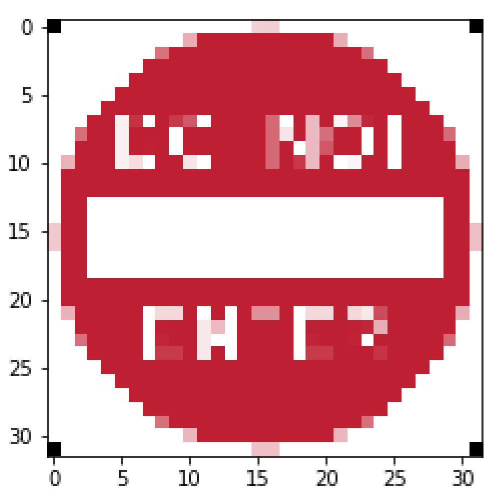
CrossRoad.png



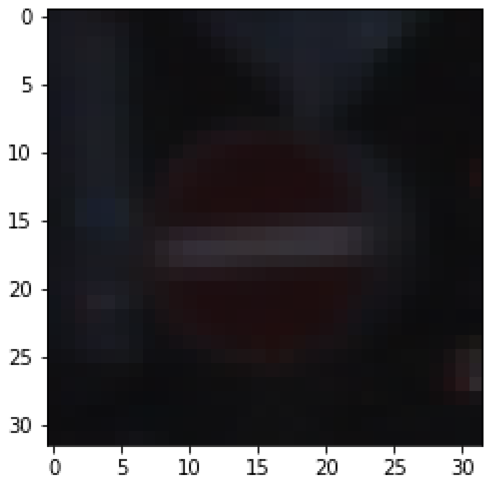
NN predicted 20



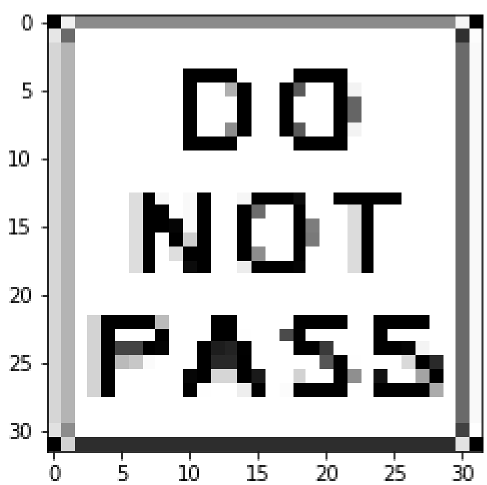
DonotEnter.png



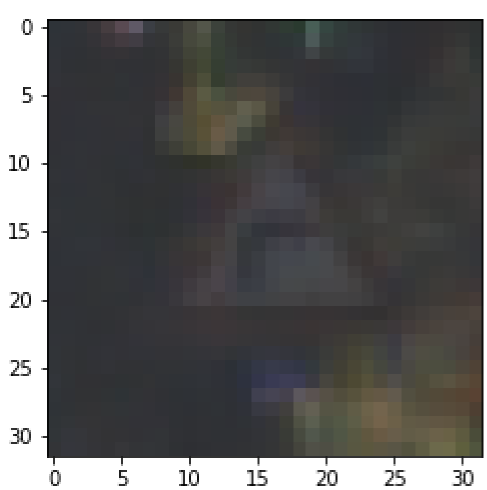
NN predicted 17



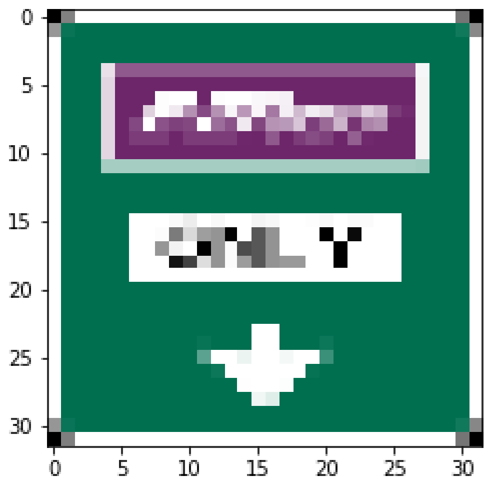
DoNotPass.png



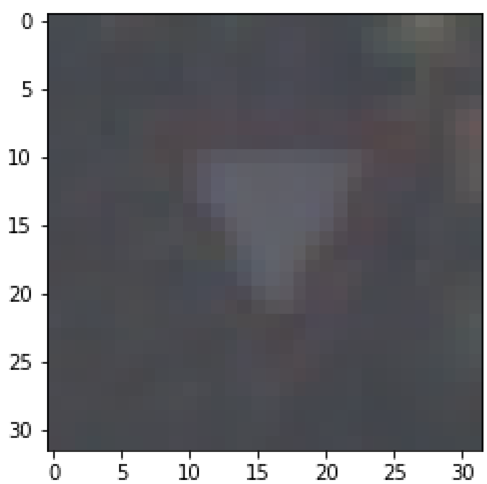
NN predicted 20



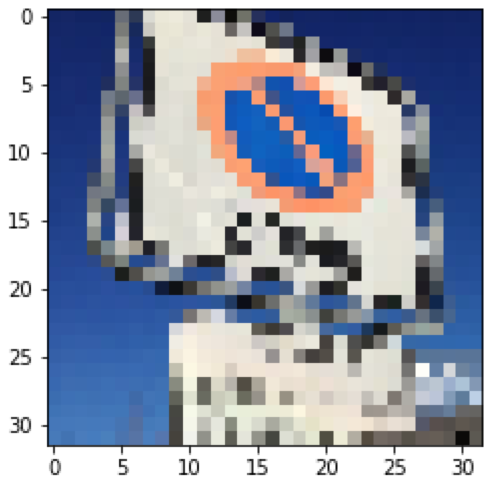
EZPass.png



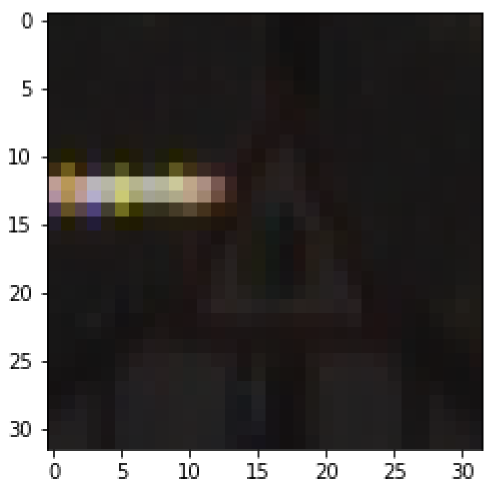
NN predicted 13



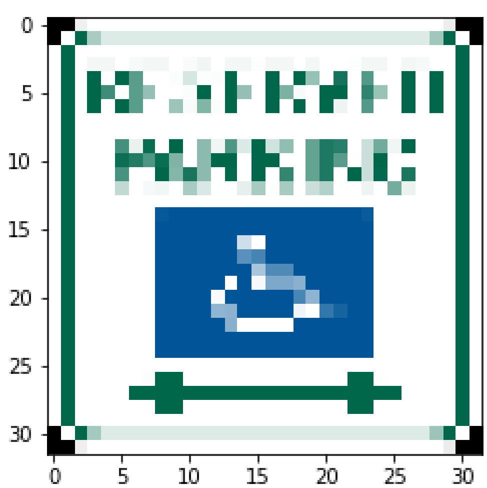
german_sign.png



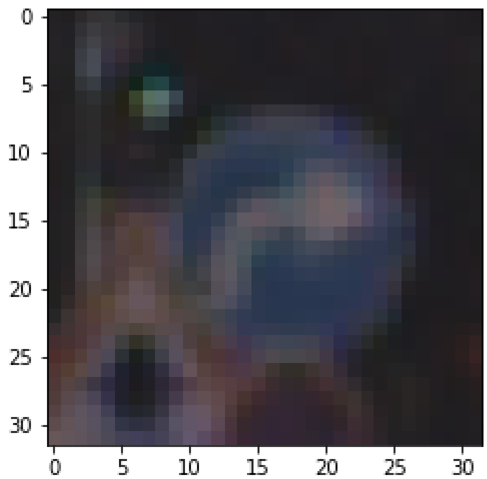
NN predicted 30



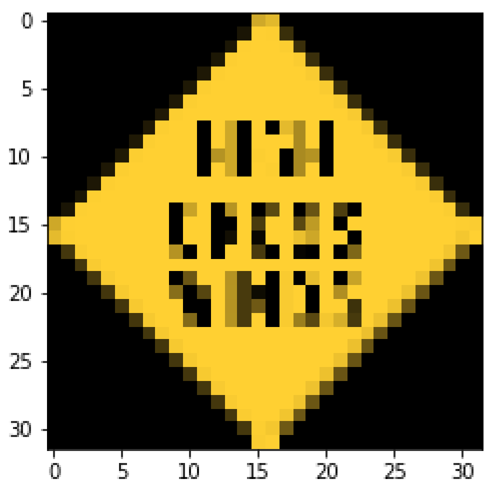
HCparking.png



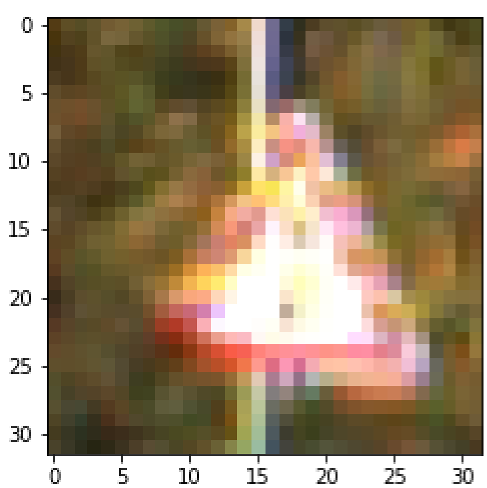
NN predicted 33



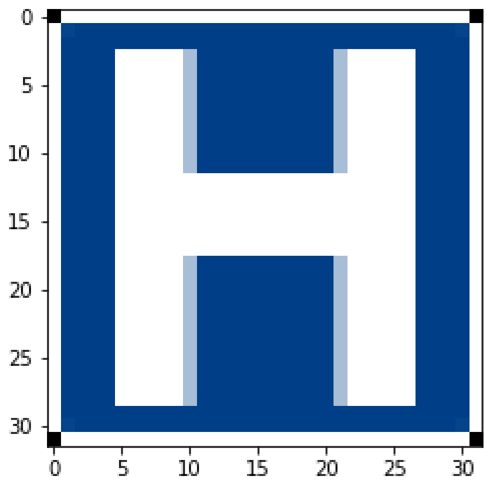
HighXWinds.png



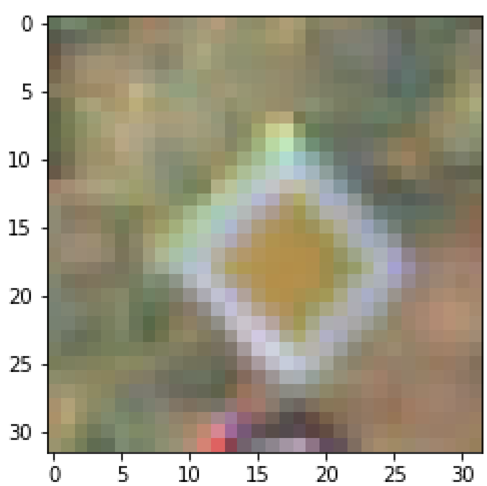
NN predicted 26



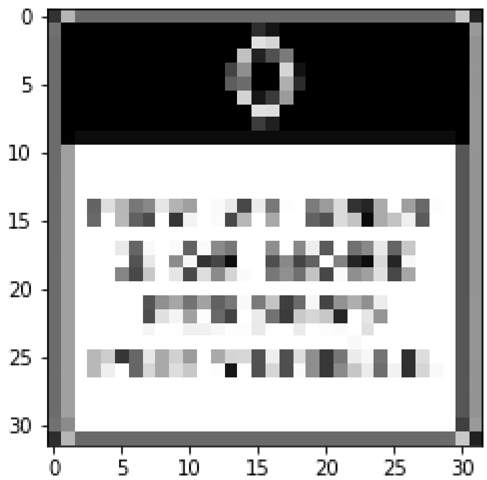
Hospital.png



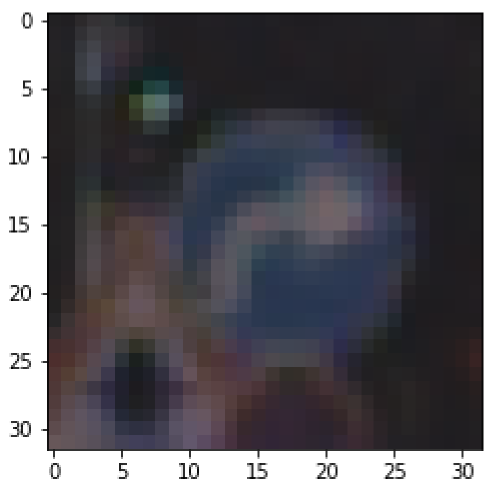
NN predicted 12



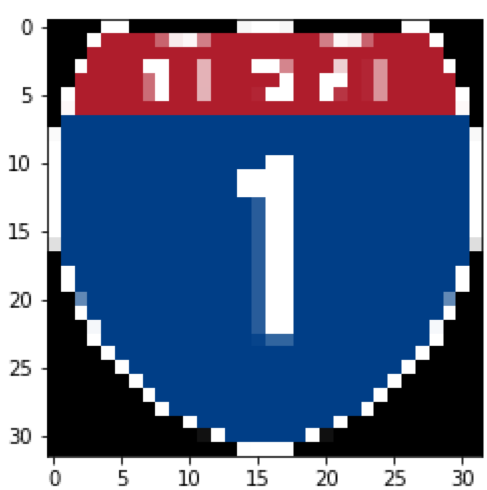
HOW.png



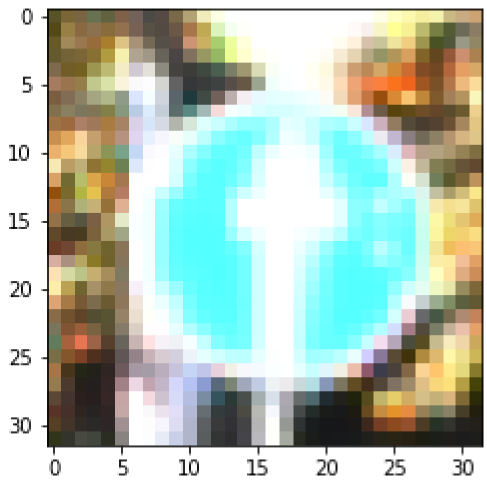
NN predicted 33



i1.png

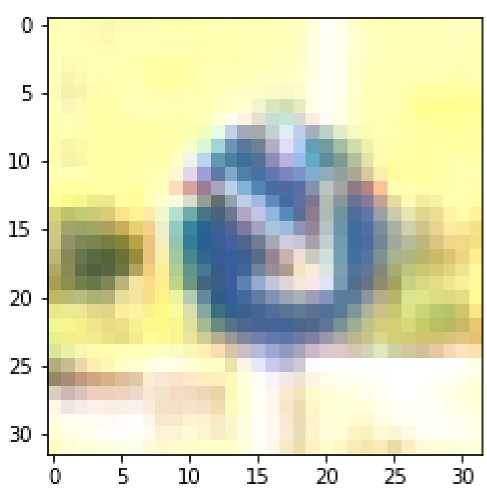


NN predicted 35

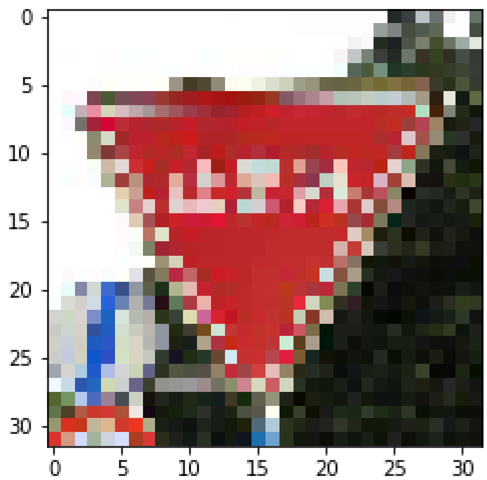


i22.png

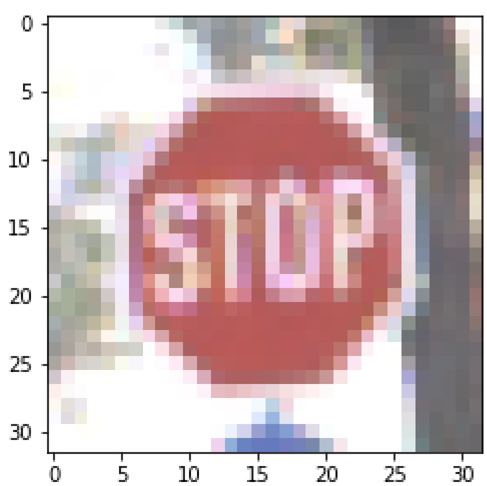
NN predicted 38



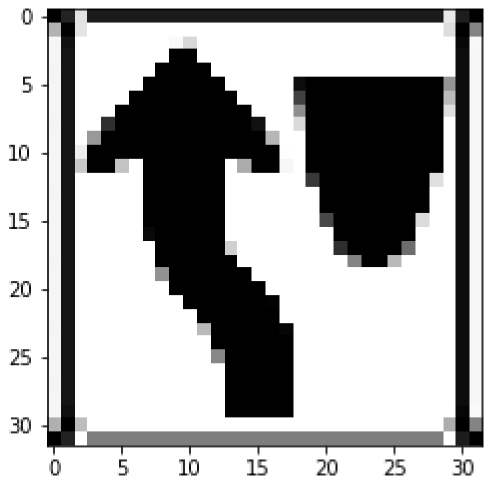
japanese_sign_resized.png



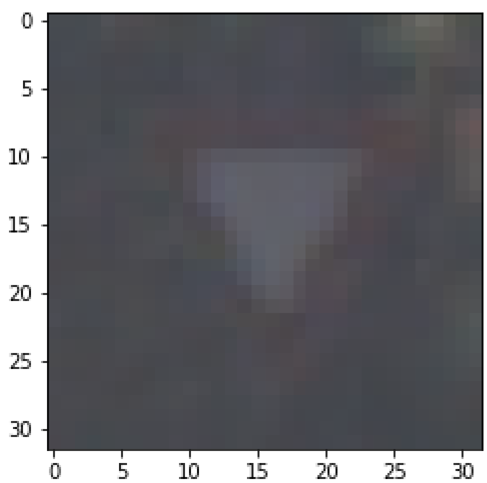
NN predicted 14



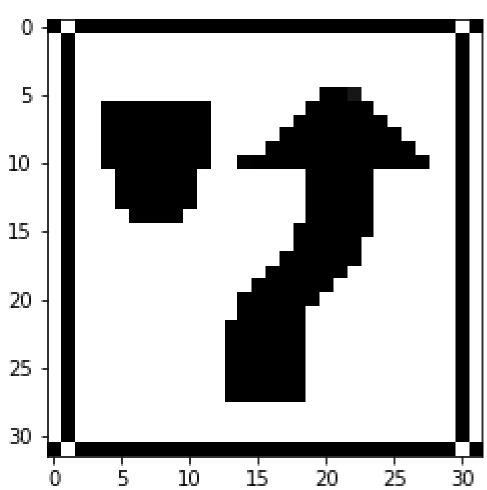
keepleft.png



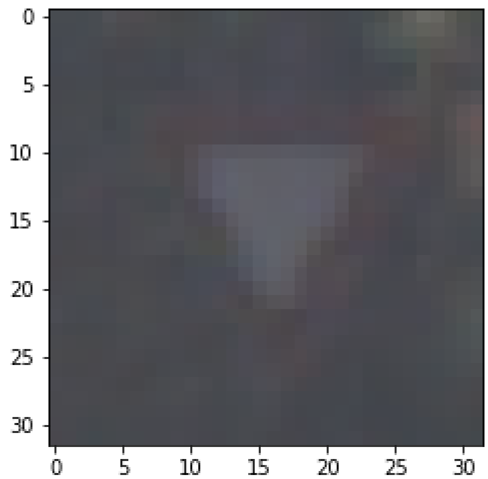
NN predicted 13



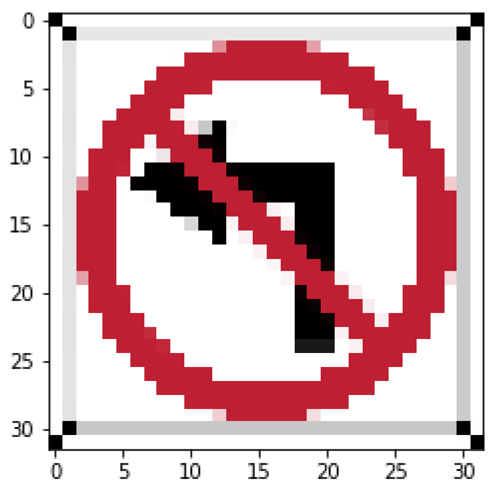
keepright.png



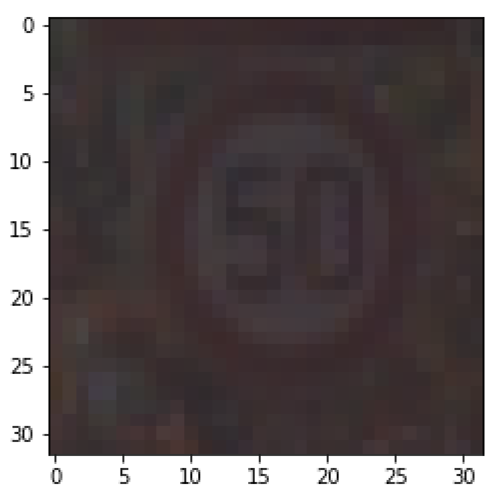
NN predicted 13



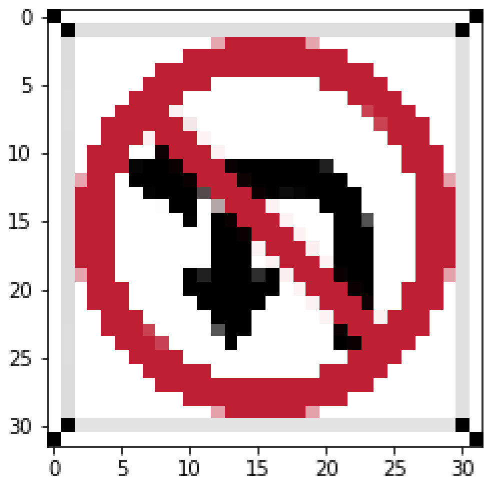
noleft.png



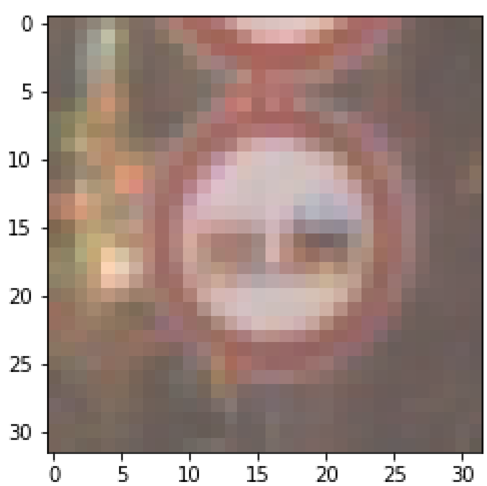
NN predicted 2



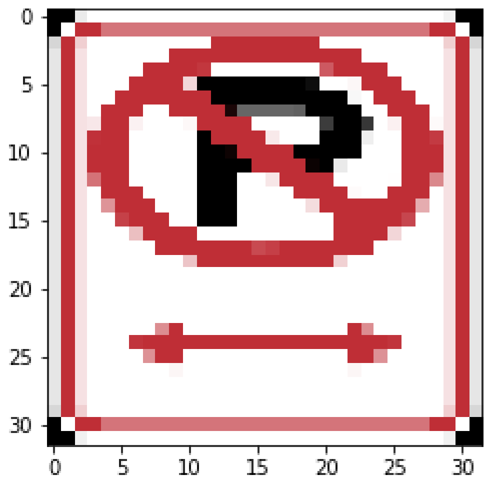
noleftUturn.png



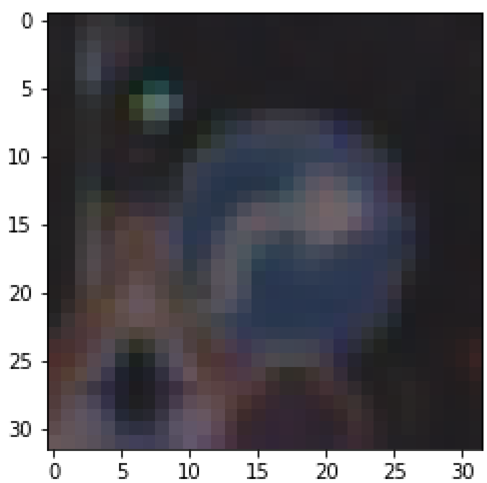
NN predicted 9



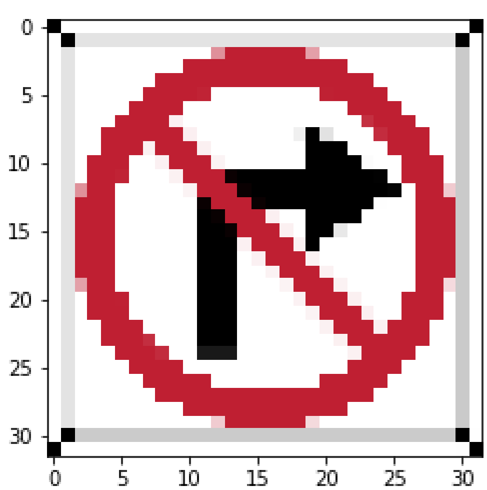
NoParking.png



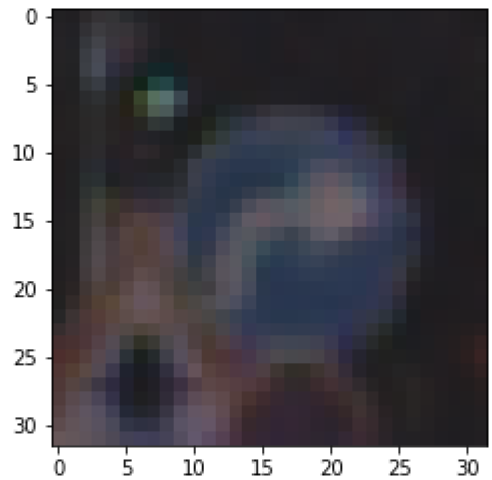
NN predicted 33



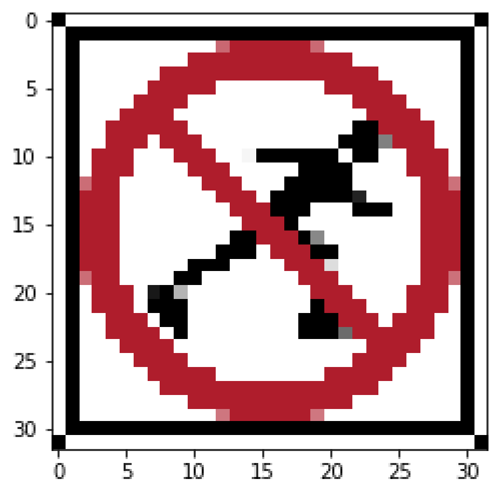
noright.png



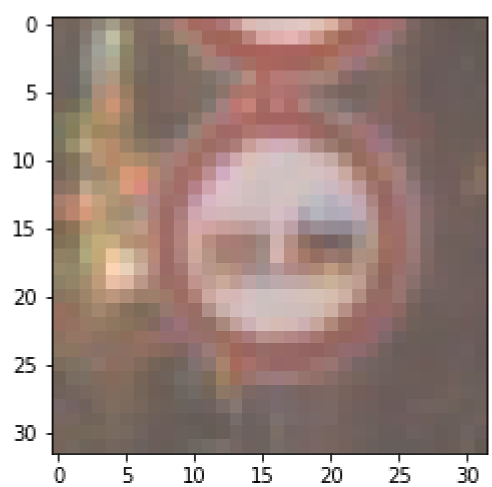
NN predicted 33



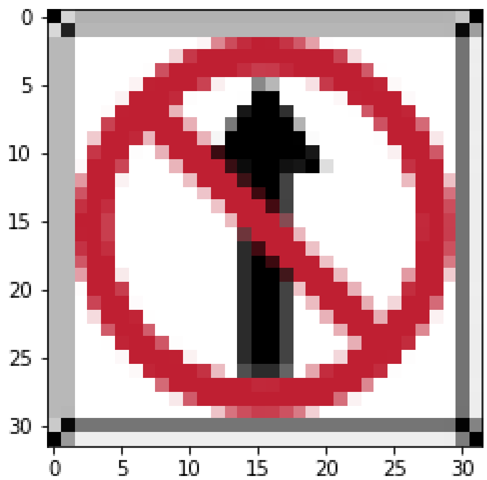
noRoller.png



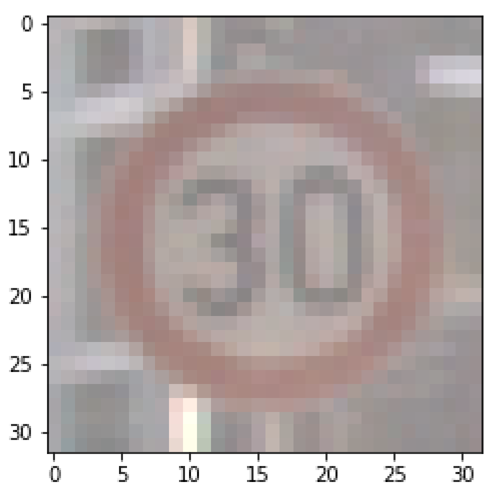
NN predicted 9



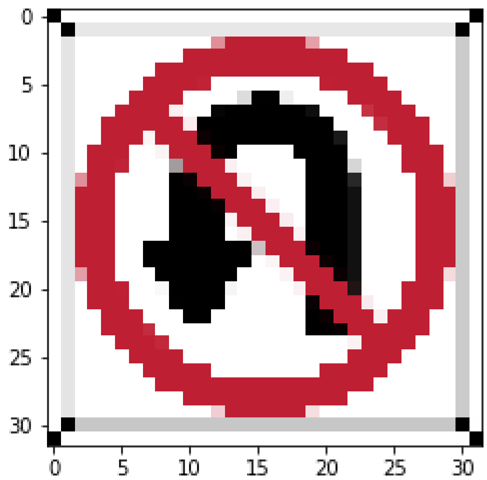
nostraight.png



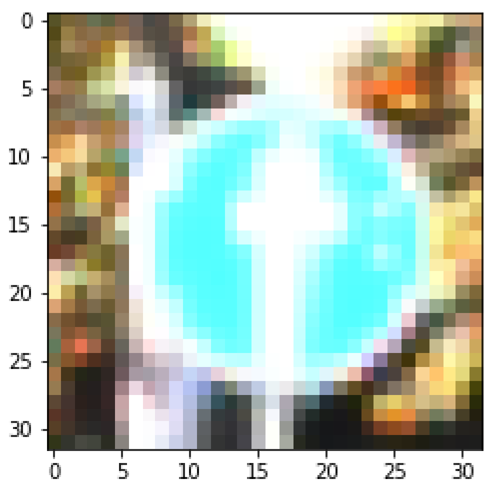
NN predicted 1



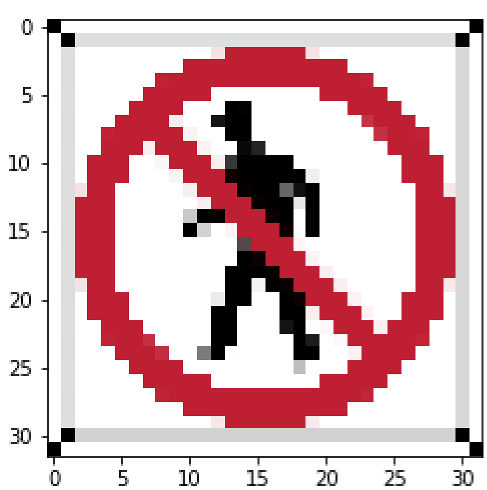
noUturn.png



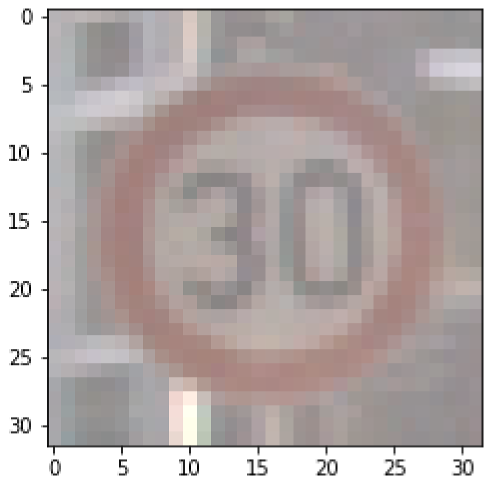
NN predicted 35



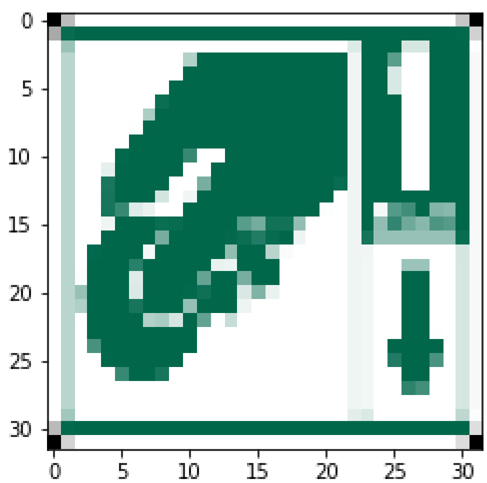
noWalking.png



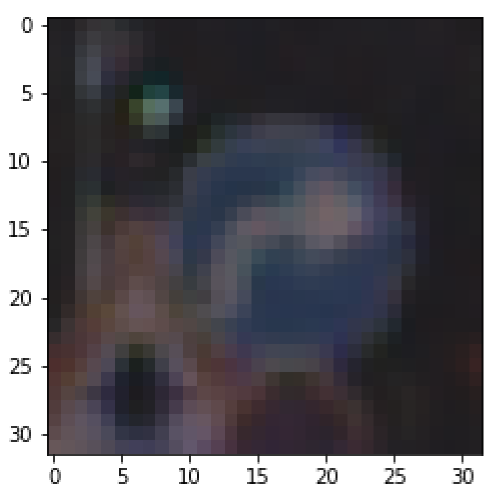
NN predicted 1



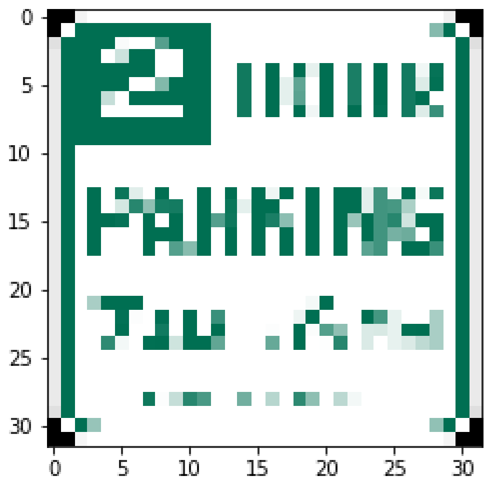
paidParking.png



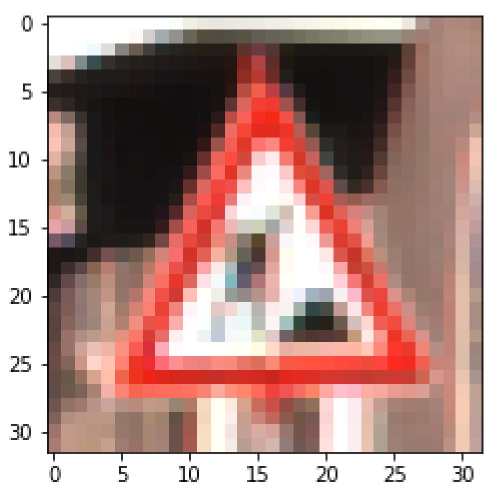
NN predicted 33



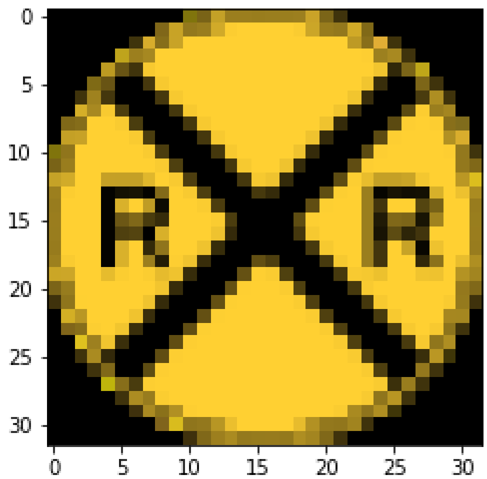
parking2hr.png



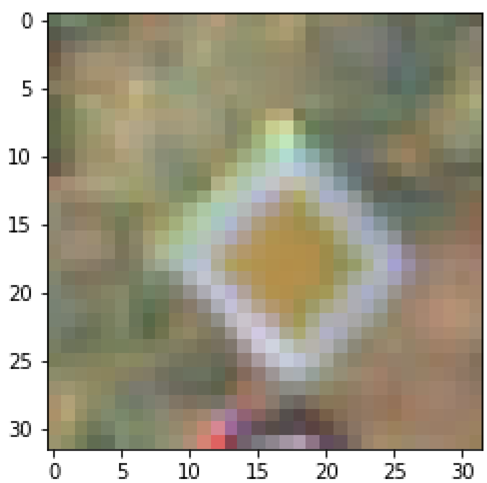
NN predicted 25



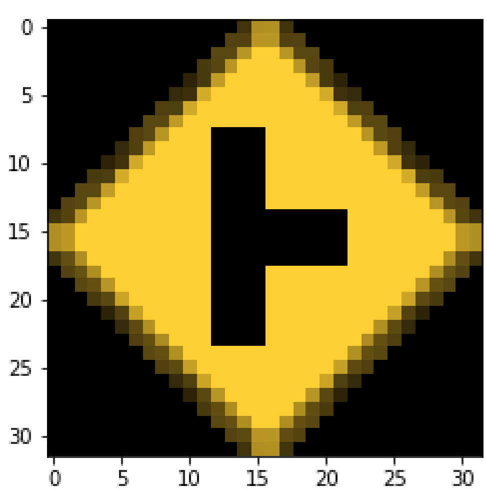
RailRoad.png



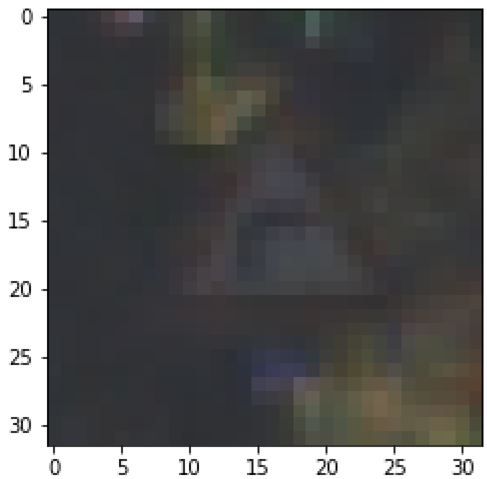
NN predicted 12



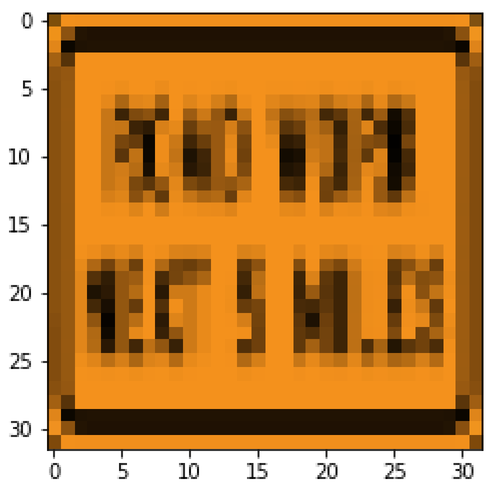
RightCrossing.png



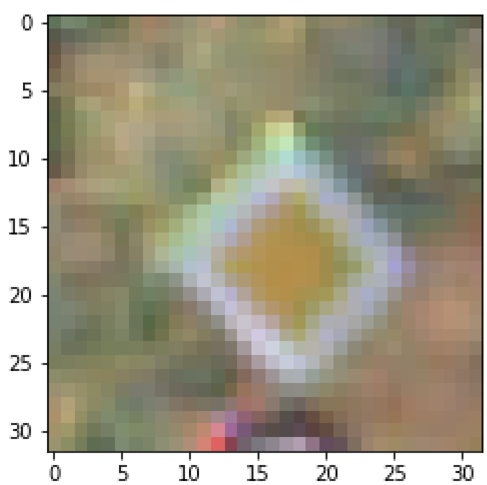
NN predicted 20



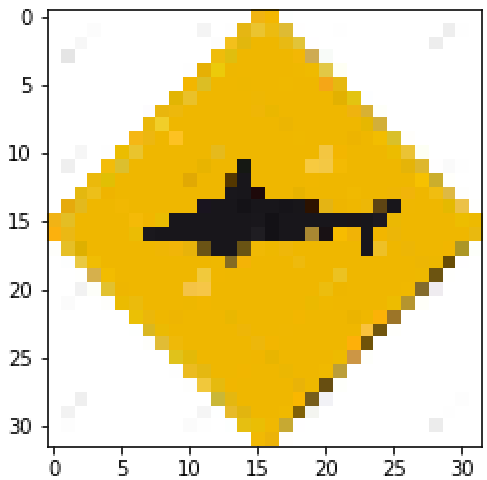
roadwork.png



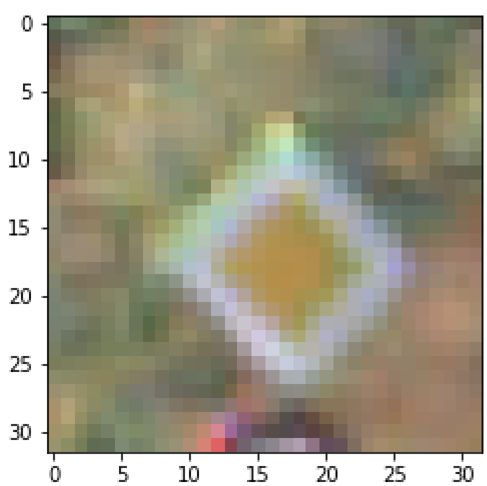
NN predicted 12



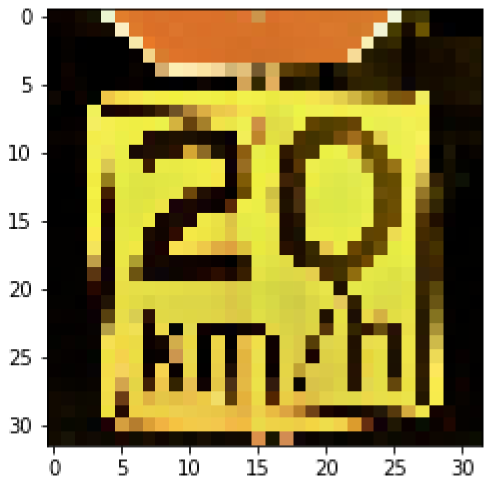
shark_sign.png



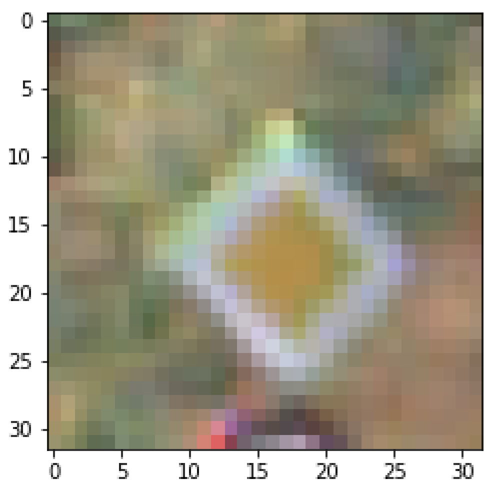
NN predicted 12



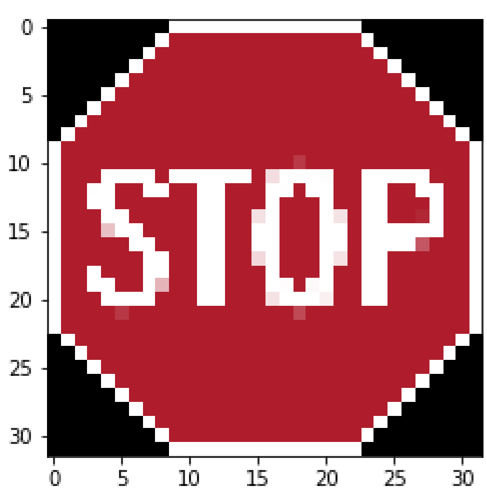
speed_limit_stop.png



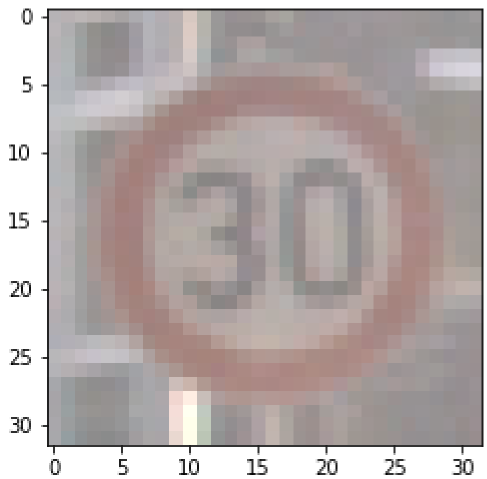
NN predicted 12



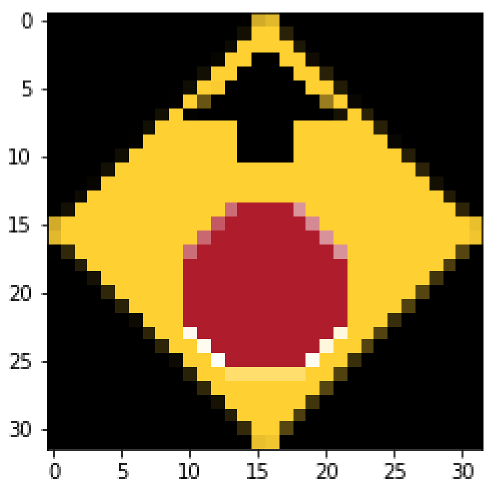
stop.png



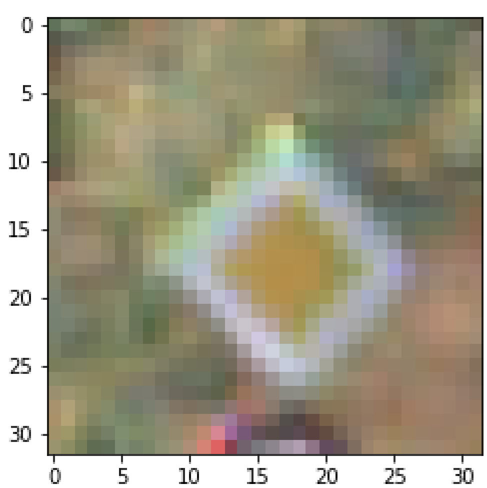
NN predicted 1



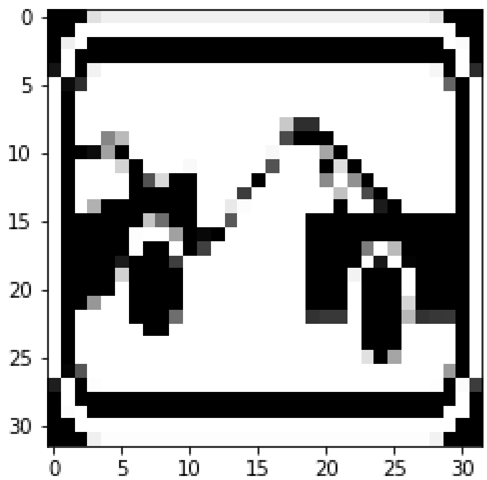
StopAhead.png



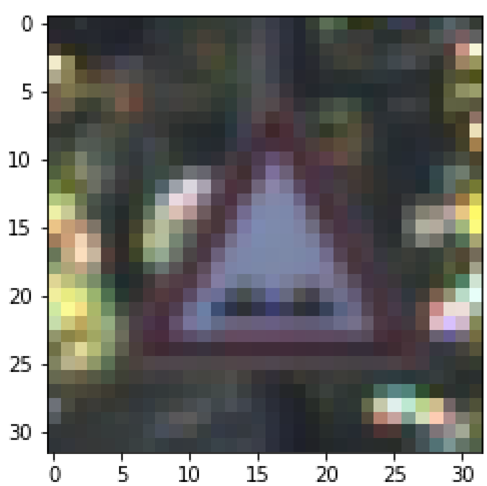
NN predicted 12



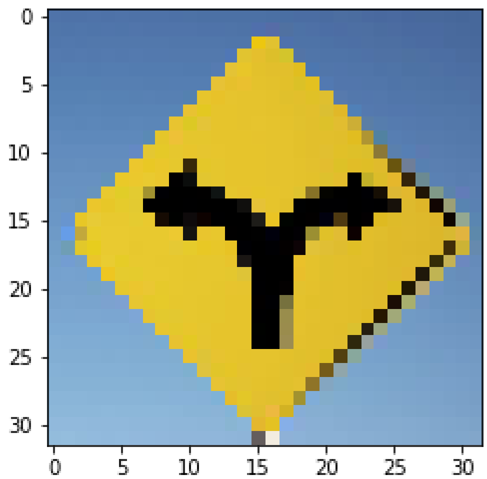
TowAway.png



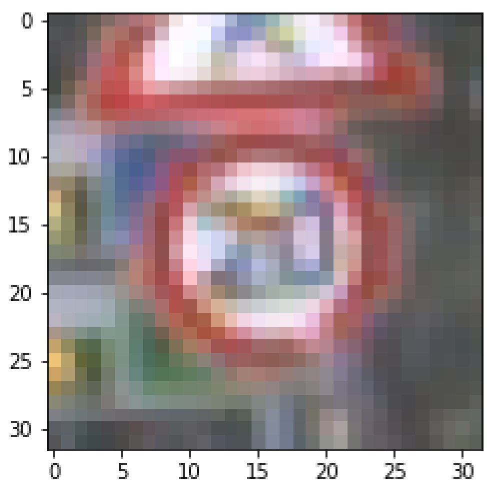
NN predicted 22



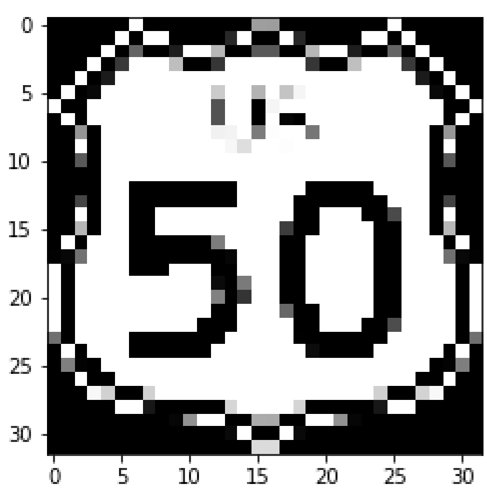
two_way_sign.png



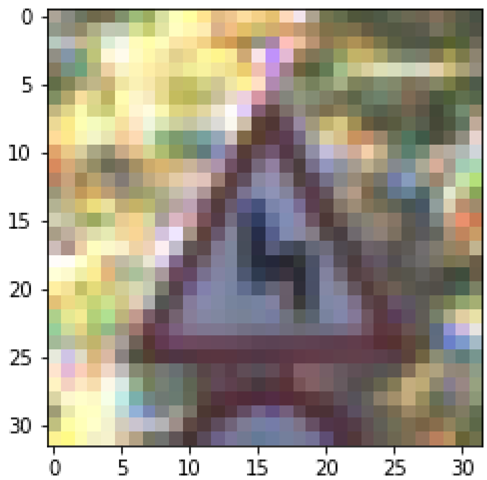
NN predicted 0



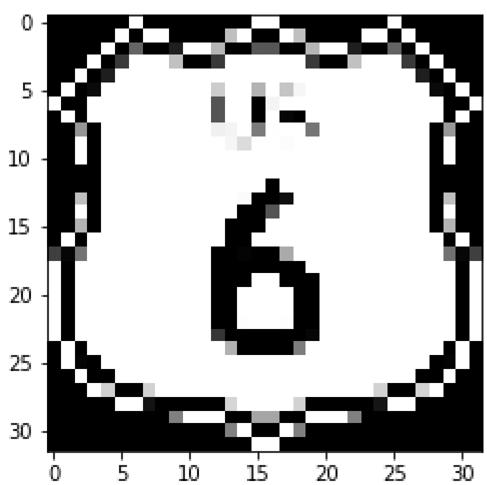
US50.png



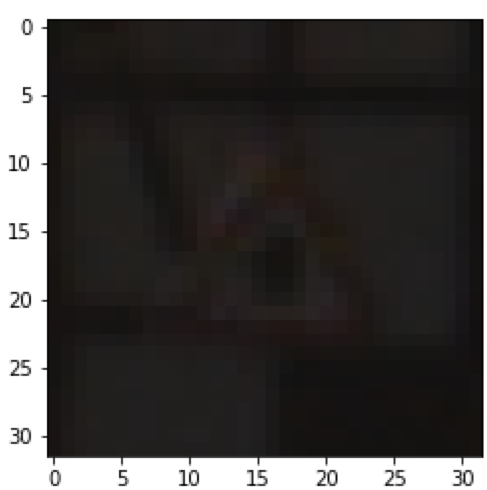
NN predicted 21



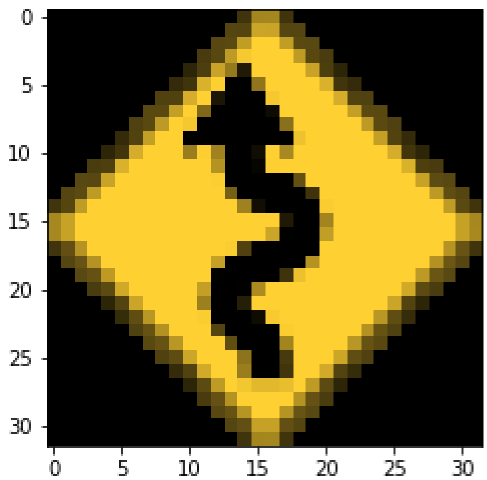
US6.png



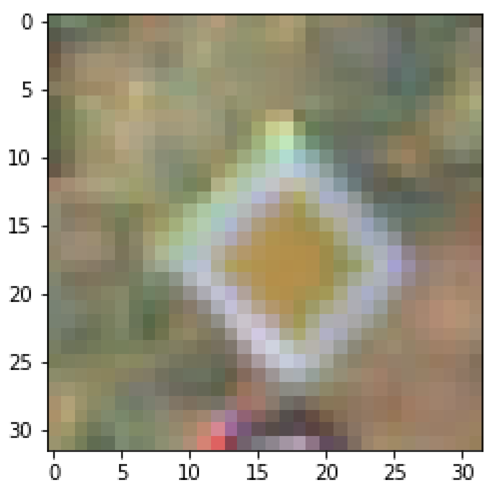
NN predicted 11



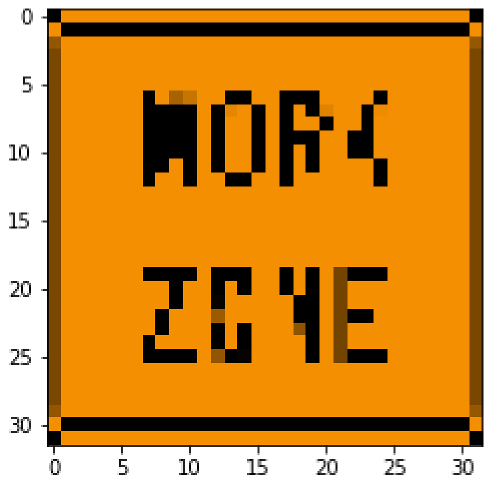
windyRight.png



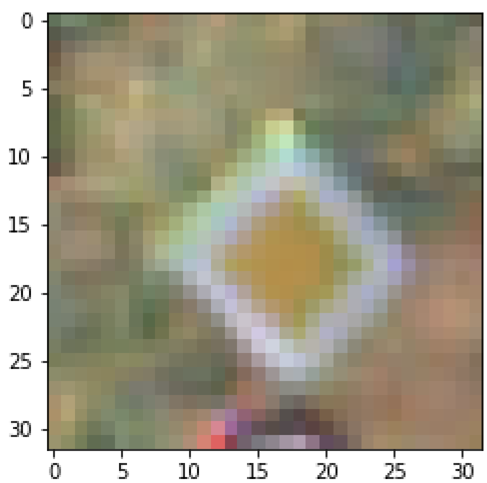
NN predicted 12



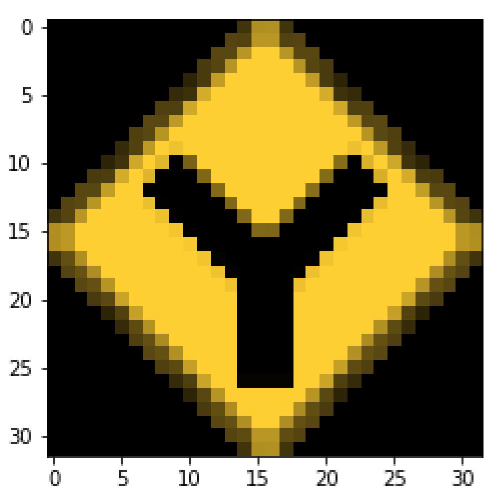
workzone.png



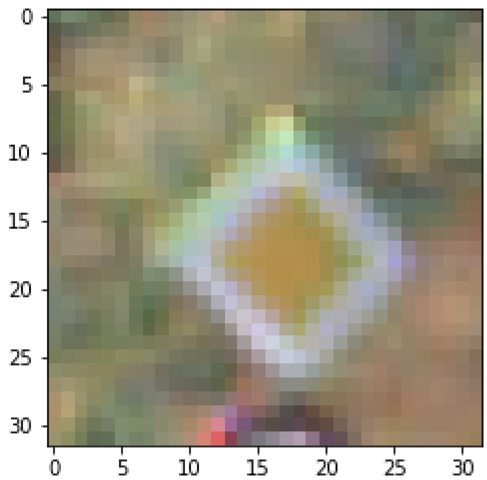
NN predicted 12



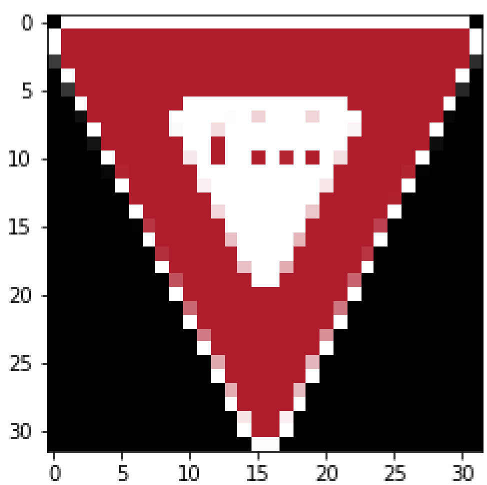
YCrossing.png



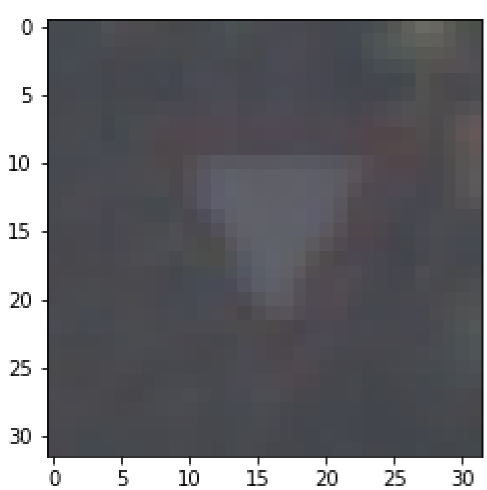
NN predicted 12



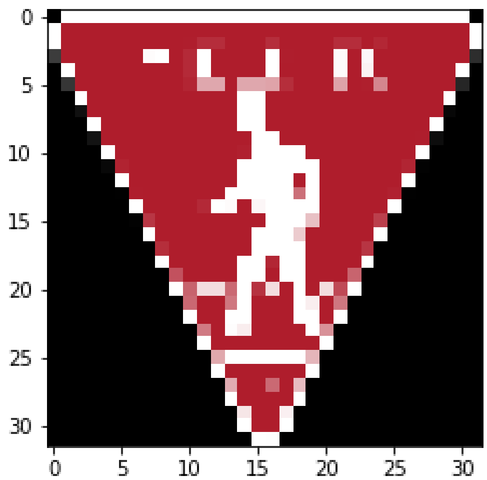
yeild.png



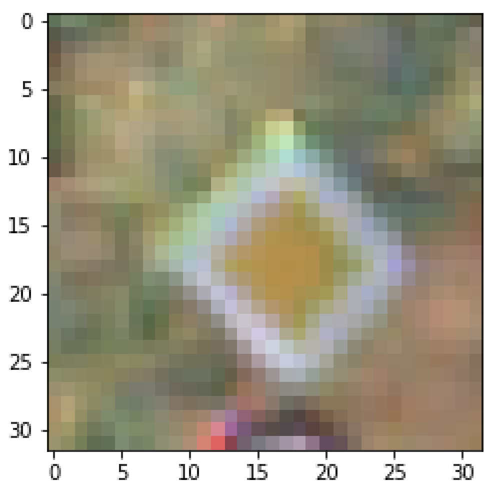
NN predicted 13



```
yield_pedestrian.png
```



```
NN predicted 12
```



No, it does not perform equally well on captured images. It has a performance of 0% accuracy on captured images as opposed to 79% on the test set. •The images not included in the dataset are not exactly the same road signs so there is additional difficulty because the model needs to generalise well to classify these new signs correctly. The •Some road signs such as the shark sign may not even be included in the 43 categories. •The images are also processed (e.g. cropped) differently.

It seems that the model is classifying 'unknown signs' as Roundabout Mandatory signs.

Question 8

*Use the model's softmax probabilities to visualize the **certainty** of its predictions, [`tf.nn.top_k`](https://www.tensorflow.org/versions/r0.12/api_docs/python/nn.html#top_k) (https://www.tensorflow.org/versions/r0.12/api_docs/python/nn.html#top_k) could prove helpful here. Which predictions is the model certain of? Uncertain? If the model was incorrect in its initial prediction, does the correct prediction appear in the top k? (k should be 5 at most)*

`tf.nn.top_k` will return the values and indices (class ids) of the top k predictions. So if k=3, for each sign, it'll return the 3 largest probabilities (out of a possible 43) and the correspoding class ids.

Take this numpy array as an example:

```
# (5, 6) array
a = np.array([[ 0.24879643,  0.07032244,  0.12641572,  0.34763842,  0.07893497,
         0.12789202],
       [ 0.28086119,  0.27569815,  0.08594638,  0.0178669 ,  0.18063401,
         0.15899337],
       [ 0.26076848,  0.23664738,  0.08020603,  0.07001922,  0.1134371 ,
         0.23892179],
       [ 0.11943333,  0.29198961,  0.02605103,  0.26234032,  0.1351348 ,
         0.16505091],
       [ 0.09561176,  0.34396535,  0.0643941 ,  0.16240774,  0.24206137,
         0.09155967]])
```

Running it through `sess.run(tf.nn.top_k(tf.constant(a), k=3))` produces:

```
TopKV2(values=array([[ 0.34763842,  0.24879643,  0.12789202],
       [ 0.28086119,  0.27569815,  0.18063401],
       [ 0.26076848,  0.23892179,  0.23664738],
       [ 0.29198961,  0.26234032,  0.16505091],
       [ 0.34396535,  0.24206137,  0.16240774]]), indices=array([[3, 0, 5],
       [0, 1, 4],
       [0, 5, 1],
       [1, 3, 5],
       [1, 4, 3]], dtype=int32))
```

Looking just at the first row we get `[ 0.34763842,  0.24879643,  0.12789202]`, you can confirm these are the 3 largest probabilities in a. You'll also notice `[3, 0, 5]` are the corresponding indices.

Answer:

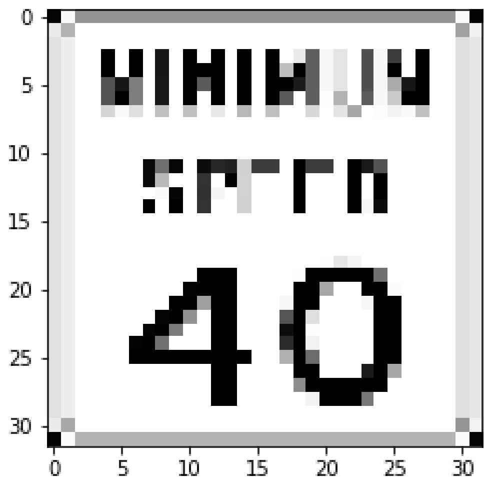
•The model is certain of all of its predictions even though some are wrong. •The model also predicts different outcomes confidently for the two times I ran the predictions on each sign.

These are both strange outcomes.

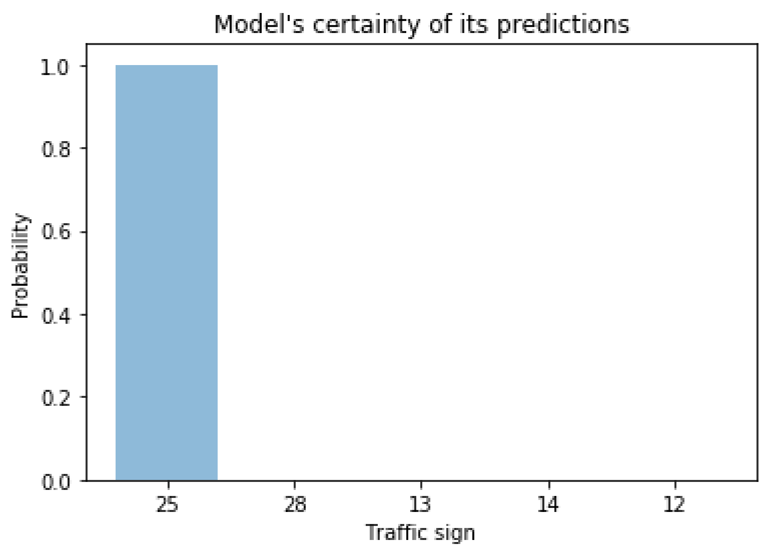
> **Note**: Once you have completed all of the code implementations and successfully answered each question above, you may finalize your work by exporting the iPython Notebook as an HTML document. You can do this by using the menu above and navigating to \n", "**File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.

In [23]:
```
for i in range(len(namenewdata)):
    print('\n\n\n\n')
    print(namenewdata[i])
    plt.imshow(newdata[i]+.5)
    plt.show()
    top_5_predictions(newdata[i])
```

40mph.png

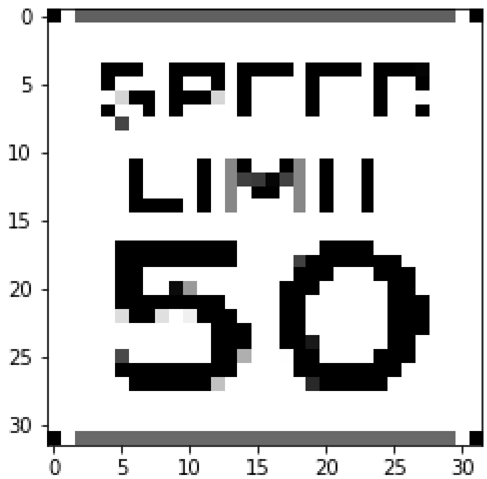



```
Top five:  TopKV2(values=array([[  9.99965072e-01,   3.48573485e-05,   9.5365
5004e-08,
          5.30022311e-11,   4.23061922e-14]], dtype=float32), indices=array
([[25, 28, 13, 14, 12]]))
```

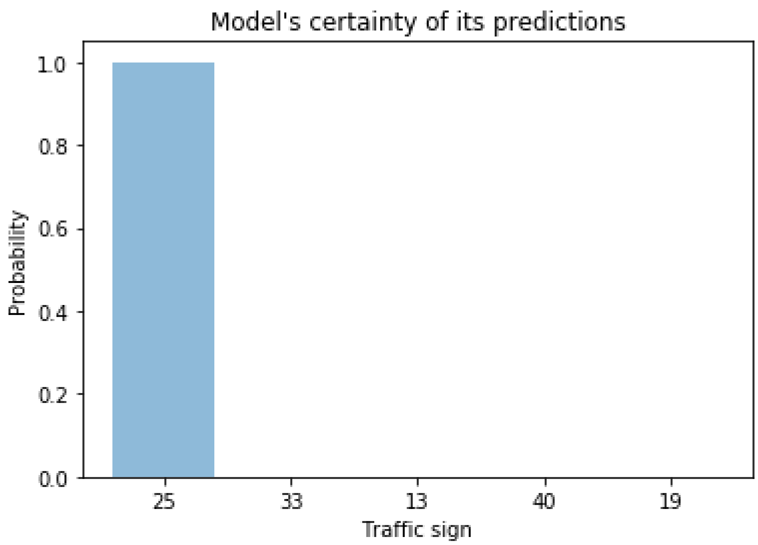



```
Traffic Sign Key
25 :  Road work
28 :  Children crossing
13 :  Yield
14 :  Stop
12 :  Priority road
```

50mph.png

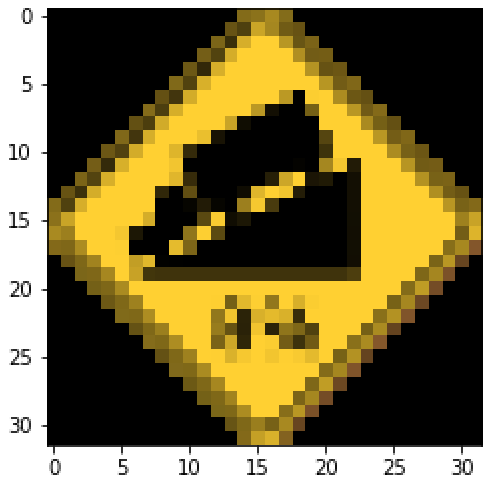


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   1.46745028e-29,   1.3583
8156e-29,
          1.21232870e-30,   4.28406213e-32]], dtype=float32), indices=array
([[25, 33, 13, 40, 19]]))
```

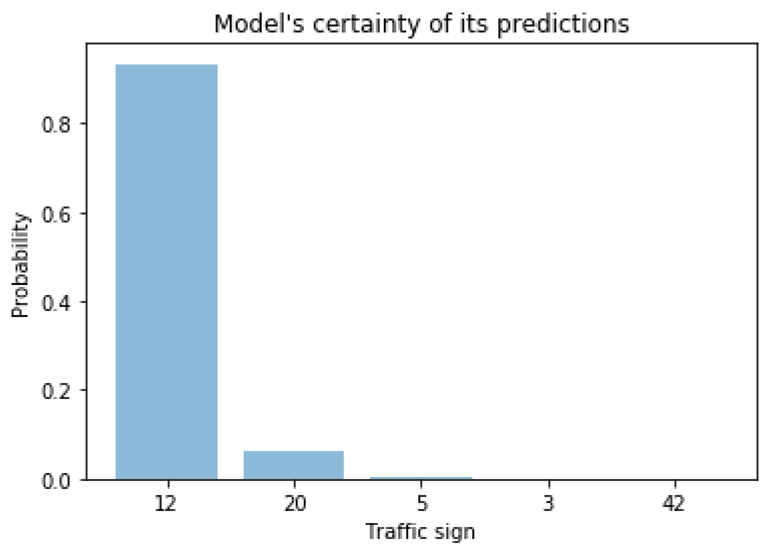


Traffic Sign Key
25 : Road work
33 : Turn right ahead
13 : Yield
40 : Roundabout mandatory
19 : Dangerous curve to the left

8pcGrade.png

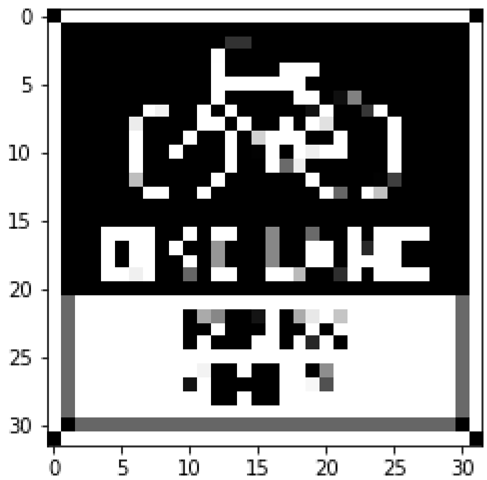


```
Top five:  TopKV2(values=array([[  9.34373081e-01,   6.01442643e-02,   5.2391
7377e-03,
          2.43519113e-04,   1.50220853e-14]], dtype=float32), indices=array
([[12, 20,  5,  3, 42]]))
```

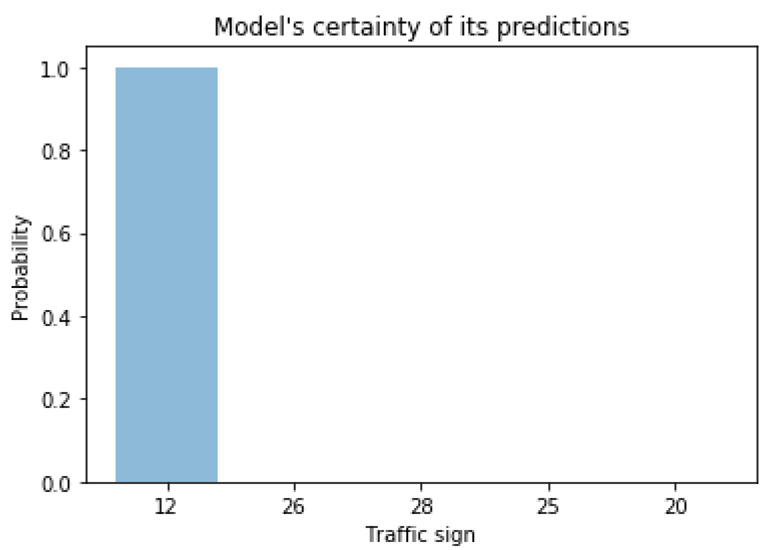



```
Traffic Sign Key
12 :  Priority road
20 :  Dangerous curve to the right
5 :  Speed limit (80km/h)
3 :  Speed limit (60km/h)
42 :  End of no passing by vehicles over 3.5 metric tons
```

bikelane.png

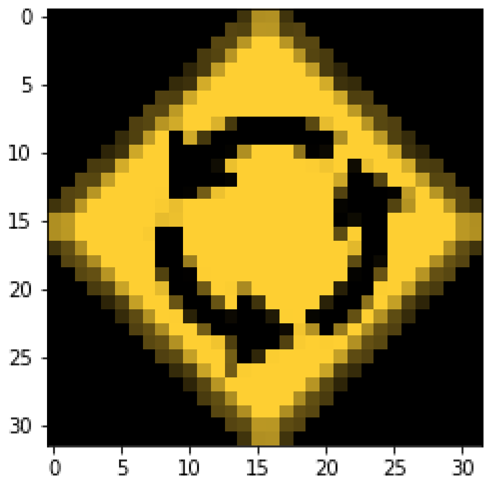


```
Top five:  TopKV2(values=array([[  9.99993324e-01,   6.67676613e-06,   1.7200
0980e-09,
          2.67864536e-10,   1.98939309e-10]], dtype=float32), indices=array
([[12, 26, 28, 25, 20]]))
```

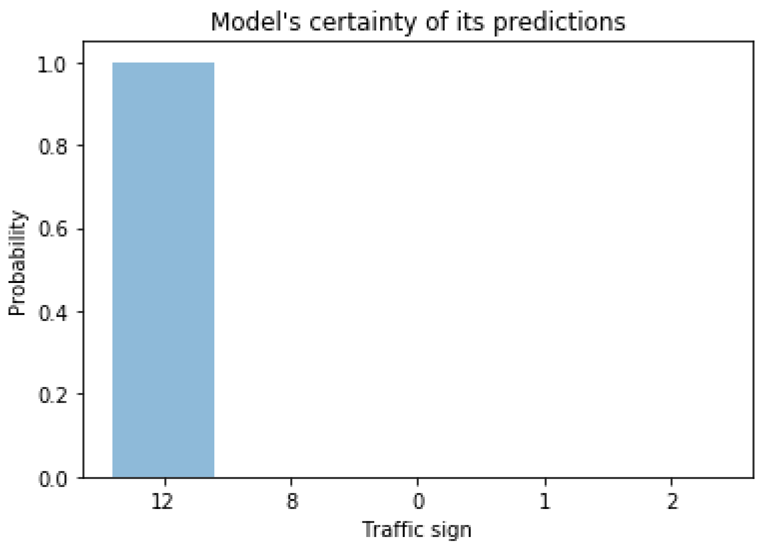


Traffic Sign Key
12 : Priority road
26 : Traffic signals
28 : Children crossing
25 : Road work
20 : Dangerous curve to the right

circle.png

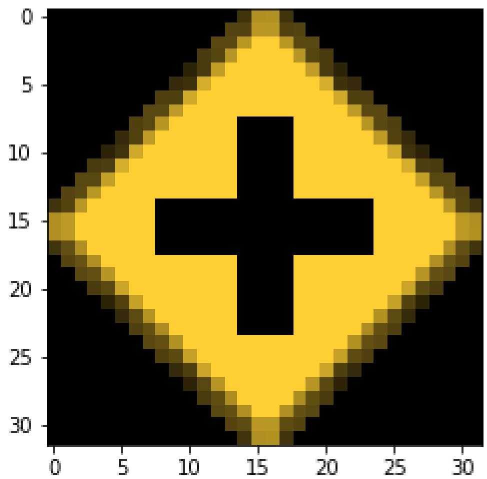



```
Top five:  TopKV2(values=array([[  1.00000000e+00,   1.11131870e-33,   0.0000
0000e+00,
          0.00000000e+00,   0.00000000e+00]], dtype=float32), indices=array
([[12,  8,  0,  1,  2]]))
```

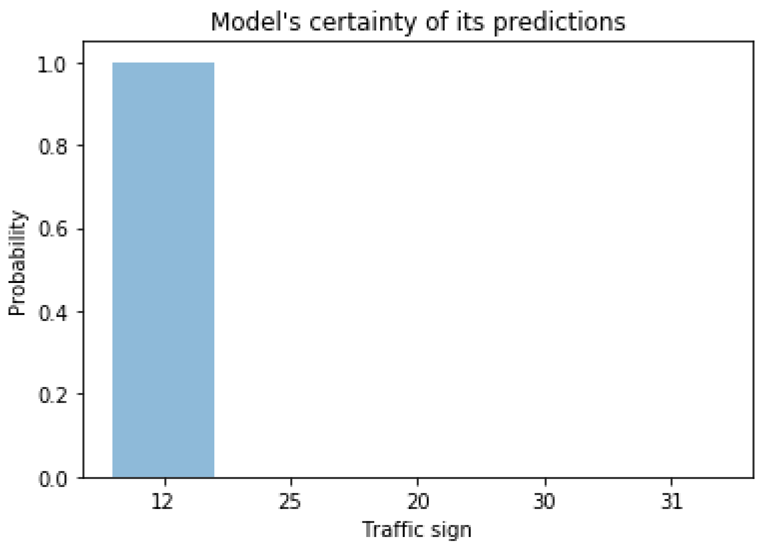



```
Traffic Sign Key
12 :  Priority road
8 :  Speed limit (120km/h)
0 :  Speed limit (20km/h)
1 :  Speed limit (30km/h)
2 :  Speed limit (50km/h)
```

CrossRoad.png

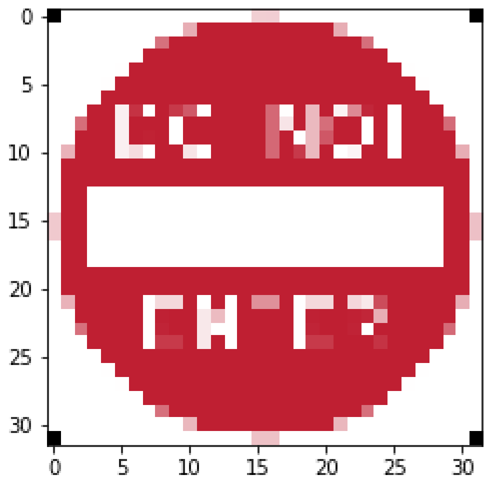


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   6.52831078e-15,   6.2836
3006e-15,
          7.22331169e-16,   5.61500953e-18]], dtype=float32), indices=array
([[12, 25, 20, 30, 31]]))
```

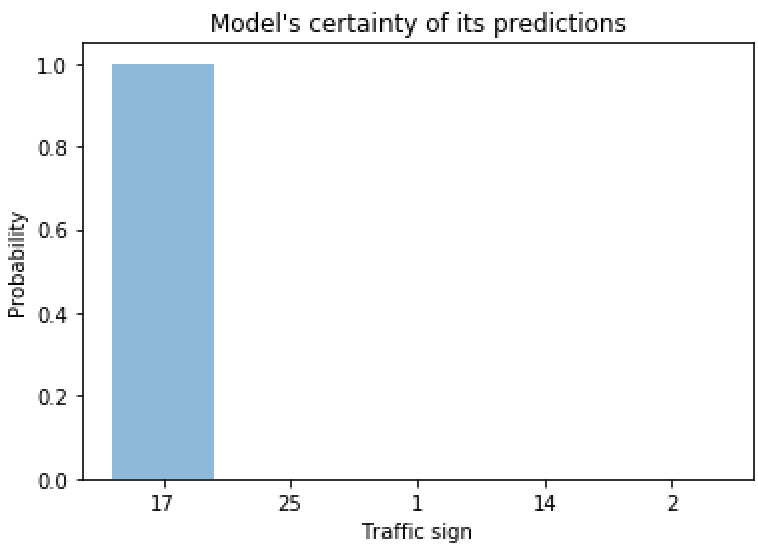


Traffic Sign Key
12 : Priority road
25 : Road work
20 : Dangerous curve to the right
30 : Beware of ice/snow
31 : Wild animals crossing

DonotEnter.png

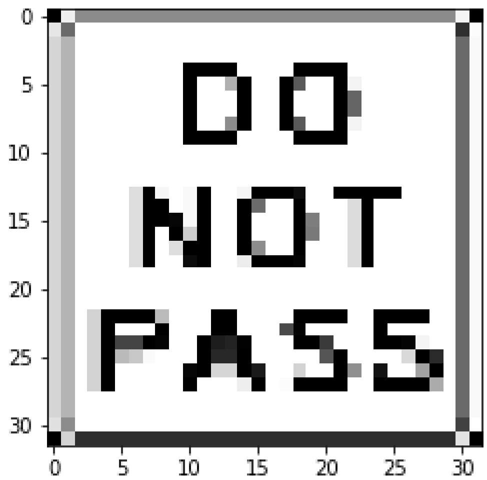


```
Top five:  TopKV2(values=array([[  9.99999523e-01,   4.68118913e-07,   7.3264
8371e-13,
          1.17335677e-17,   8.93368379e-18]], dtype=float32), indices=array
([[17, 25,  1, 14,  2]]))
```

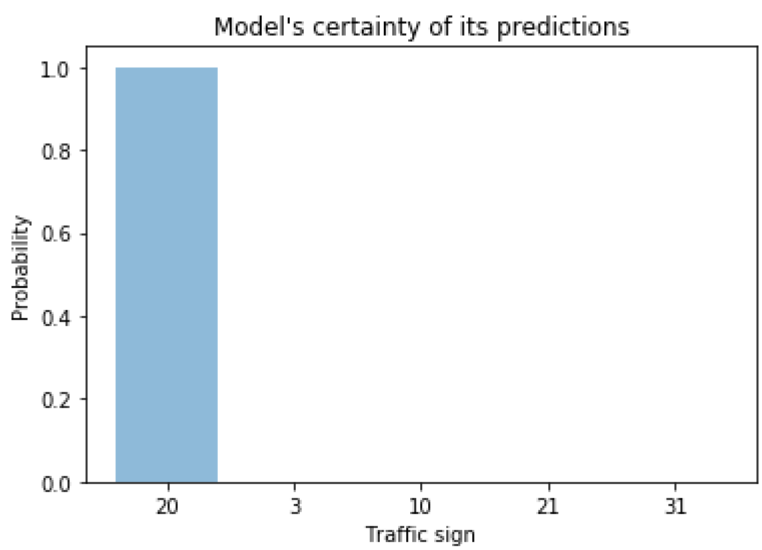


Traffic Sign Key
17 : No entry
25 : Road work
1 : Speed limit (30km/h)
14 : Stop
2 : Speed limit (50km/h)

DoNotPass.png

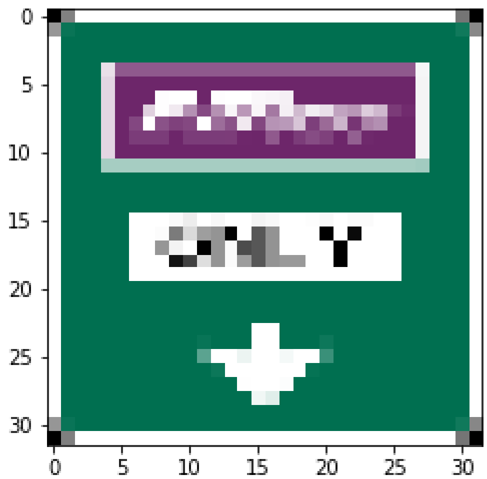



```
Top five:  TopKV2(values=array([[  9.99998689e-01,   8.35011463e-07,   4.2304
0120e-07,
          5.35495148e-10,   7.56928201e-11]], dtype=float32), indices=array
([[20,  3, 10, 21, 31]]))
```

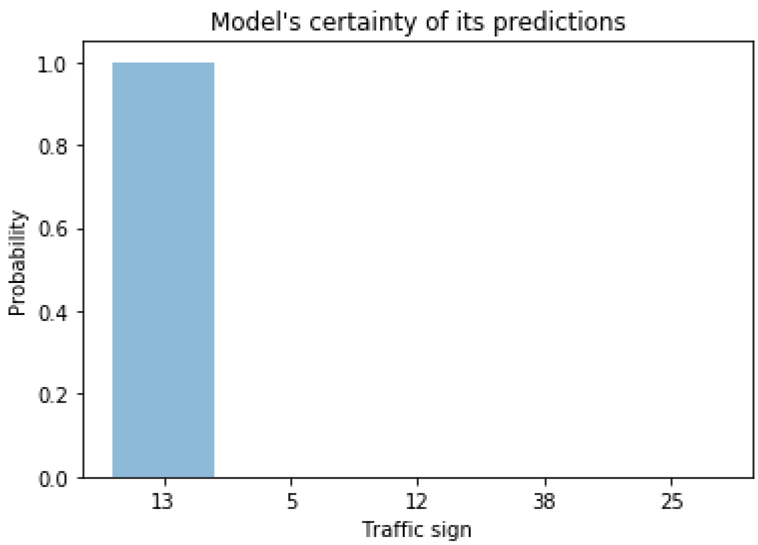



```
Traffic Sign Key
20 :  Dangerous curve to the right
3 :  Speed limit (60km/h)
10 :  No passing for vehicles over 3.5 metric tons
21 :  Double curve
31 :  Wild animals crossing
```

EZPass.png

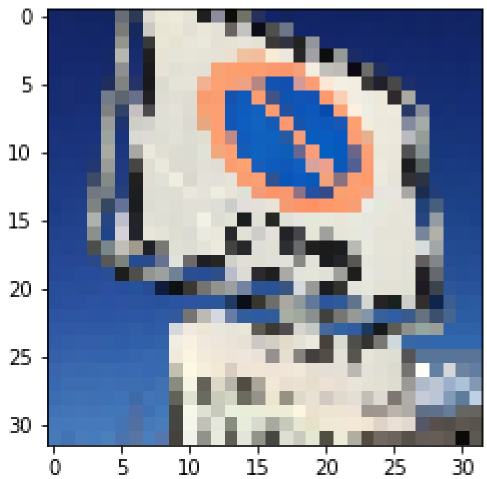


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   3.34847494e-20,   3.0174
0457e-22,
          2.34127782e-22,   5.46599749e-24]], dtype=float32), indices=array
([[13,  5, 12, 38, 25]]))
```

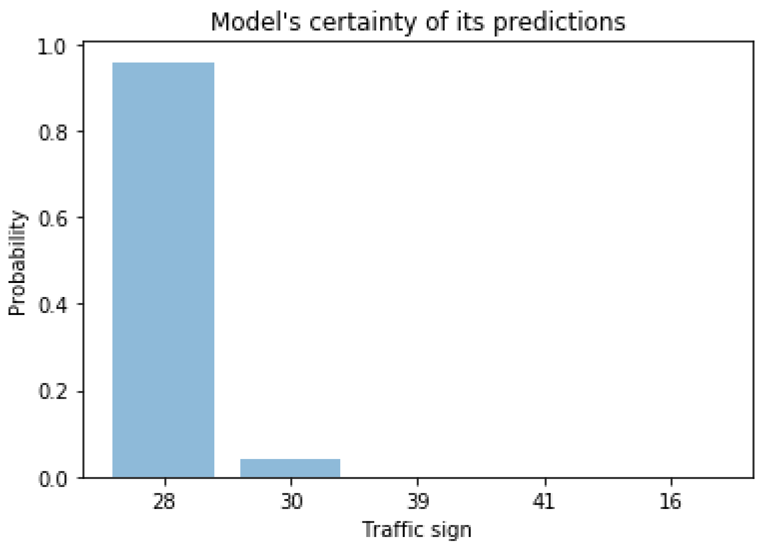


Traffic Sign Key
13 : Yield
5 : Speed limit (80km/h)
12 : Priority road
38 : Keep right
25 : Road work

german_sign.png

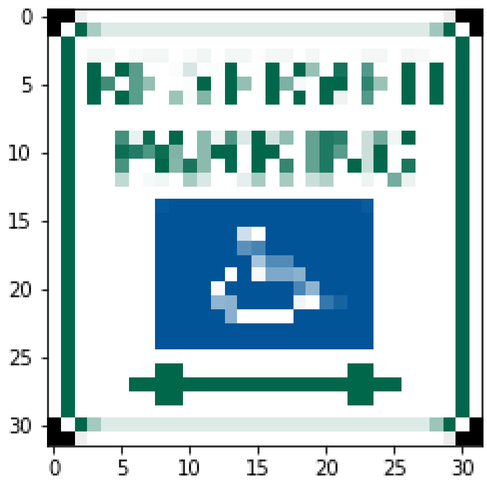


```
Top five:  TopKV2(values=array([[  9.59407389e-01,   3.94117013e-02,   1.0521
2280e-03,
          9.47257286e-05,   1.95071989e-05]], dtype=float32), indices=array
([[28, 30, 39, 41, 16]]))
```

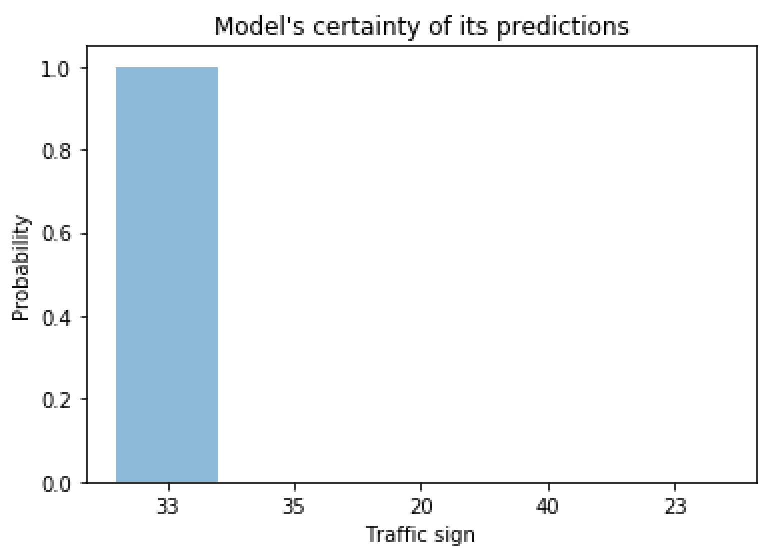


Traffic Sign Key
28 : Children crossing
30 : Beware of ice/snow
39 : Keep left
41 : End of no passing
16 : Vehicles over 3.5 metric tons prohibited

HCparking.png

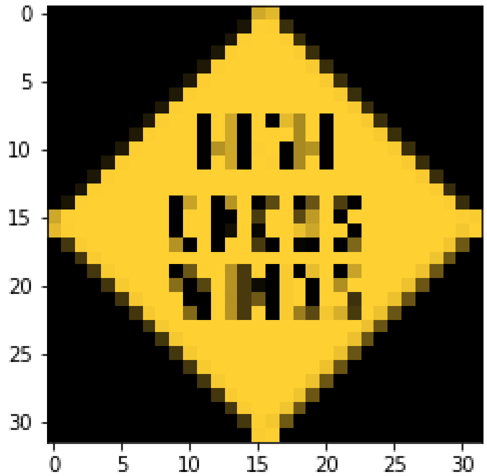


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   1.62666736e-09,   1.3097
5786e-11,
          1.23612373e-12,   6.92642399e-17]], dtype=float32), indices=array
([[33, 35, 20, 40, 23]]))
```

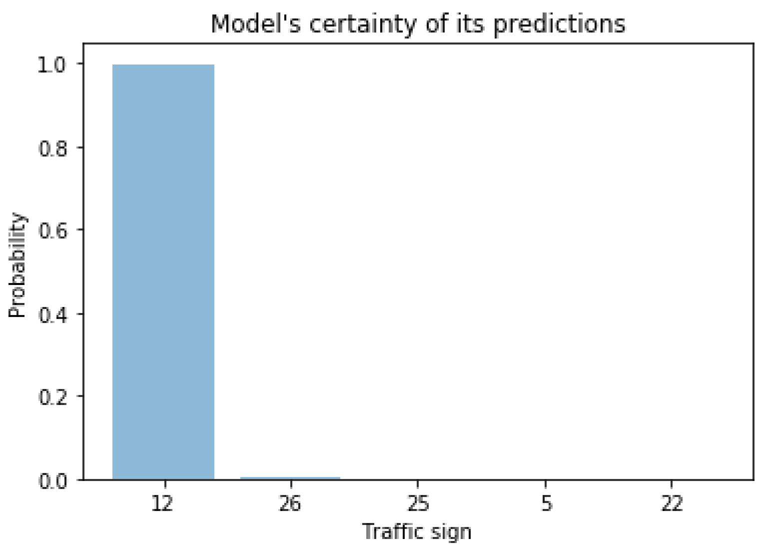



```
Traffic Sign Key
33 :  Turn right ahead
35 :  Ahead only
20 :  Dangerous curve to the right
40 :  Roundabout mandatory
23 :  Slippery road
```

HighXWinds.png

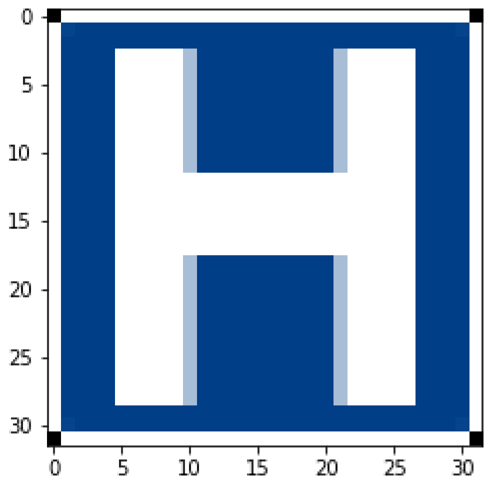


```
Top five:  TopKV2(values=array([[  9.97674763e-01,   1.59696769e-03,   7.2206
7547e-04,
          6.17395062e-06,   3.94209491e-12]], dtype=float32), indices=array
([[12, 26, 25,  5, 22]]))
```

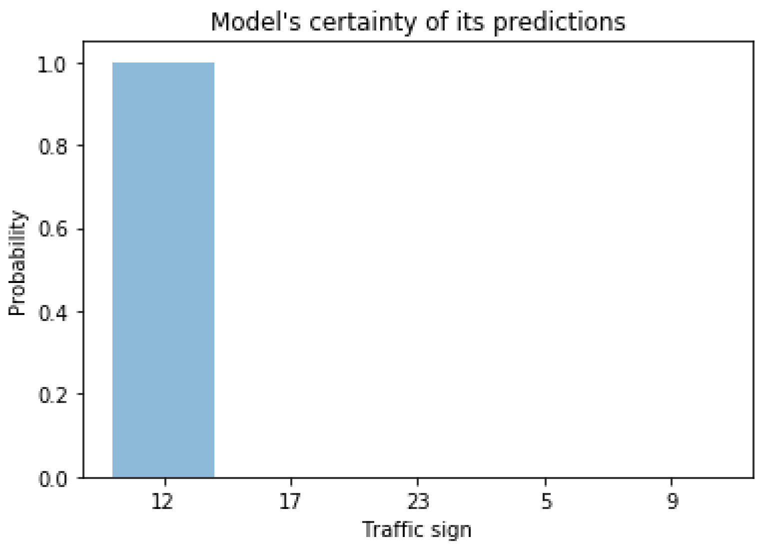



```
Traffic Sign Key
12 :  Priority road
26 :  Traffic signals
25 :  Road work
5 :  Speed limit (80km/h)
22 :  Bumpy road
```

Hospital.png

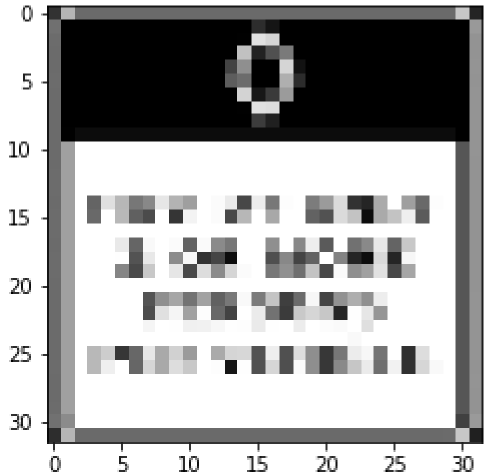



```
Top five:  TopKV2(values=array([[  1.00000000e+00,   3.00917657e-13,   7.5661
8109e-24,
          1.29688733e-24,   1.29791112e-25]], dtype=float32), indices=array
([[12, 17, 23,  5,  9]]))
```

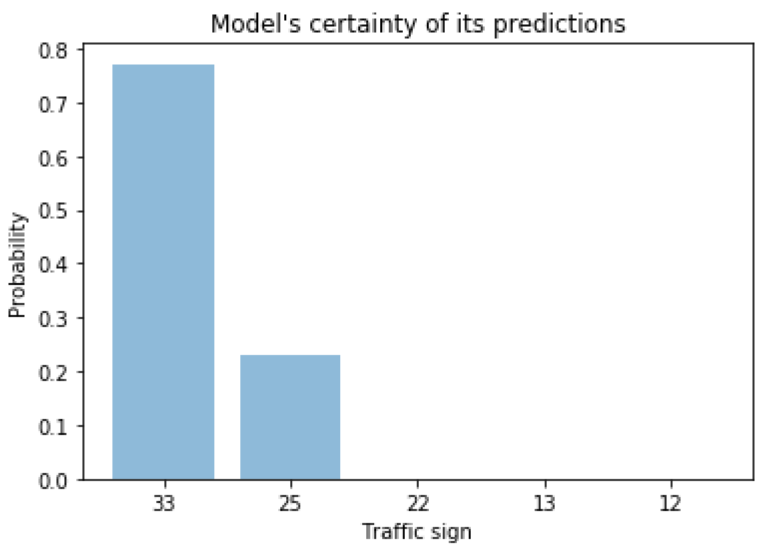



```
Traffic Sign Key
12 :  Priority road
17 :  No entry
23 :  Slippery road
5 :  Speed limit (80km/h)
9 :  No passing
```

HOW.png

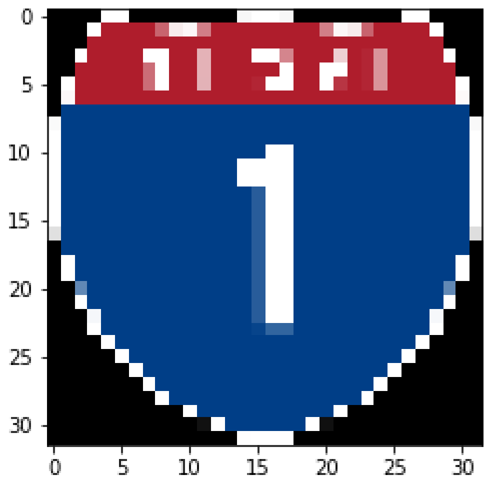



```
Top five:  TopKV2(values=array([[  7.71307647e-01,   2.28692353e-01,   6.4090
6439e-09,
          3.23991187e-13,   1.66075717e-14]], dtype=float32), indices=array
([[33, 25, 22, 13, 12]]))
```

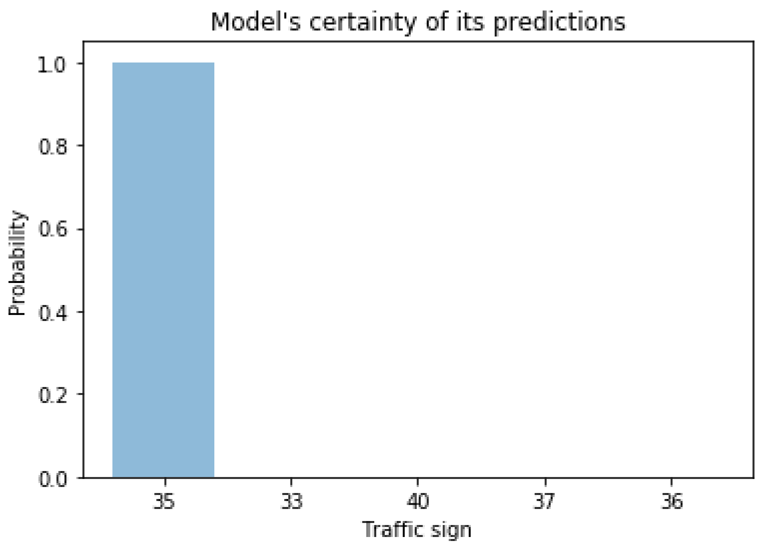


Traffic Sign Key
33 : Turn right ahead
25 : Road work
22 : Bumpy road
13 : Yield
12 : Priority road

i1.png



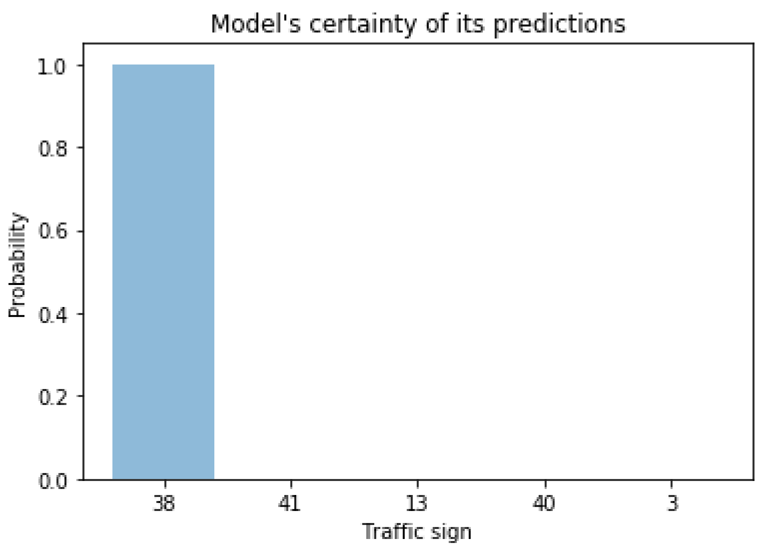

```
Top five:  TopKV2(values=array([[  1.00000000e+00,   4.19434503e-18,   1.0867
7887e-29,
          6.71084346e-30,   1.48594288e-30]], dtype=float32), indices=array
([[35, 33, 40, 37, 36]]))
```




```
Traffic Sign Key
35 :  Ahead only
33 :  Turn right ahead
40 :  Roundabout mandatory
37 :  Go straight or left
36 :  Go straight or right
```

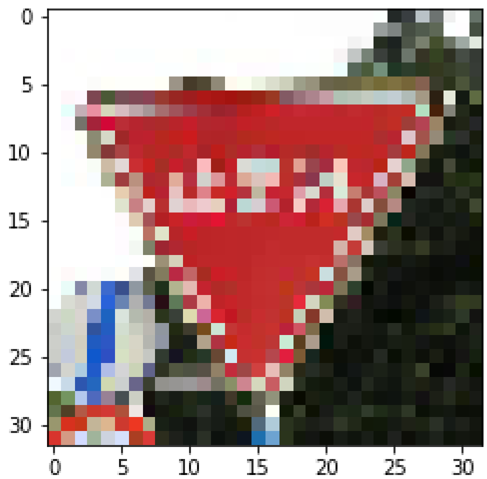
i22.png

```
Top five:  TopKV2(values=array([[  1.00000000e+00,   6.12729160e-13,   9.18513549e-15,
          6.62731006e-19,   4.33373360e-25]], dtype=float32), indices=array([[38, 41, 13, 40,  3]]))
```



Traffic Sign Key
38 : Keep right
41 : End of no passing
13 : Yield
40 : Roundabout mandatory
3 : Speed limit (60km/h)

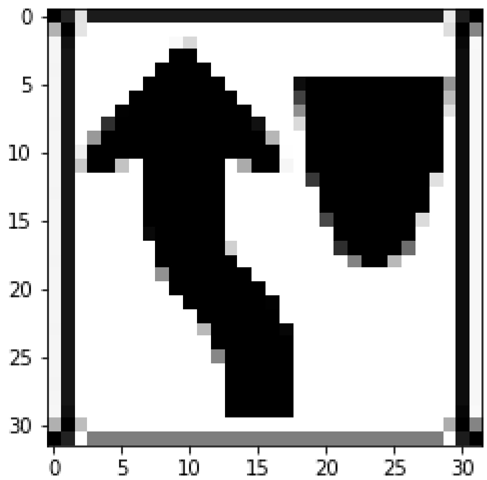
japanese_sign_resized.png



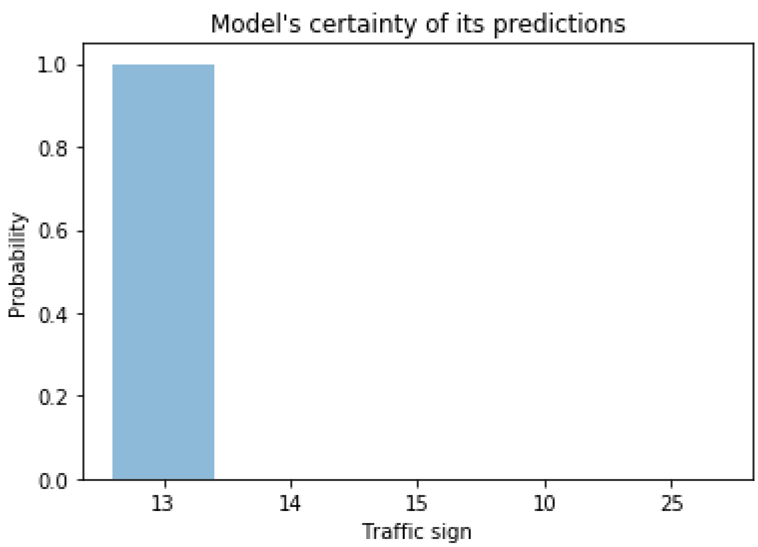
```
Top five:  TopKV2(values=array([[  1.00000000e+00,   5.30353143e-23,   0.0000
0000e+00,
          0.00000000e+00,   0.00000000e+00]], dtype=float32), indices=array
([[17, 14,  0,  1,  2]]))
```


```
Traffic Sign Key
17 :  No entry
14 :  Stop
0 :  Speed limit (20km/h)
1 :  Speed limit (30km/h)
2 :  Speed limit (50km/h)
```

keepleft.png

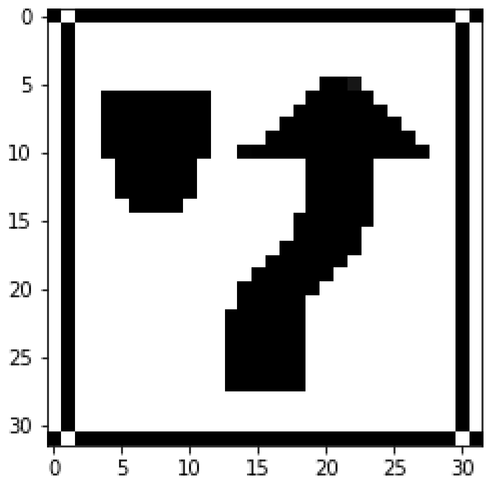


```
Top five:  TopKV2(values=array([[  9.99683142e-01,   3.16423189e-04,   4.5891
0677e-07,
          5.36083290e-14,   8.27646354e-20]], dtype=float32), indices=array
([[13, 14, 15, 10, 25]]))
```

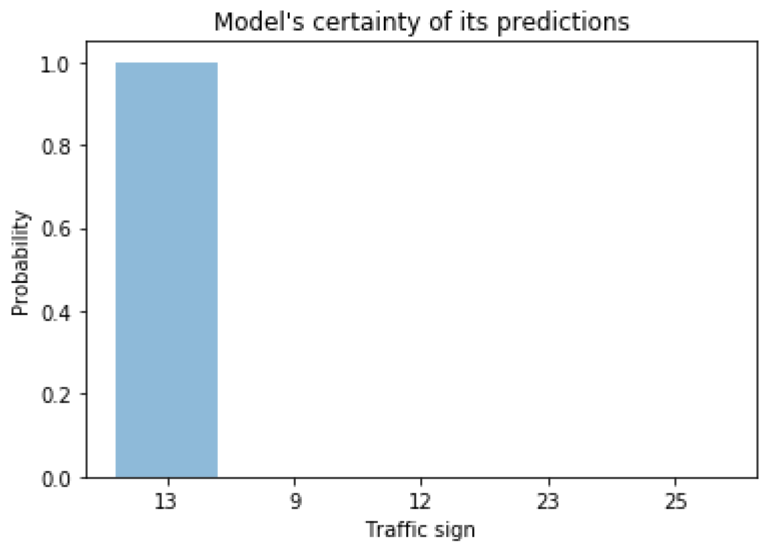



```
Traffic Sign Key
13 :  Yield
14 :  Stop
15 :  No vehicles
10 :  No passing for vehicles over 3.5 metric tons
25 :  Road work
```

keepright.png

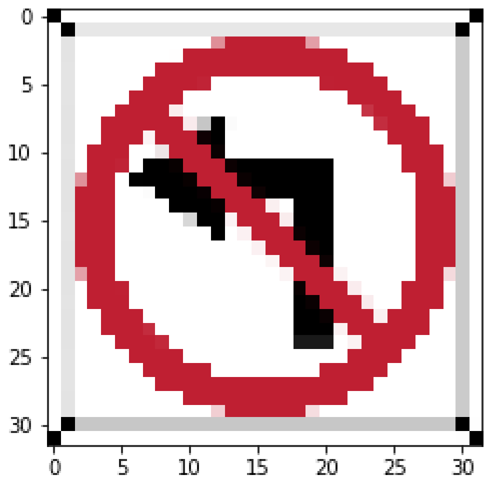


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   6.64526323e-10,   3.4601
7215e-10,
          3.10718324e-15,   1.88433491e-16]], dtype=float32), indices=array
([[13,  9, 12, 23, 25]]))
```

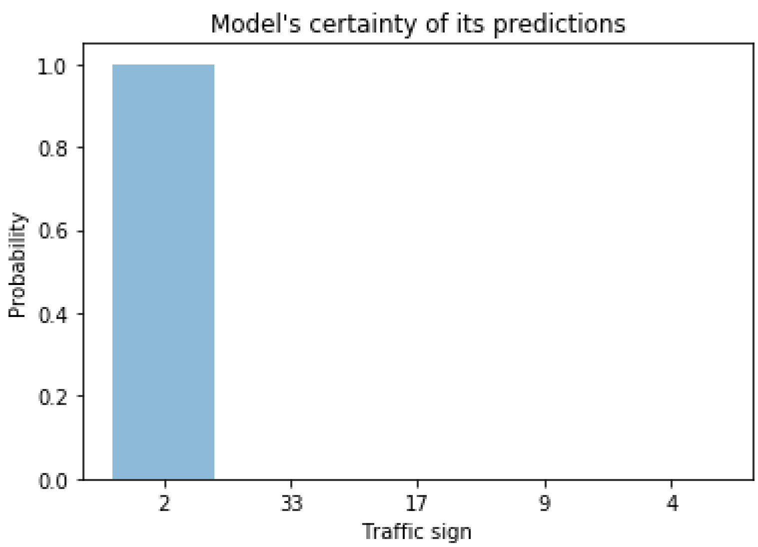



```
Traffic Sign Key
13 :  Yield
9 :  No passing
12 :  Priority road
23 :  Slippery road
25 :  Road work
```

noleft.png

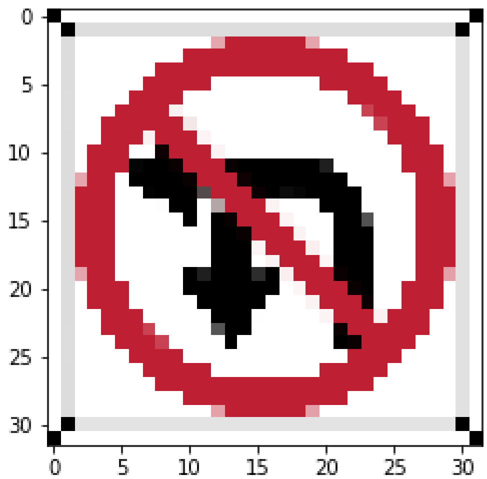


```
Top five:  TopKV2(values=array([[  9.99995589e-01,   4.41855764e-06,   6.2493
5936e-11,
          8.73254207e-15,   1.22476697e-15]], dtype=float32), indices=array
([[ 2, 33, 17,  9,  4]]))
```

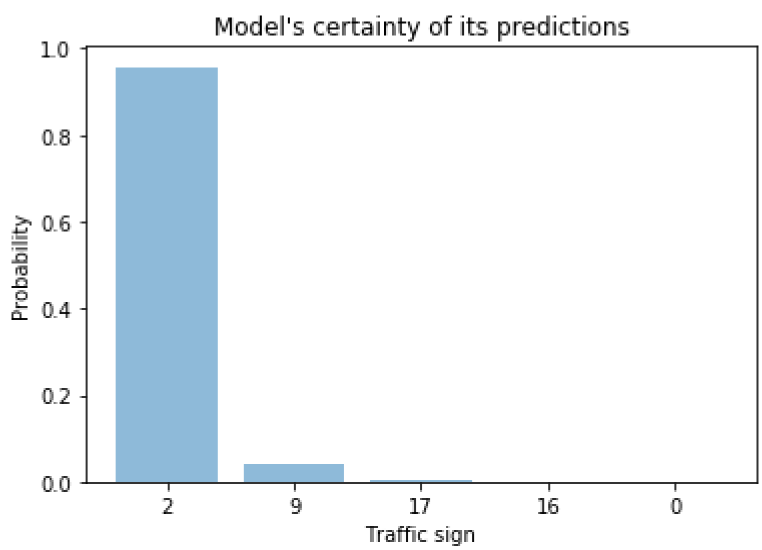



```
Traffic Sign Key
2 :  Speed limit (50km/h)
33 :  Turn right ahead
17 :  No entry
9 :  No passing
4 :  Speed limit (70km/h)
```

noleftUturn.png

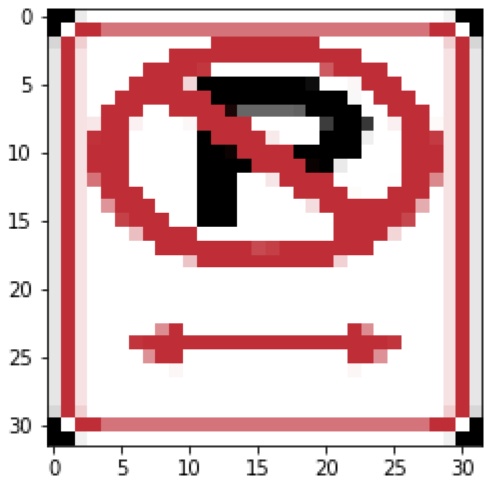


```
Top five:  TopKV2(values=array([[  9.57131743e-01,   3.91714312e-02,   3.0928
0888e-03,
          4.61697055e-04,   1.42223202e-04]], dtype=float32), indices=array
([[ 2,  9, 17, 16,  0]]))
```

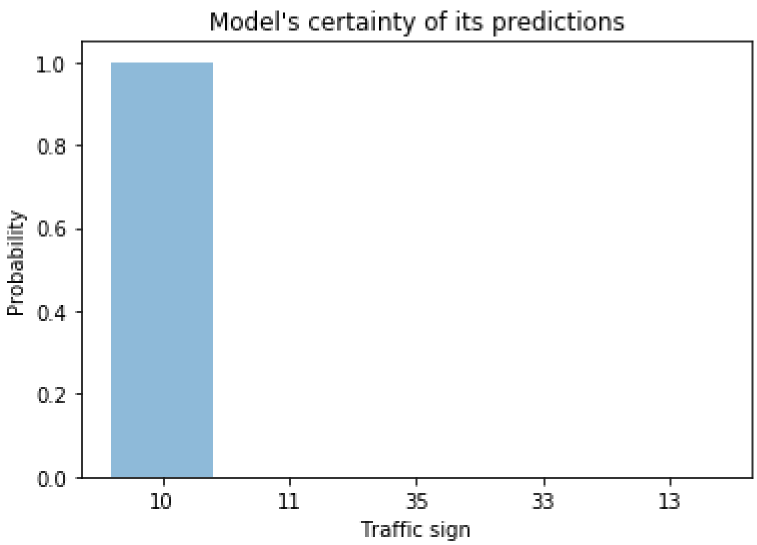



```
Traffic Sign Key
2 :  Speed limit (50km/h)
9 :  No passing
17 :  No entry
16 :  Vehicles over 3.5 metric tons prohibited
0 :  Speed limit (20km/h)
```

NoParking.png

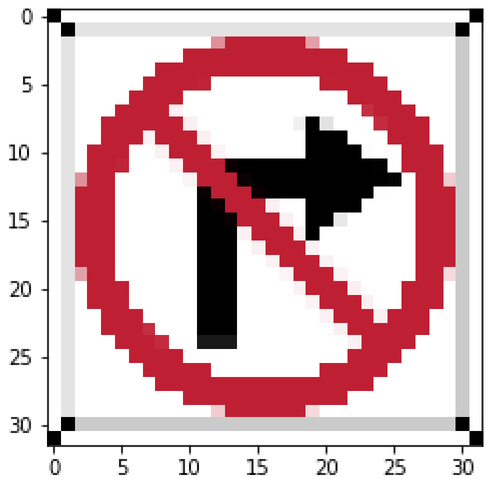



```
Top five:  TopKV2(values=array([[  9.99999642e-01,   3.51883159e-07,   1.3362
8820e-11,
          8.08097946e-12,   6.12855469e-12]], dtype=float32), indices=array
([[10, 11, 35, 33, 13]]))
```

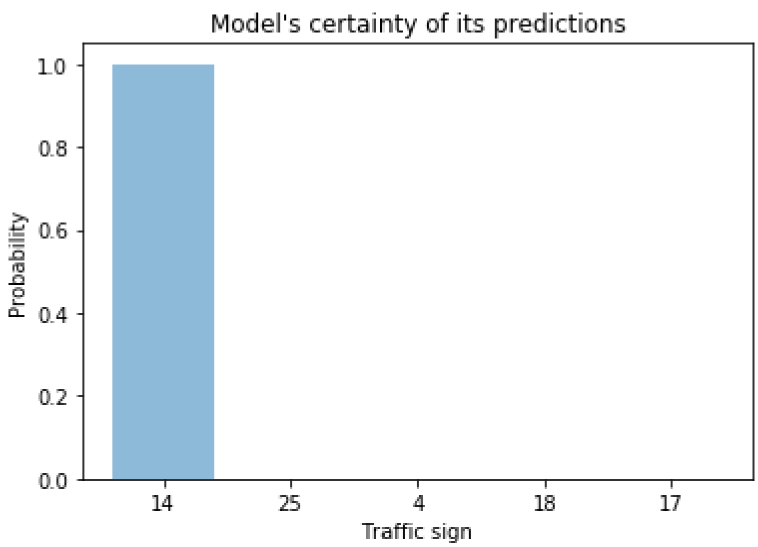



```
Traffic Sign Key
10 :  No passing for vehicles over 3.5 metric tons
11 :  Right-of-way at the next intersection
35 :  Ahead only
33 :  Turn right ahead
13 :  Yield
```

noright.png

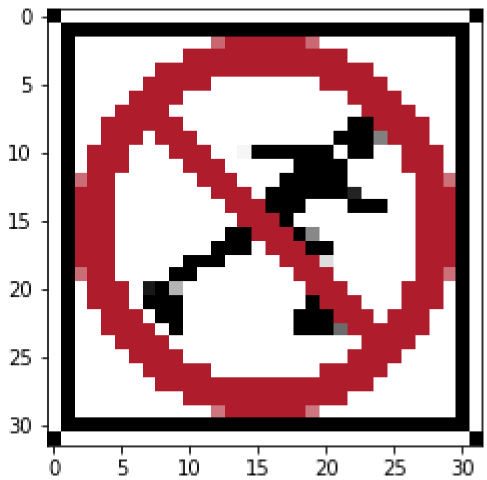



```
Top five:  TopKV2(values=array([[  9.99990463e-01,   6.16097032e-06,   3.3919
5935e-06,
          4.63099292e-09,   8.33453098e-11]], dtype=float32), indices=array
([[14, 25,  4, 18, 17]]))
```

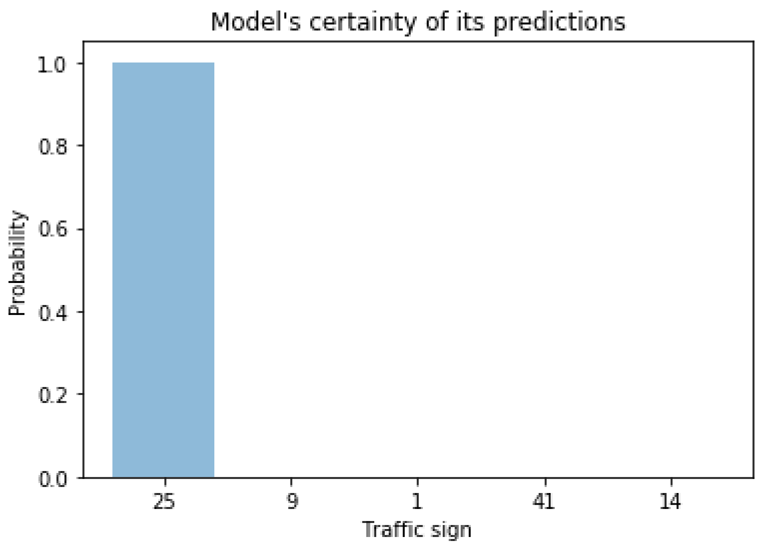



```
Traffic Sign Key
14 :  Stop
25 :  Road work
4 :  Speed limit (70km/h)
18 :  General caution
17 :  No entry
```

noRoller.png

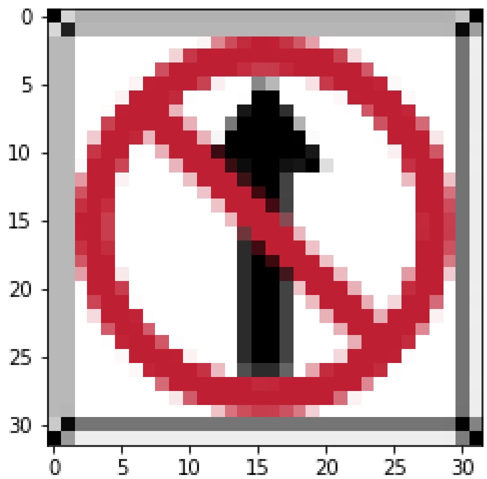


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   1.76973664e-16,   2.1071
6522e-20,
          3.50180884e-32,   4.68891931e-34]], dtype=float32), indices=array
([[25,  9,  1, 41, 14]]))
```

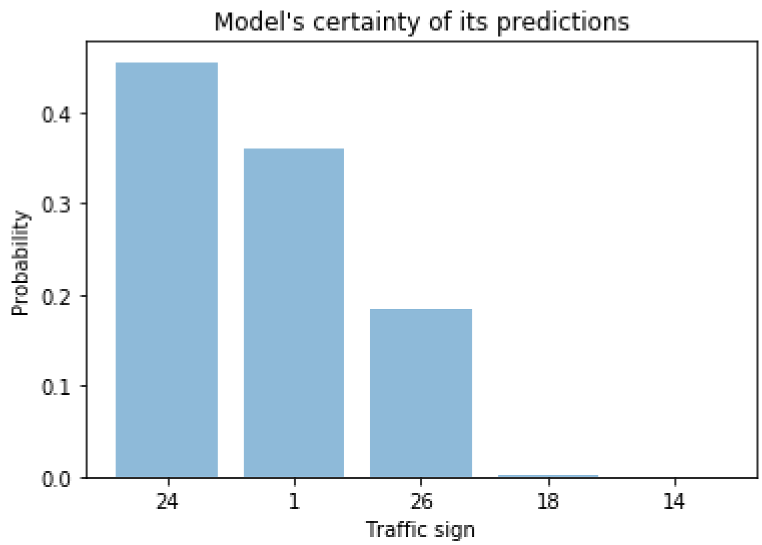



```
Traffic Sign Key
25 :  Road work
9 :  No passing
1 :  Speed limit (30km/h)
41 :  End of no passing
14 :  Stop
```

nostraight.png

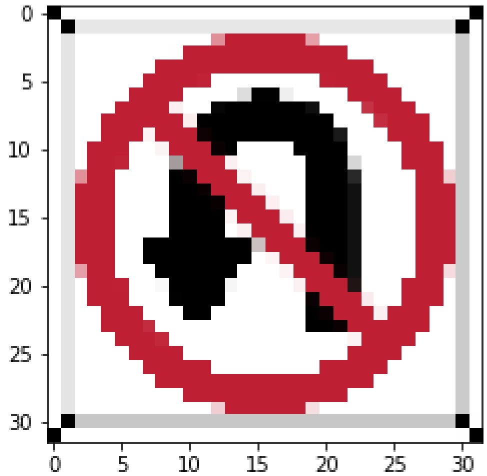



```
Top five:  TopKV2(values=array([[  4.55018729e-01,   3.59127194e-01,   1.8500
7110e-01,
          7.56068039e-04,   4.96152534e-05]], dtype=float32), indices=array
([[24,  1, 26, 18, 14]]))
```

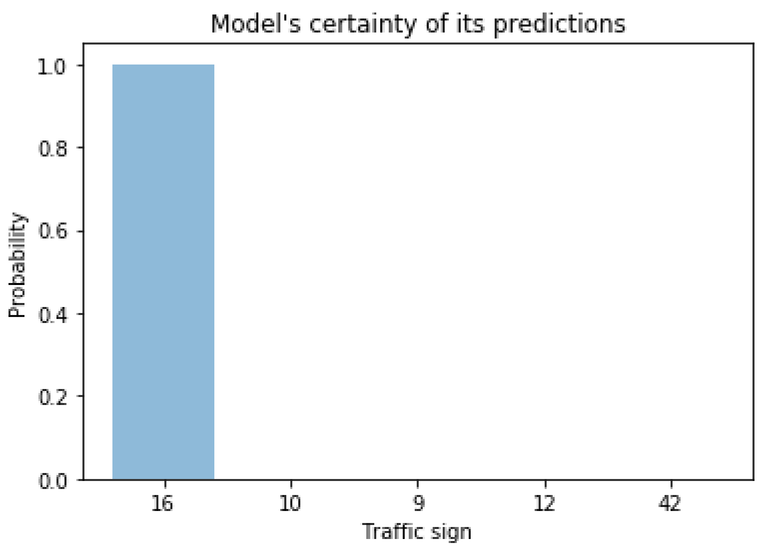



```
Traffic Sign Key
24 :  Road narrows on the right
1 :  Speed limit (30km/h)
26 :  Traffic signals
18 :  General caution
14 :  Stop
```

noUturn.png

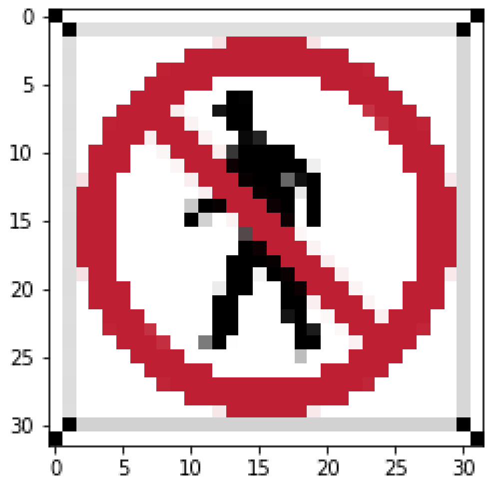


```
Top five:  TopKV2(values=array([[  9.99811232e-01,   1.67322883e-04,   2.0816
3110e-05,
          6.42379177e-07,   6.93807500e-09]], dtype=float32), indices=array
([[16, 10,  9, 12, 42]]))
```



Traffic Sign Key
16 : Vehicles over 3.5 metric tons prohibited
10 : No passing for vehicles over 3.5 metric tons
9 : No passing
12 : Priority road
42 : End of no passing by vehicles over 3.5 metric tons

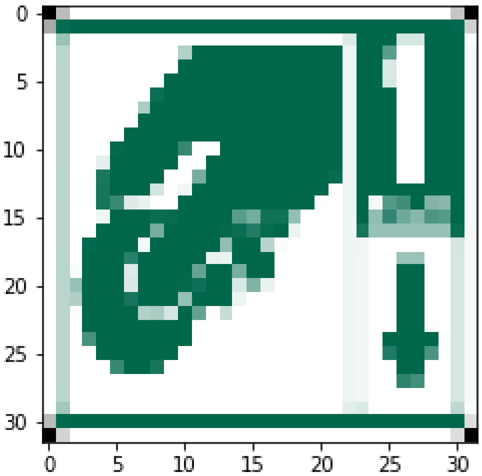
noWalking.png



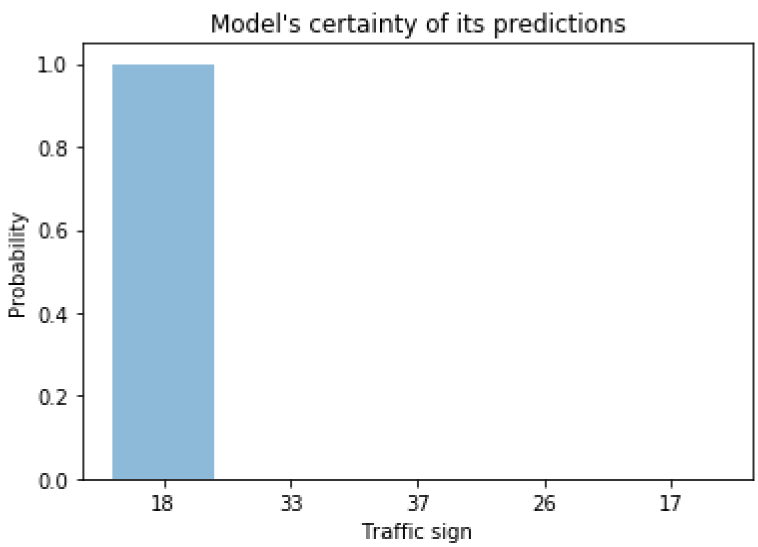
```
Top five:  TopKV2(values=array([[  9.99984145e-01,   1.53274432e-05,   4.4499
7141e-07,
          4.76872763e-08,   2.59136844e-11]], dtype=float32), indices=array
([[ 1,  3,  2,  5, 21]]))
```


```
Traffic Sign Key
1 :  Speed limit (30km/h)
3 :  Speed limit (60km/h)
2 :  Speed limit (50km/h)
5 :  Speed limit (80km/h)
21 :  Double curve
```

paidParking.png

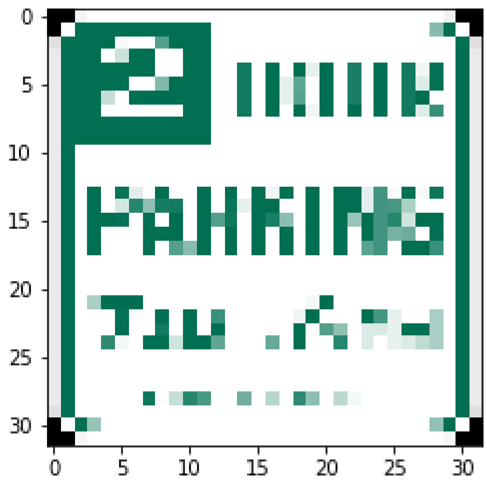


```
Top five:  TopKV2(values=array([[  9.99614239e-01,   3.81746097e-04,   3.8407
4065e-06,
          9.72145244e-08,   7.92053445e-09]], dtype=float32), indices=array
([[18, 33, 37, 26, 17]]))
```

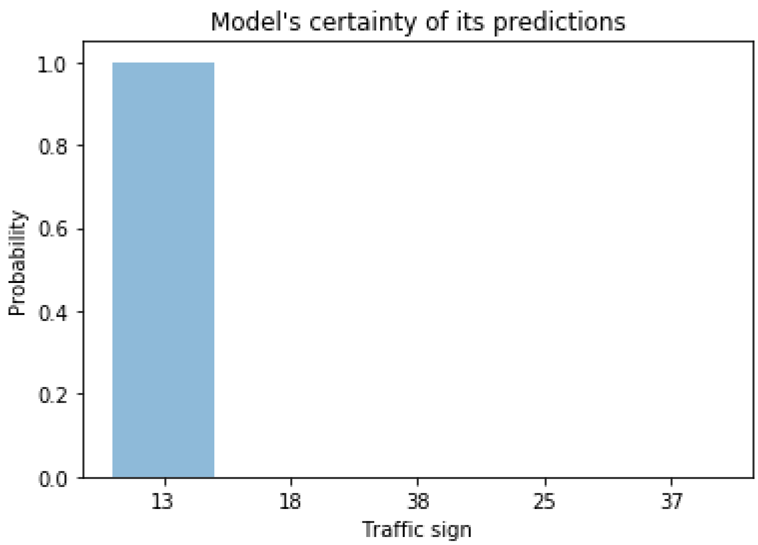



```
Traffic Sign Key
18 :  General caution
33 :  Turn right ahead
37 :  Go straight or left
26 :  Traffic signals
17 :  No entry
```

parking2hr.png

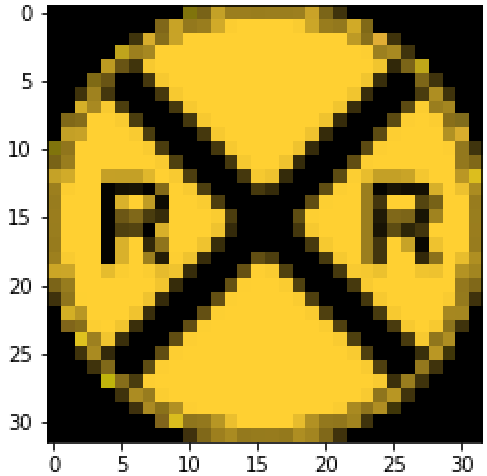


Top five: TopKV2(values=array([[9.99770820e-01,   2.25819371e-04,   3.05190792e-06,
          2.56343213e-07,   7.55058245e-16]], dtype=float32), indices=array([[13, 18, 38, 25, 37]]))

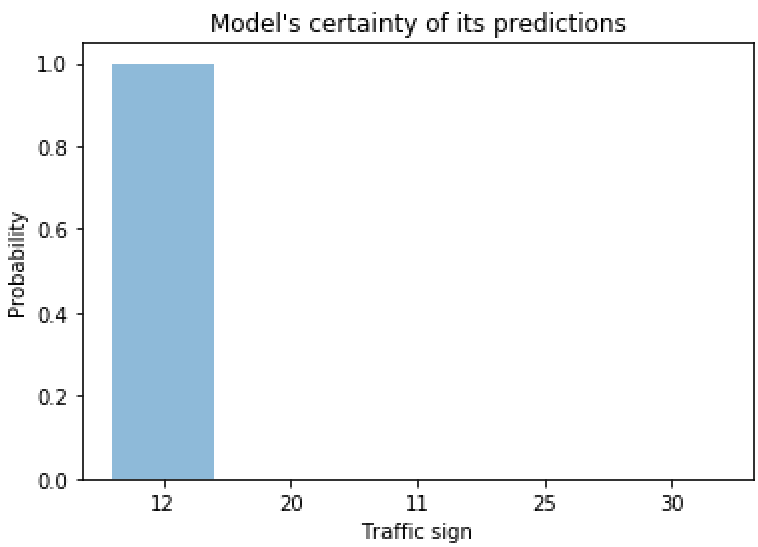


Traffic Sign Key
13 : Yield
18 : General caution
38 : Keep right
25 : Road work
37 : Go straight or left

RailRoad.png

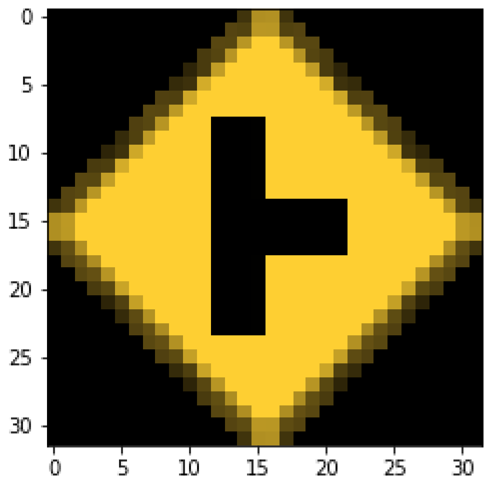



```
Top five:  TopKV2(values=array([[  9.99515653e-01,   4.32657776e-04,   5.1168
1137e-05,
          5.79016614e-07,   1.90898430e-09]], dtype=float32), indices=array
([[12, 20, 11, 25, 30]]))
```

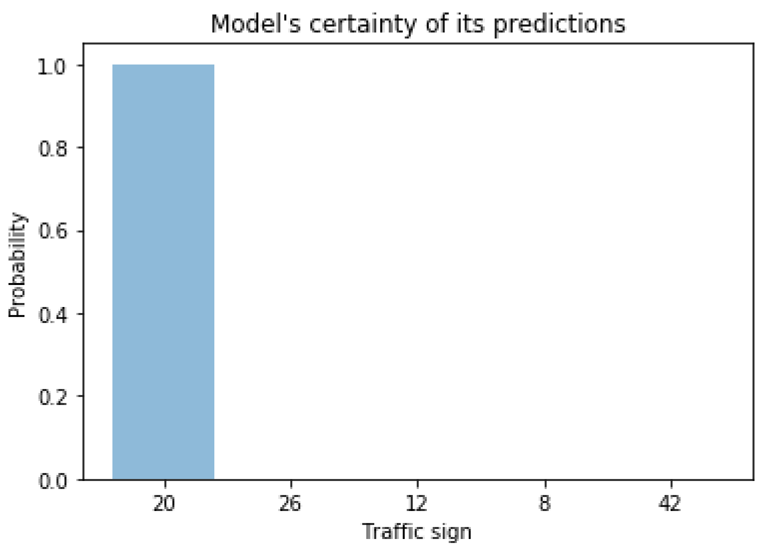



```
Traffic Sign Key
12 :  Priority road
20 :  Dangerous curve to the right
11 :  Right-of-way at the next intersection
25 :  Road work
30 :  Beware of ice/snow
```

RightCrossing.png

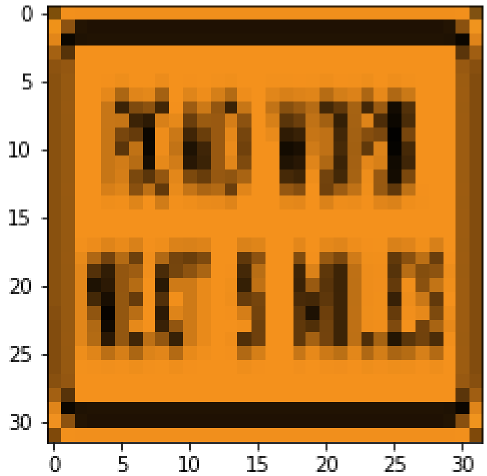


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   8.59899988e-22,   2.7182
2030e-22,
          1.24089544e-27,   3.18170511e-30]], dtype=float32), indices=array
([[20, 26, 12,  8, 42]]))
```

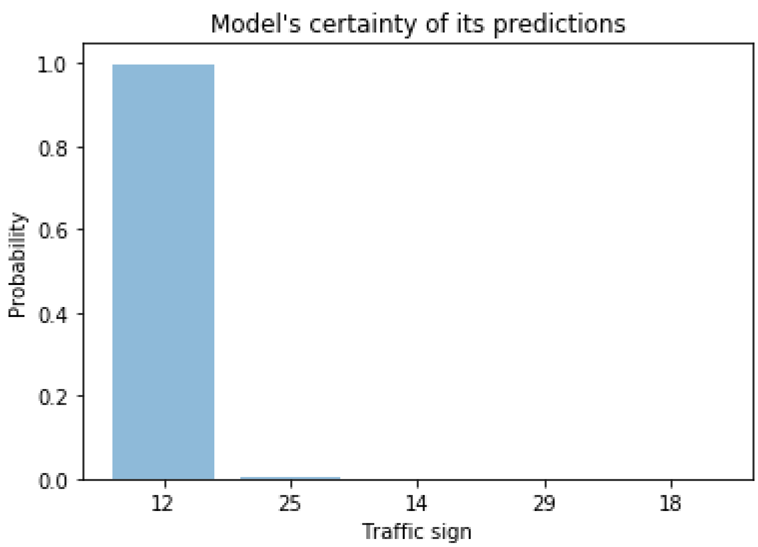



```
Traffic Sign Key
20 :  Dangerous curve to the right
26 :  Traffic signals
12 :  Priority road
8 :  Speed limit (120km/h)
42 :  End of no passing by vehicles over 3.5 metric tons
```

roadwork.png

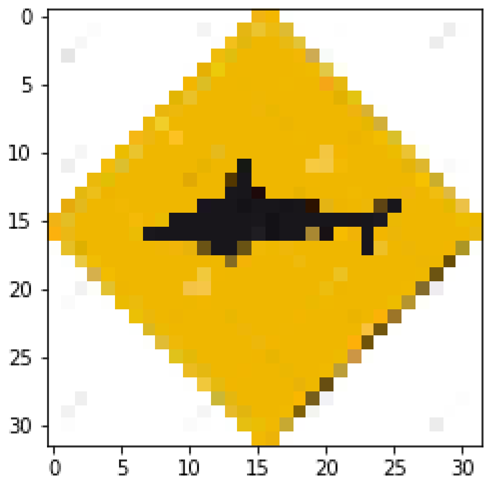


```
Top five:  TopKV2(values=array([[  9.97832477e-01,   2.16756505e-03,   1.6694
3620e-23,
          3.95174151e-25,   1.41113320e-27]], dtype=float32), indices=array
([[12, 25, 14, 29, 18]]))
```

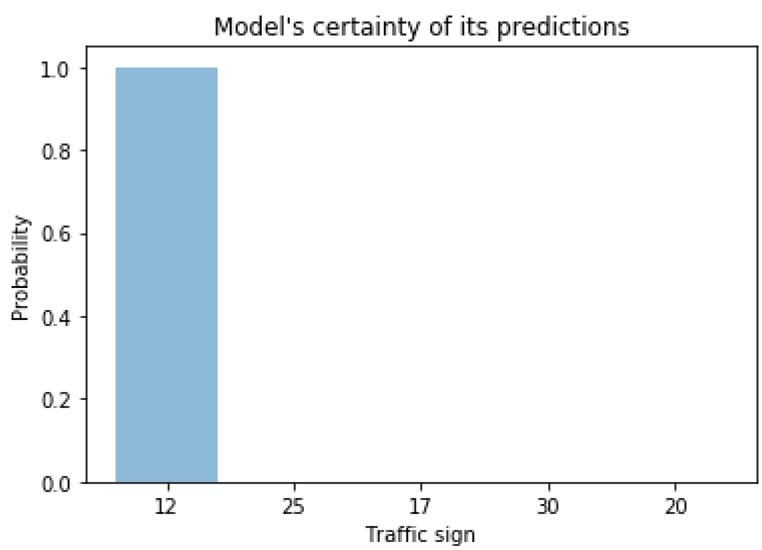



```
Traffic Sign Key
12 :  Priority road
25 :  Road work
14 :  Stop
29 :  Bicycles crossing
18 :  General caution
```

shark_sign.png

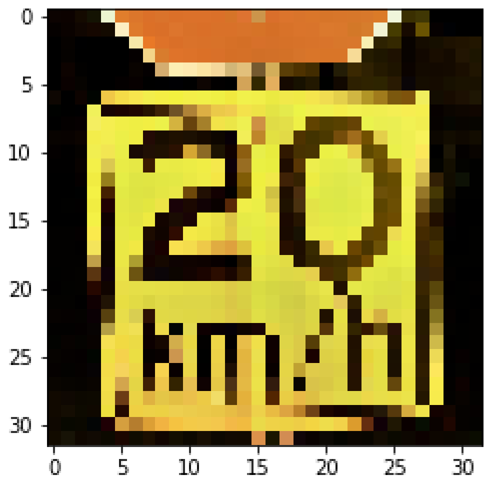



```
Top five:  TopKV2(values=array([[  1.00000000e+00,   3.56363076e-20,   4.2239
7344e-31,
          8.22733639e-33,   5.29473108e-33]], dtype=float32), indices=array
([[12, 25, 17, 30, 20]]))
```

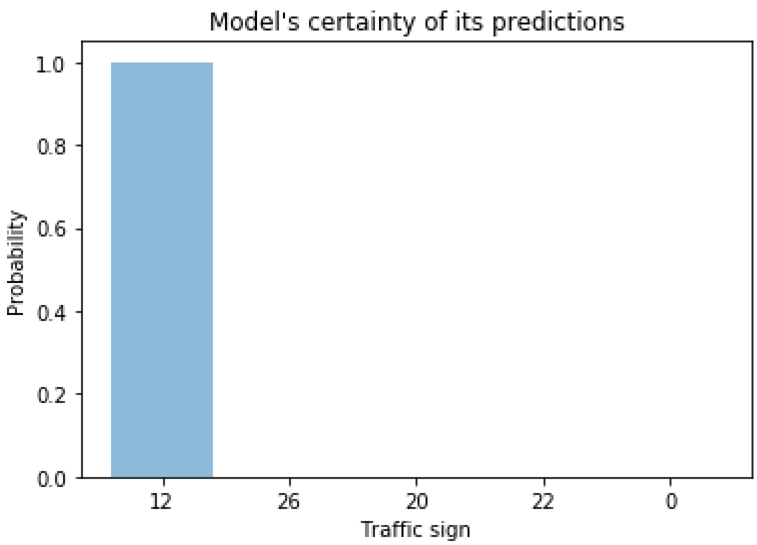



```
Traffic Sign Key
12 :  Priority road
25 :  Road work
17 :  No entry
30 :  Beware of ice/snow
20 :  Dangerous curve to the right
```

```
speed_limit_stop.png
```

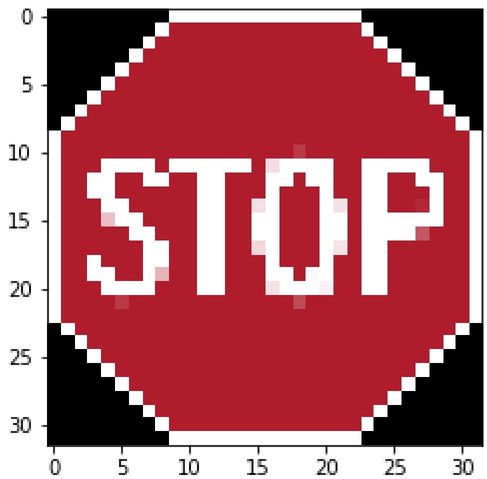


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   5.79819976e-26,   2.6442
0888e-34,
          1.73645782e-34,   0.00000000e+00]], dtype=float32), indices=array
([[12, 26, 20, 22,  0]]))
```

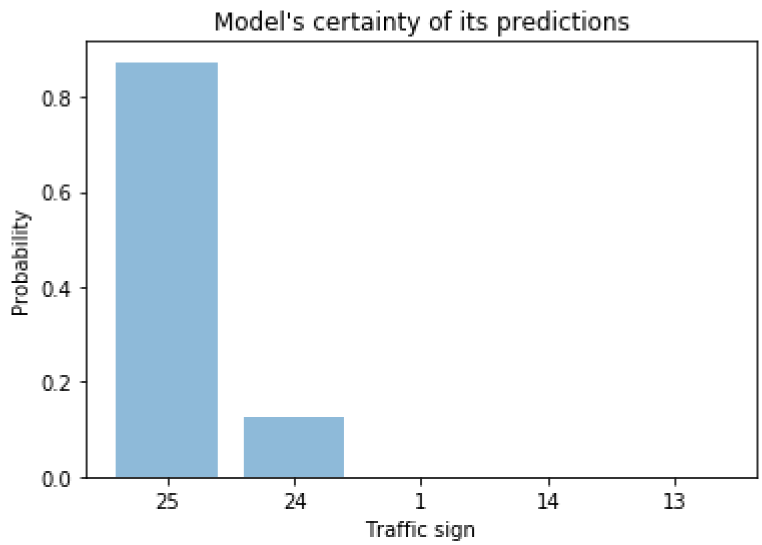



```
Traffic Sign Key
12 :  Priority road
26 :  Traffic signals
20 :  Dangerous curve to the right
22 :  Bumpy road
0 :  Speed limit (20km/h)
```

stop.png

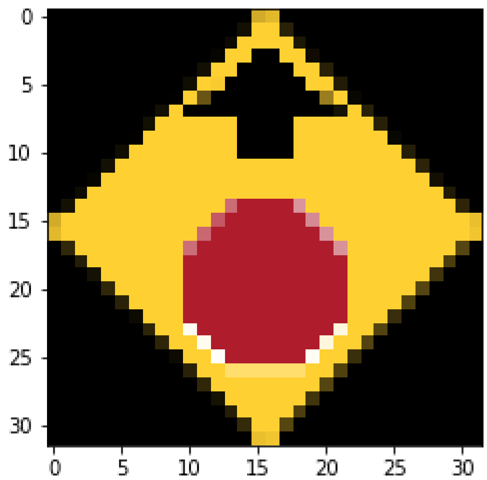


```
Top five:  TopKV2(values=array([[  8.73517990e-01,   1.26350164e-01,   1.2537
0047e-04,
          6.48536616e-06,   1.15652359e-08]], dtype=float32), indices=array
([[25, 24,  1, 14, 13]]))
```

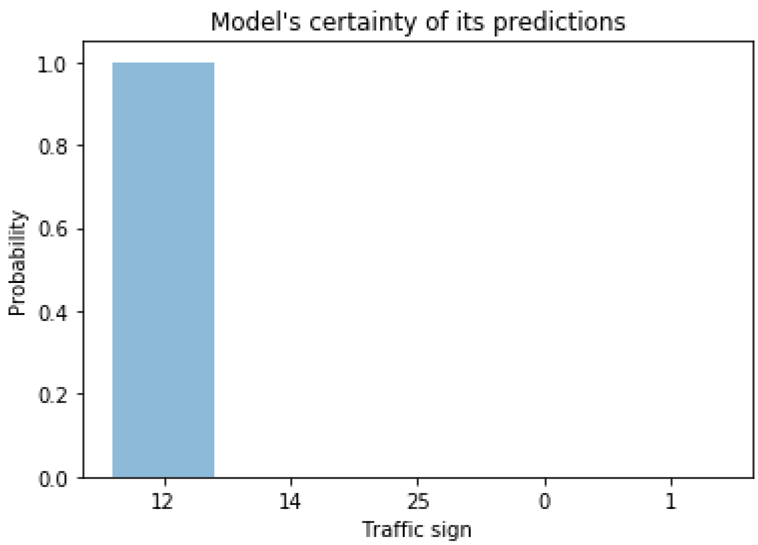



```
Traffic Sign Key
25 :  Road work
24 :  Road narrows on the right
1 :  Speed limit (30km/h)
14 :  Stop
13 :  Yield
```

StopAhead.png

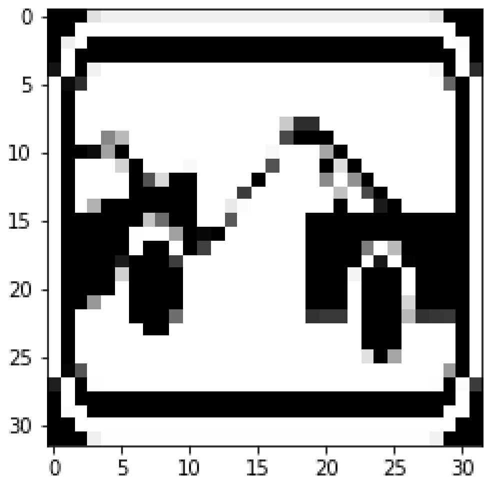



```
Top five:  TopKV2(values=array([[  1.00000000e+00,   5.42289935e-10,   1.0578
3150e-30,
          0.00000000e+00,   0.00000000e+00]], dtype=float32), indices=array
([[12, 14, 25,  0,  1]]))
```

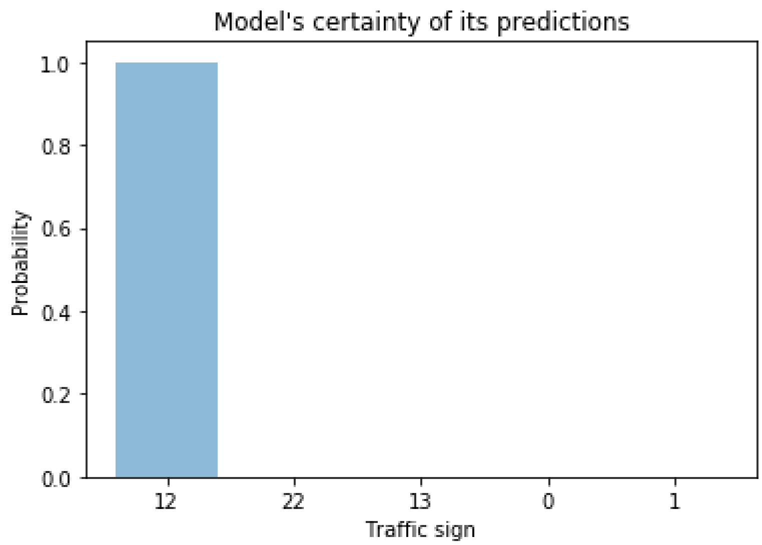



```
Traffic Sign Key
12 :  Priority road
14 :  Stop
25 :  Road work
0 :  Speed limit (20km/h)
1 :  Speed limit (30km/h)
```

TowAway.png

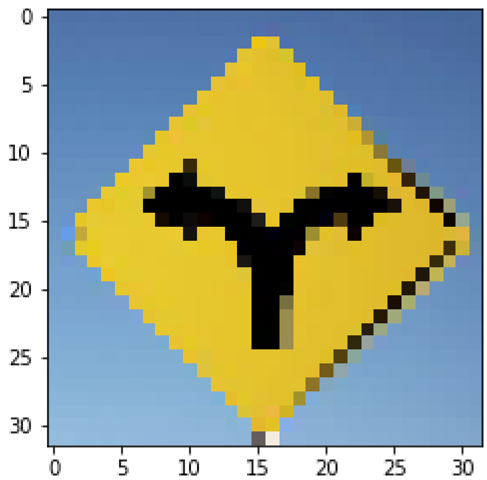



```
Top five:  TopKV2(values=array([[  1.00000000e+00,   8.72576265e-28,   5.7555
7000e-37,
          0.00000000e+00,   0.00000000e+00]], dtype=float32), indices=array
([[12, 22, 13,  0,  1]]))
```

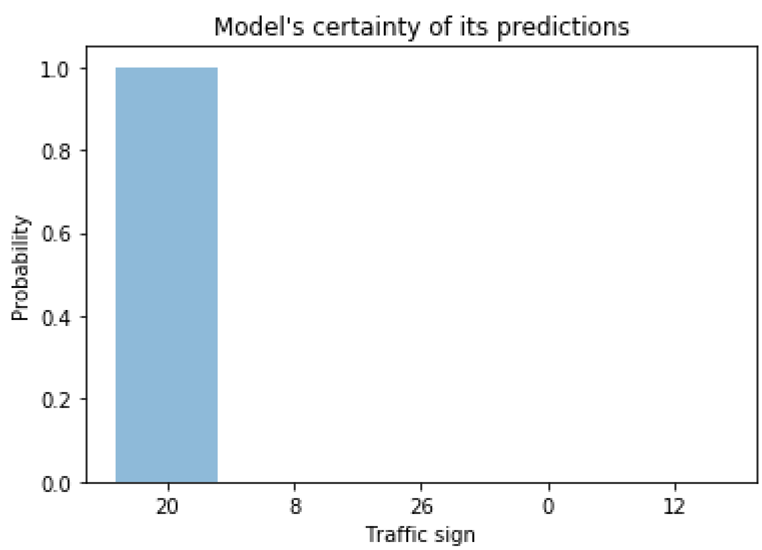



```
Traffic Sign Key
12 :  Priority road
22 :  Bumpy road
13 :  Yield
0 :  Speed limit (20km/h)
1 :  Speed limit (30km/h)
```

two_way_sign.png

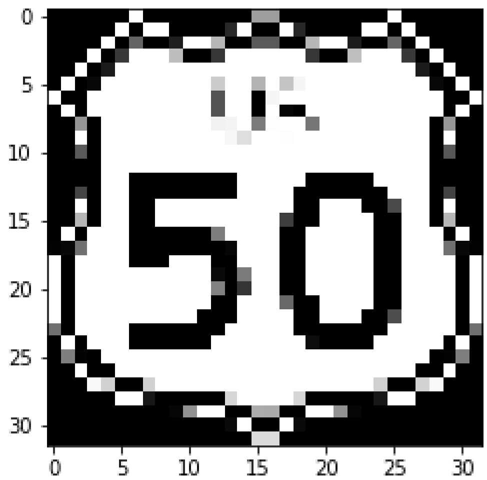


Top five: TopKV2(values=array([[1.00000000e+00,   1.29474698e-09,   2.46179077e-10,
         1.58991700e-12,   5.65064525e-22]], dtype=float32), indices=array([[20, 8, 26, 0, 12]]))

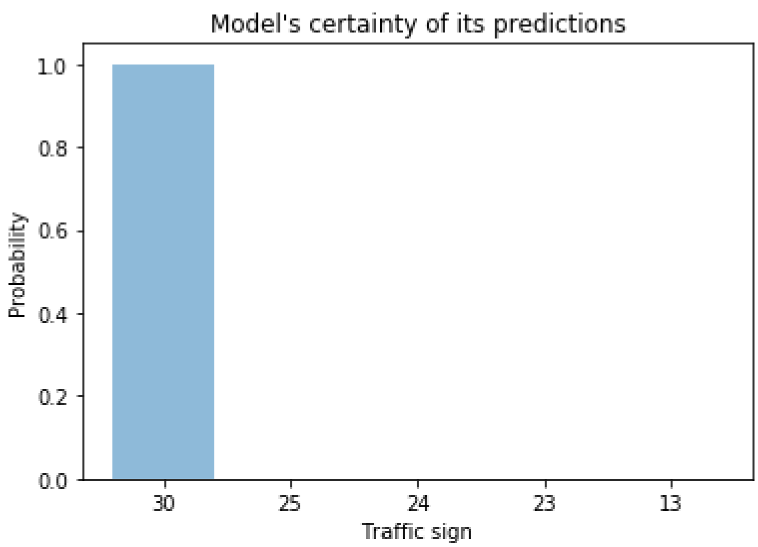


Traffic Sign Key
20 : Dangerous curve to the right
8 : Speed limit (120km/h)
26 : Traffic signals
0 : Speed limit (20km/h)
12 : Priority road

US50.png

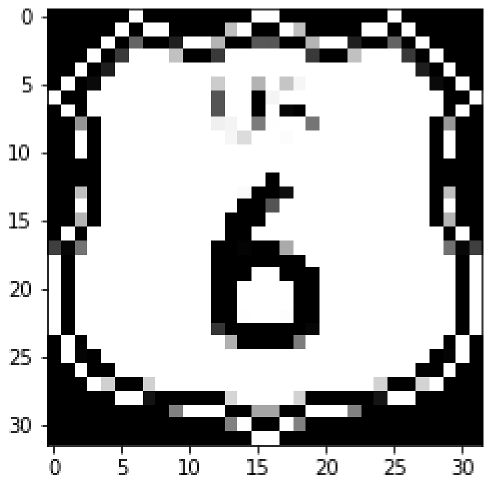



```
Top five:  TopKV2(values=array([[  1.00000000e+00,   1.77870145e-08,   9.3471
3529e-10,
          1.83235033e-13,   7.02551962e-14]], dtype=float32), indices=array
([[30, 25, 24, 23, 13]]))
```

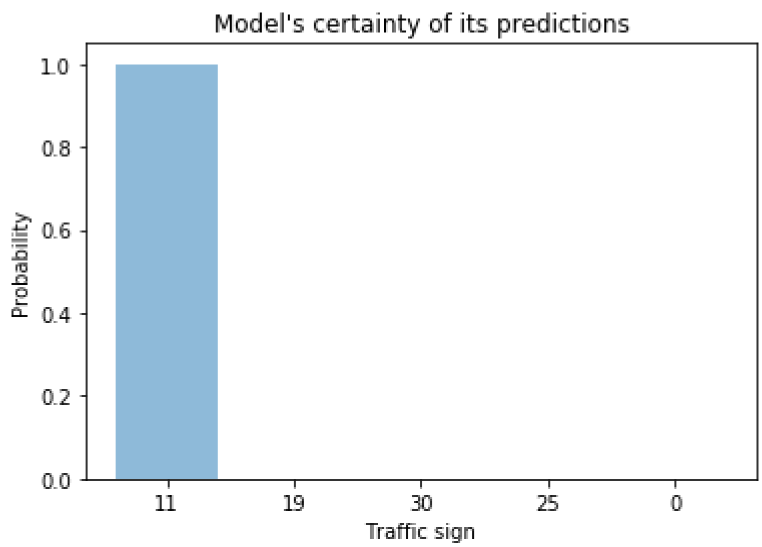



```
Traffic Sign Key
30 :  Beware of ice/snow
25 :  Road work
24 :  Road narrows on the right
23 :  Slippery road
13 :  Yield
```

US6.png

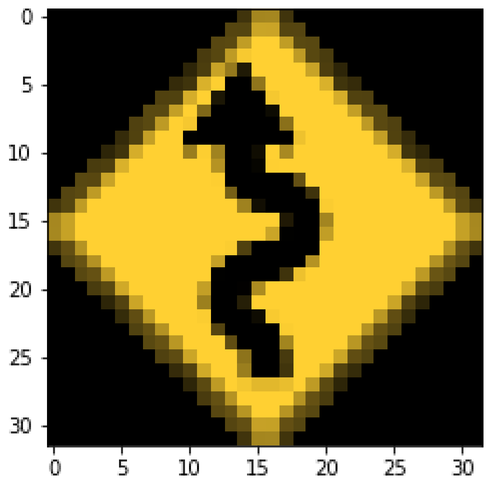



```
Top five:  TopKV2(values=array([[  1.00000000e+00,   3.07357118e-09,   1.4580
3882e-19,
          3.46409604e-28,   1.43348339e-30]], dtype=float32), indices=array
([[11, 19, 30, 25,  0]]))
```

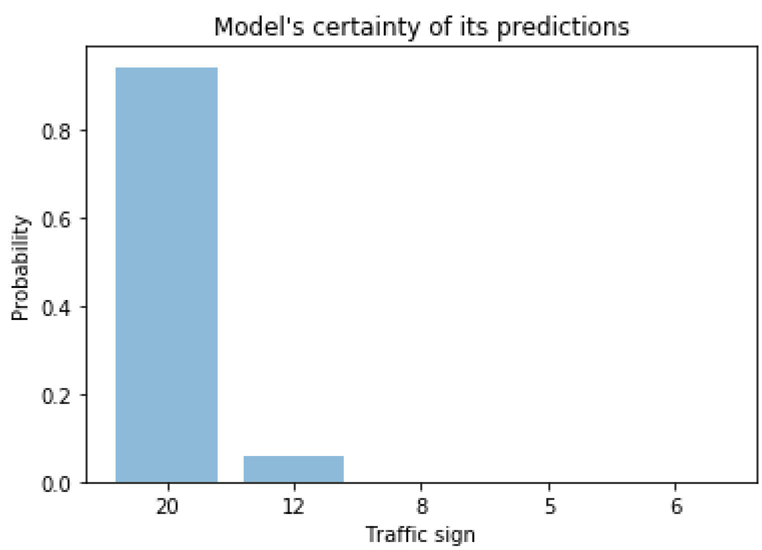



```
Traffic Sign Key
11 :  Right-of-way at the next intersection
19 :  Dangerous curve to the left
30 :  Beware of ice/snow
25 :  Road work
0 :  Speed limit (20km/h)
```

windyRight.png

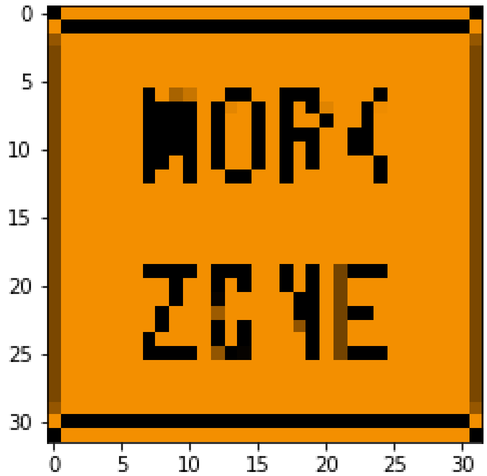


```
Top five:  TopKV2(values=array([[  9.42513764e-01,   5.74862510e-02,   5.9984
3388e-17,
          2.31940568e-24,   2.27948836e-30]], dtype=float32), indices=array
([[20, 12,  8,  5,  6]]))
```

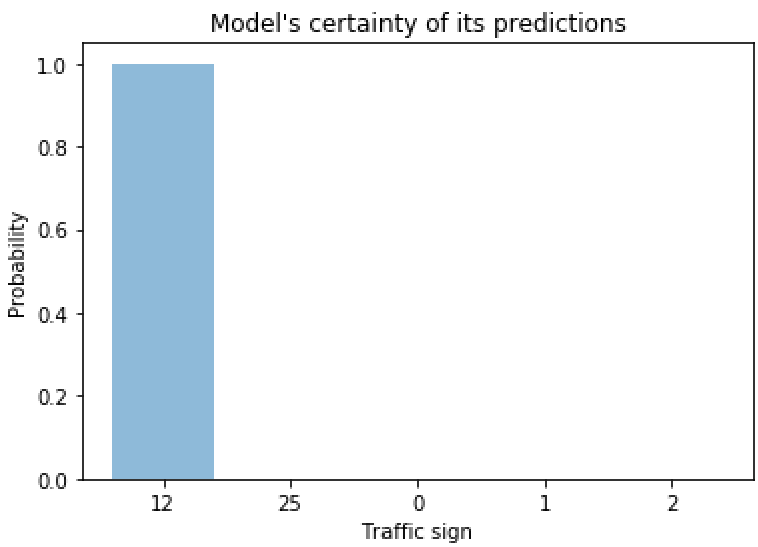


Traffic Sign Key
20 : Dangerous curve to the right
12 : Priority road
8 : Speed limit (120km/h)
5 : Speed limit (80km/h)
6 : End of speed limit (80km/h)

workzone.png

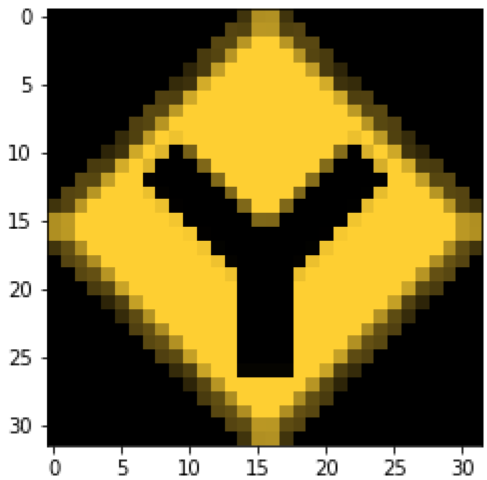


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   3.10213411e-10,   0.0000
0000e+00,
          0.00000000e+00,   0.00000000e+00]], dtype=float32), indices=array
([[12, 25,  0,  1,  2]]))
```

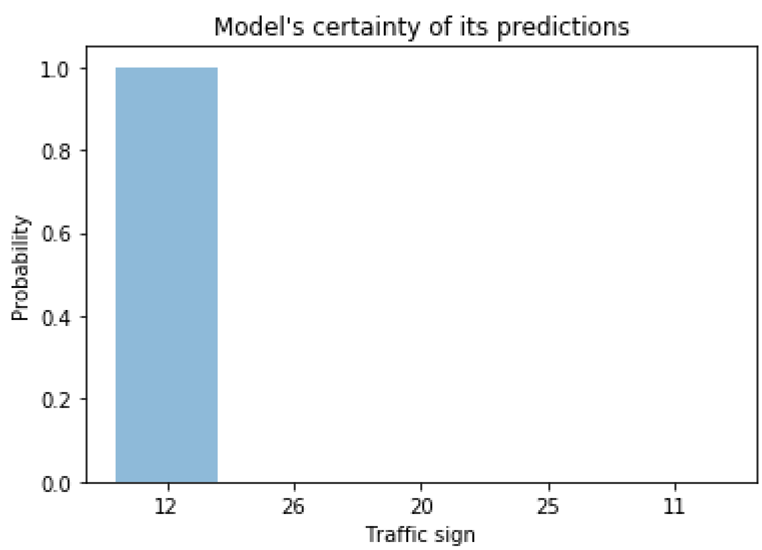



```
Traffic Sign Key
12 :  Priority road
25 :  Road work
0 :  Speed limit (20km/h)
1 :  Speed limit (30km/h)
2 :  Speed limit (50km/h)
```

YCrossing.png

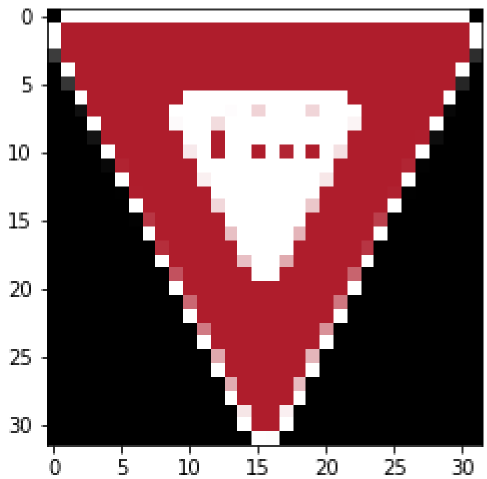


```
Top five:  TopKV2(values=array([[  1.00000000e+00,   2.00721084e-09,   2.3914
6881e-27,
          1.22845360e-32,   7.74104907e-34]], dtype=float32), indices=array
([[12, 26, 20, 25, 11]]))
```




```
Traffic Sign Key
12 :  Priority road
26 :  Traffic signals
20 :  Dangerous curve to the right
25 :  Road work
11 :  Right-of-way at the next intersection
```

yeild.png




```
Top five:  TopKV2(values=array([[ 1.,  0.,  0.,  0.,  0.]], dtype=float32), i
ndices=array([[13,  0,  1,  2,  3]]))
```


```
Traffic Sign Key
13 :  Yield
0 :  Speed limit (20km/h)
1 :  Speed limit (30km/h)
2 :  Speed limit (50km/h)
3 :  Speed limit (60km/h)
```

yield_pedestrian.png