Traffic_Sign_Classifier

March 26, 2017

In [135]:
```
# Load pickled data
import pickle, os

# TODO: Fill this in based on where you saved the training and testing da

training_file =   os.path.join(os.getcwd(), './train.p')
validation_file = os.path.join(os.getcwd(), './valid.p')
testing_file =    os.path.join(os.getcwd(), './test.p')

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

X_train, y_train = train['features'], train['labels']
X_valid, y_valid = valid['features'], valid['labels']
X_test, y_test = test['features'], test['labels']
```

In [136]:
```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import cv2
%matplotlib inline

import numpy as np
from sklearn.utils import shuffle
# Number of training examples
n_train = X_train.shape[0]
n_valid = X_valid.shape[0]
# Number of testing examples.
n_test = X_test.shape[0]

# What's the shape of an traffic sign image?
image_shape = X_train.shape[1:3]

# TODO: How many unique classes/labels there are in the dataset.
```

```
n_classes = np.unique(y_train).size

print("Number of training examples =", n_train)
print("Number of testing examples =", n_test)
print("Number of validation examples = {0}".format(n_valid))
print("Image data shape =", image_shape)
print("Number of classes =", n_classes)
```

```
Number of training examples = 34799
Number of testing examples = 12630
Number of validation examples = 4410
Image data shape = (32, 32)
Number of classes = 43
```

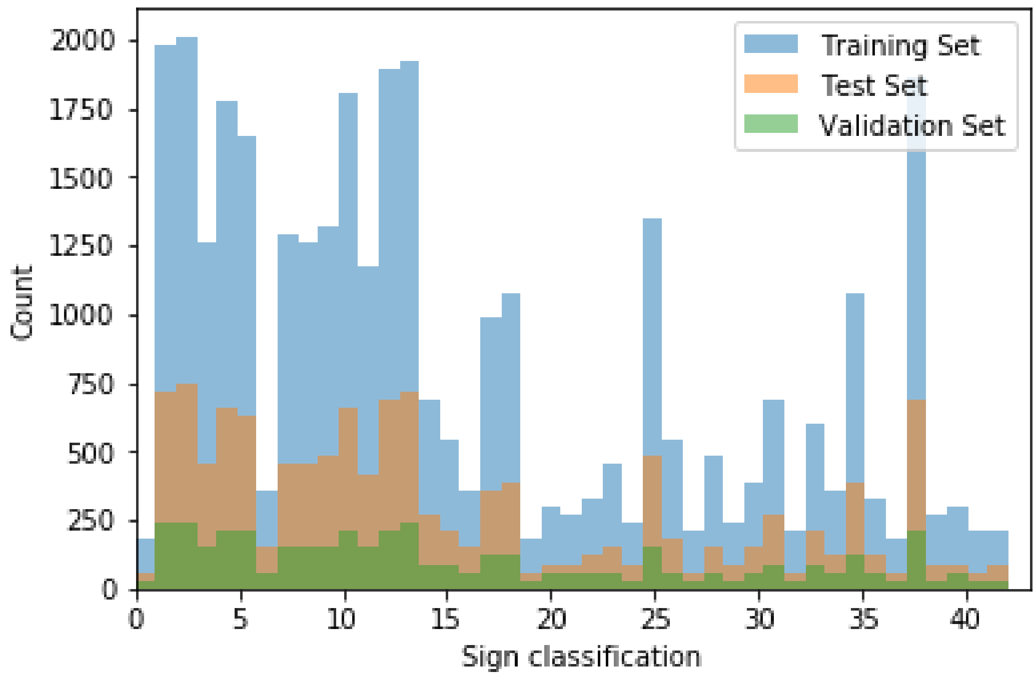
In [137]:
```
# Signnames CSV loaded to make sure sign names stay attached with data du
import pandas as pd
sign_names = pd.read_csv('signnames.csv', index_col=0)
sign_names['SignName'][0]
```

Out[137]: 'Speed limit (20km/h)'

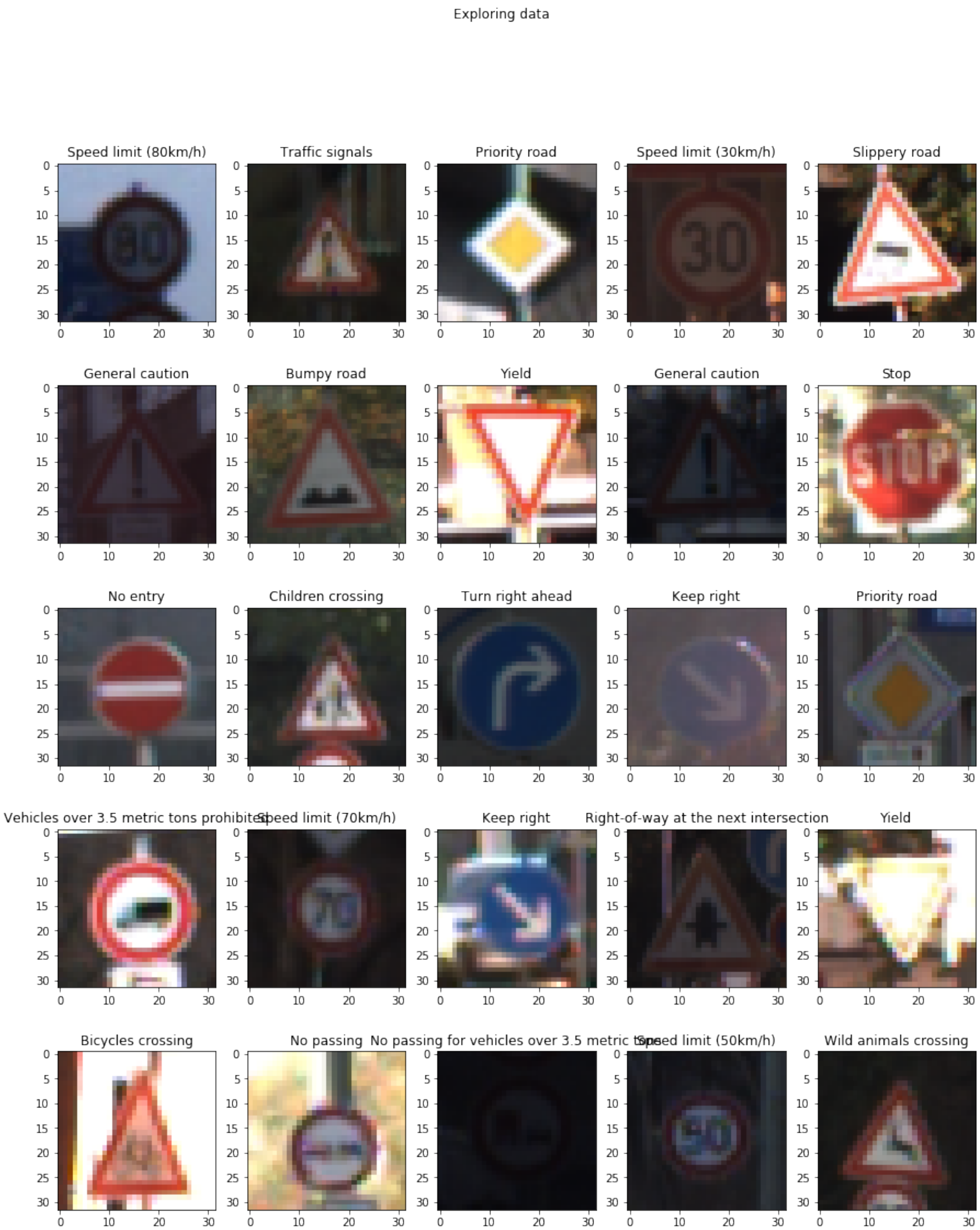
1 Data Exploration

- Data plotted to show relative number of test examples for each sign in each of training, validation, and test set.
- Datasets are not represented equally.
- Images and names of signs shown from testing and validation set

In [138]:
```
plt.hist(y_train, n_classes, alpha=0.5, label='Training Set')
plt.hist(y_test, n_classes, alpha=0.5, label='Test Set')
plt.hist(y_valid, n_classes, alpha=0.5, label='Validation Set')
plt.xlabel('Sign classification')
plt.ylabel('Count')
plt.xlim(xmin=0, xmax=n_classes)
plt.legend(loc='upper right')
plt.show()
```

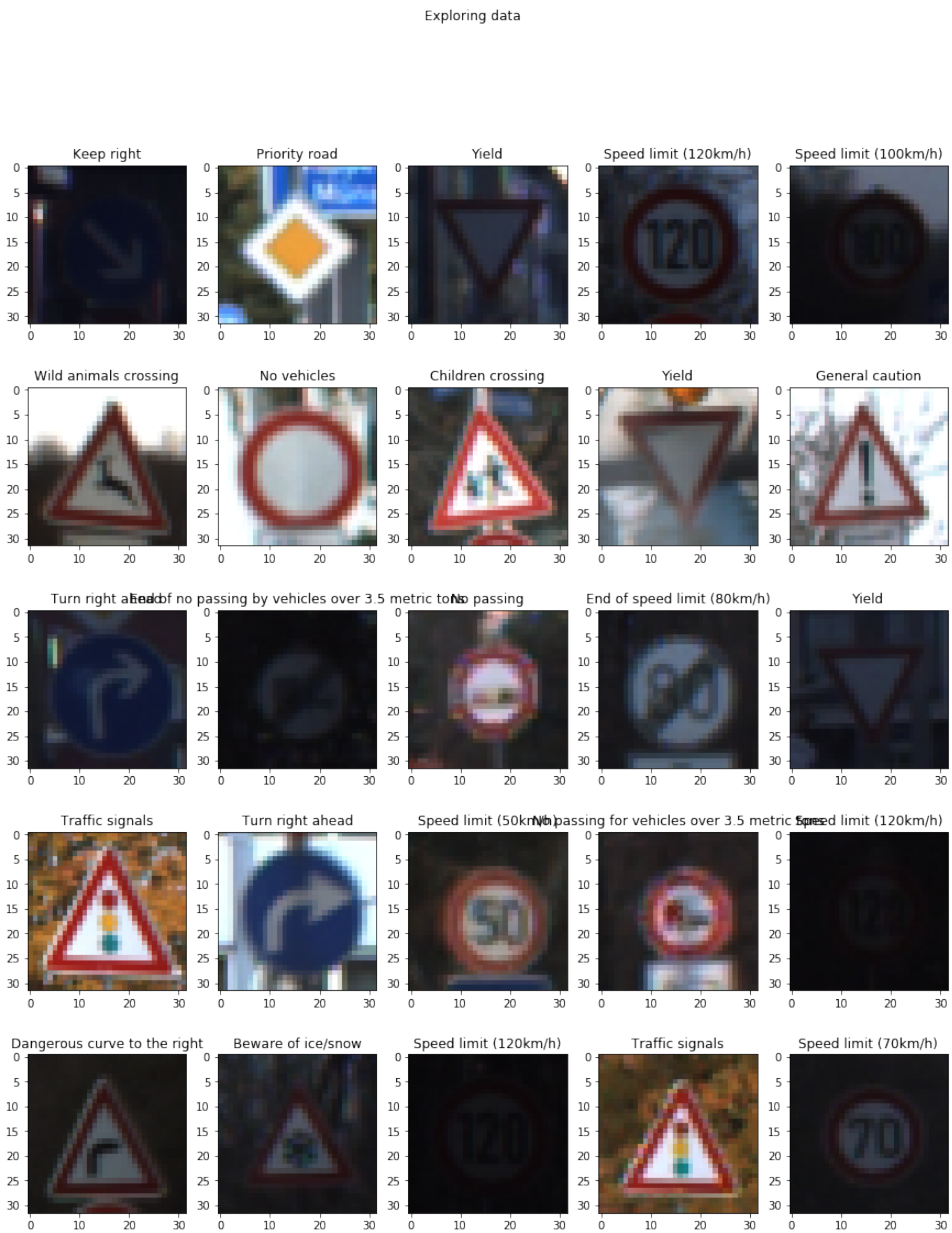



```
In [148]: X_train, y_train = shuffle(X_train, y_train)
          fig = plt.figure(figsize=(15,18))
          fig.suptitle('Exploring data')
          for i in range(1,26):
              ax = plt.subplot(5,5,i)
              ax.set_title(sign_names['SignName'][y_train[i]])
              plt.imshow(X_train[i])
          plt.show()
```




```
In [147]: X_valid, y_valid = shuffle(X_valid, y_valid)
          fig = plt.figure(figsize=(15,18))
          fig.suptitle('Exploring data')
          for i in range(1,26):
              ax = plt.subplot(5,5,i)
```

```
        ax.set_title(sign_names['SignName'][y_valid[i]])
        plt.imshow(X_valid[i])
    plt.show()
```



2 Data Amplification

1. Rotation
2. Histogram equalization (enhance contrast)
3. Contrast limited adaptive histogram equalization image contrast
4. Conorm (enhance edge with difference of gaussian)

2.1 Rotation +/- 5 degrees

- Traffic signs may not be oriented the same as in the training images.
- Images show greater rotation for visual clarity, smaller angles expected in real world
- Border mode changed from constant (black) to replicate. I expect the large shift in color from constant border could impact gradients at the edges and confuse the model.

```
In [149]: def rotate_images(X, deg):
              rows, cols = X.shape[1], X.shape[2]
              M_pos = cv2.getRotationMatrix2D((rows//2, cols//2), deg, 1)
              M_neg = cv2.getRotationMatrix2D((rows//2, cols//2), -1*deg, 1)
              X_rot_pos = np.copy(X)
              X_rot_neg = np.copy(X)
              for i in range(X.shape[0]):
                  X_rot_pos[i] = cv2.warpAffine(X[i], M_pos, (rows, cols), borderMo
                  X_rot_neg[i] = cv2.warpAffine(X[i], M_neg, (rows, cols), borderMo
              print('Dataset rotated +/-{0} degrees.'.format(deg))
              return X_rot_pos, X_rot_neg
```

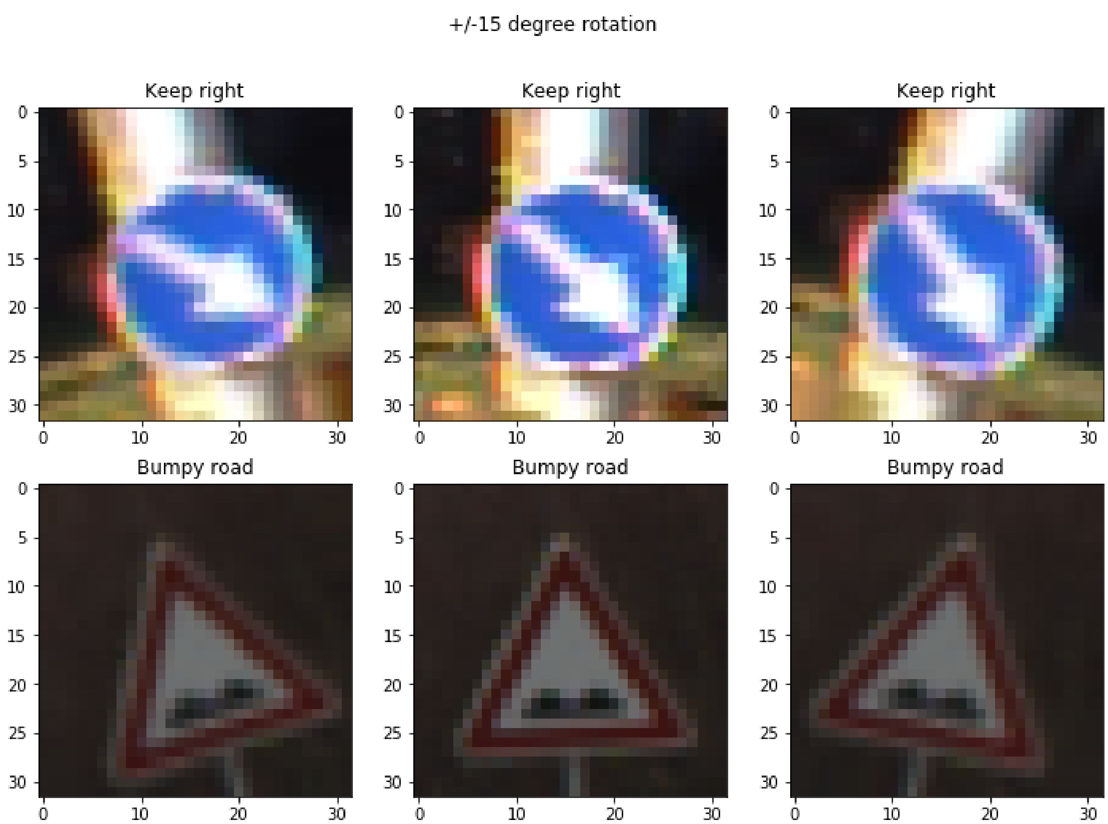
```
In [150]: def rotate_images_black(X, deg):
              rows, cols = X.shape[1], X.shape[2]
              M_pos = cv2.getRotationMatrix2D((rows//2, cols//2), deg, 1)
              M_neg = cv2.getRotationMatrix2D((rows//2, cols//2), -1*deg, 1)
              X_rot_pos = np.copy(X)
              X_rot_neg = np.copy(X)
              for i in range(X.shape[0]):
                  X_rot_pos[i] = cv2.warpAffine(X[i], M_pos, (rows, cols))
                  X_rot_neg[i] = cv2.warpAffine(X[i], M_neg, (rows, cols))
              print('Dataset rotated +/-{0} degrees.'.format(deg))
              return X_rot_pos, X_rot_neg
```

2.1.1 Replicated border

```
In [151]: degrees = 15
          X_pos, X_neg = rotate_images(X_train, degrees)
          X_train, y_train, X_pos, X_neg = shuffle(X_train, y_train, X_pos, X_neg)
          fig = plt.figure(figsize=(12,8))
          fig.suptitle('+/-{0} degree rotation'.format(degrees))

          ax1 = plt.subplot(231)
          ax1.set_title(sign_names['SignName'][y_train[0]])
          plt.imshow(X_pos[0])
```

```
ax2 = plt.subplot(232)
ax2.set_title(sign_names['SignName'][y_train[0]])
plt.imshow(X_train[0])

ax3 = plt.subplot(233)
ax3.set_title(sign_names['SignName'][y_train[0]])
plt.imshow(X_neg[0])

ax4 = plt.subplot(234)
ax4.set_title(sign_names['SignName'][y_train[1]])
plt.imshow(X_pos[1])

ax5 = plt.subplot(235)
ax5.set_title(sign_names['SignName'][y_train[1]])
plt.imshow(X_train[1])

ax6 = plt.subplot(236)
ax6.set_title(sign_names['SignName'][y_train[1]])
plt.imshow(X_neg[1])
plt.show()
```

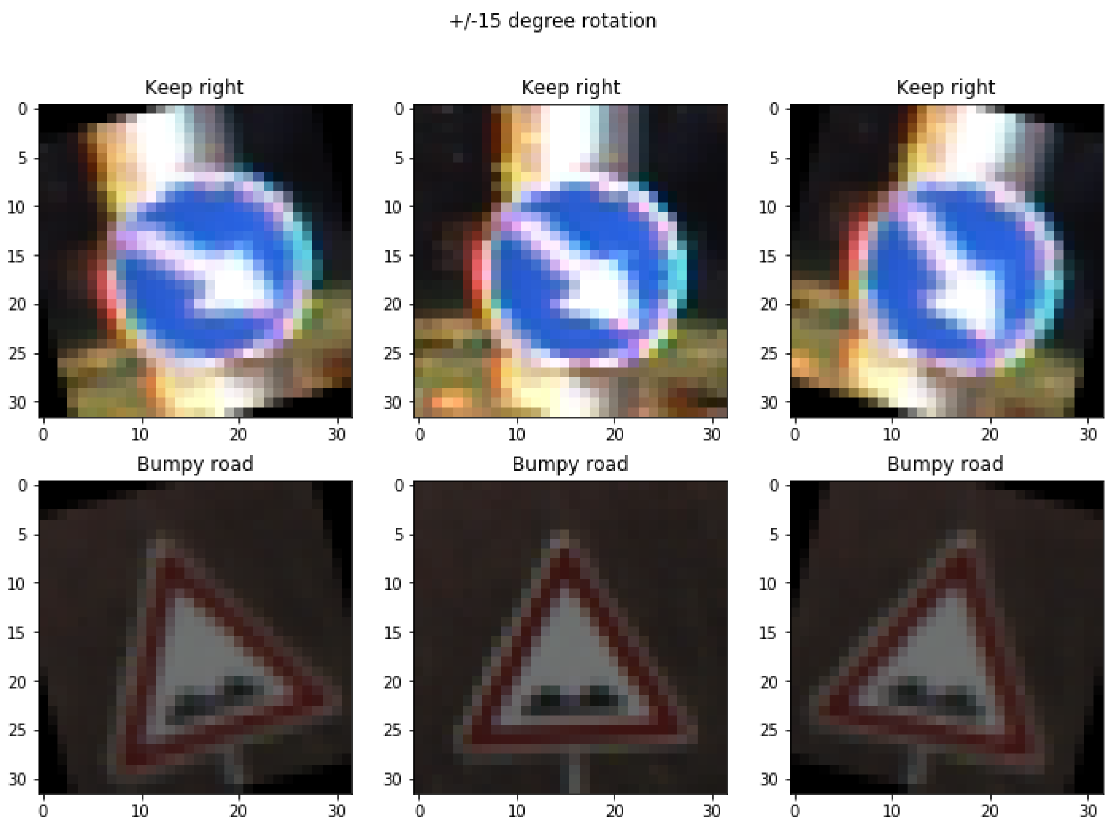
Dataset rotated +/-15 degrees.



2.1.2 Constant border

```
In [152]: degrees = 15
          X_pos, X_neg = rotate_images_black(X_train, degrees)
          fig = plt.figure(figsize=(12,8))
          fig.suptitle('+/-{0} degree rotation'.format(degrees))

          ax1 = plt.subplot(231)
          ax1.set_title(sign_names['SignName'][y_train[0]])
          plt.imshow(X_pos[0])

          ax2 = plt.subplot(232)
          ax2.set_title(sign_names['SignName'][y_train[0]])
          plt.imshow(X_train[0])

          ax3 = plt.subplot(233)
          ax3.set_title(sign_names['SignName'][y_train[0]])
          plt.imshow(X_neg[0])

          ax4 = plt.subplot(234)
          ax4.set_title(sign_names['SignName'][y_train[1]])
          plt.imshow(X_pos[1])

          ax5 = plt.subplot(235)
          ax5.set_title(sign_names['SignName'][y_train[1]])
          plt.imshow(X_train[1])

          ax6 = plt.subplot(236)
          ax6.set_title(sign_names['SignName'][y_train[1]])
          plt.imshow(X_neg[1])
          plt.show()
```

```
Dataset rotated +/-15 degrees.
```



2.2 Increase image contrast

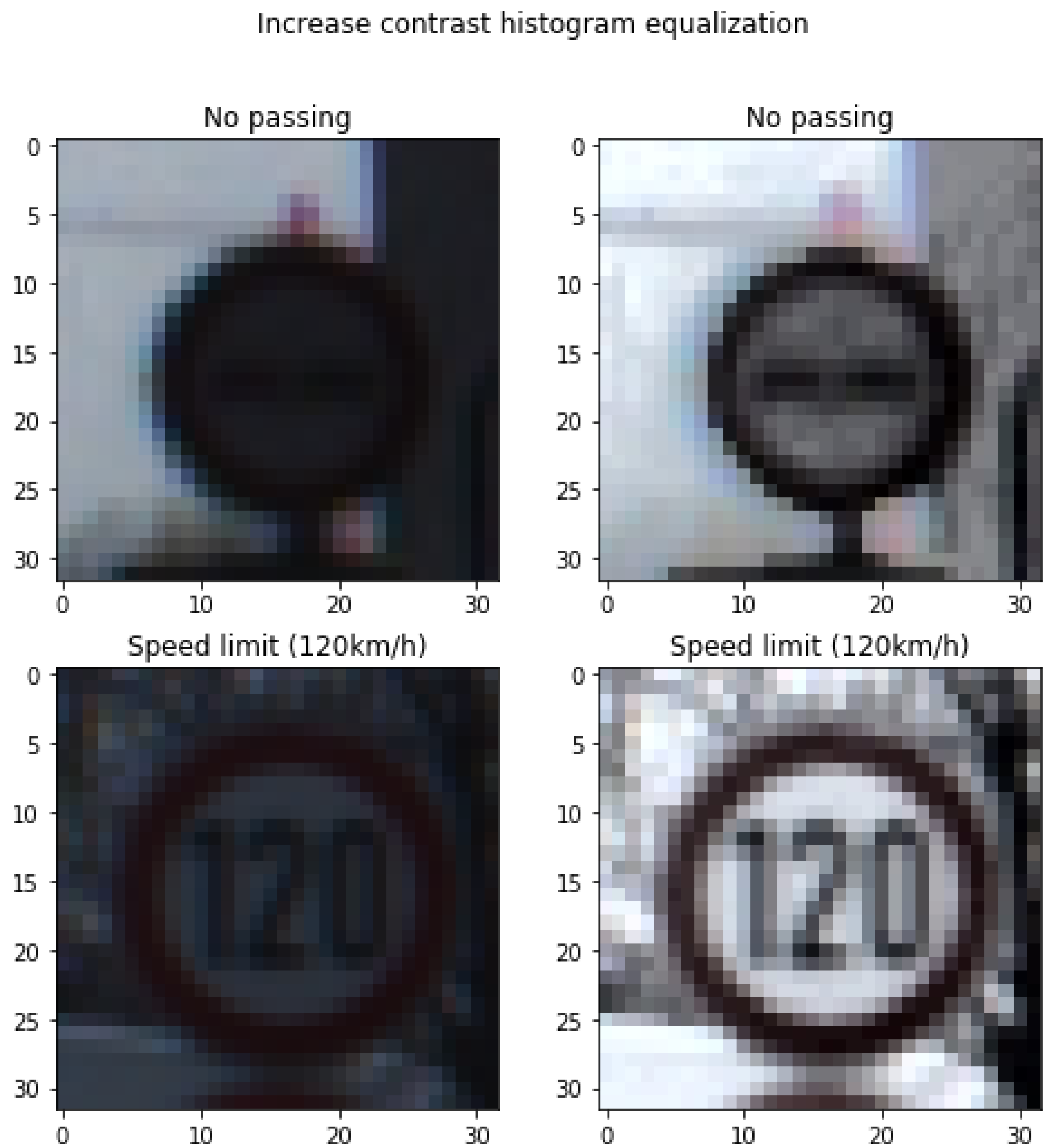
- Histogram equalization is used to increase contrast in image
- Color historgram equalization achieved by equalizing Y channel of YCrCb colorspace

```
In [153]: def amplify_contrast(X):
              X_eq = np.copy(X)
              for i in range(X.shape[0]):
                  YCrCb = cv2.cvtColor(X[i], cv2.COLOR_RGB2YCrCb)
                  Y, Cr, Cb = cv2.split(YCrCb)
                  Y_eq = cv2.equalizeHist(Y)
                  YCrCb_eq = cv2.merge((Y_eq, Cr, Cb))
                  X_eq[i] = cv2.cvtColor(YCrCb_eq, cv2.COLOR_YCrCb2RGB)
              print('Dataset histogram equalized')
              return X_eq
```

```
In [156]: X_histeq = amplify_contrast(X_train)
          X_train, y_train, X_histeq = shuffle(X_train, y_train, X_histeq)
          fig = plt.figure(figsize=(8,8))
          fig.suptitle('Increase contrast histogram equalization')
          ax1 = plt.subplot(221)
```

```
    ax1.set_title(sign_names['SignName'][y_train[0]])
    plt.imshow(X_train[0])

    ax2 = plt.subplot(222)
    ax2.set_title(sign_names['SignName'][y_train[0]])
    plt.imshow(X_histeq[0])

    ax3 = plt.subplot(223)
    ax3.set_title(sign_names['SignName'][y_train[1]])
    plt.imshow(X_train[1])

    ax4 = plt.subplot(224)
    ax4.set_title(sign_names['SignName'][y_train[1]])
    plt.imshow(X_histeq[1])
    plt.show()
```

```
Dataset histogram equalized
```



2.3 Increase image contrast (Area)

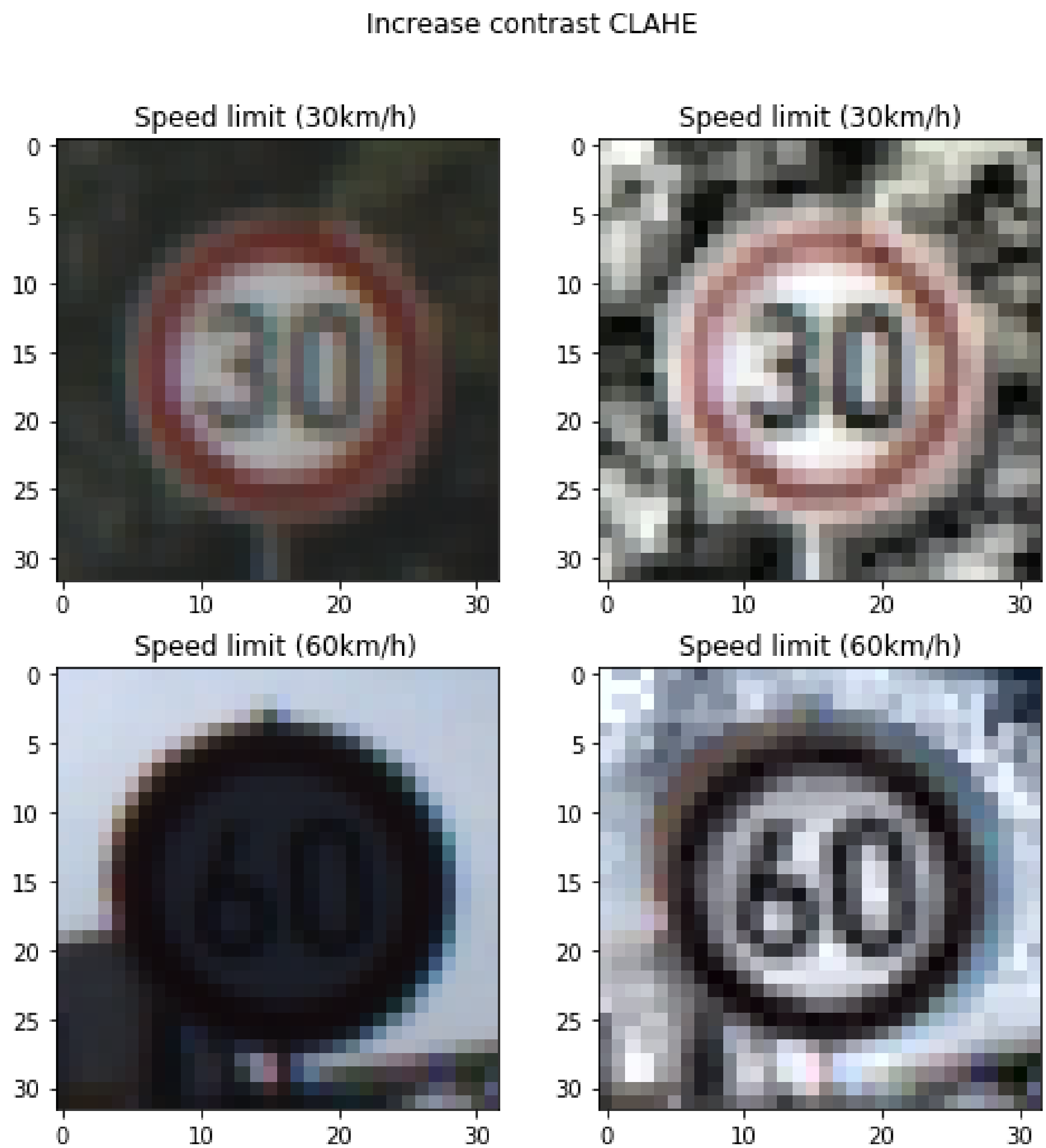
- Adaptive contrast limited histogram equalization is used to increase contrast in image
- Different from histogram equalization in that it looks at blocks of pixels.
- Color historgram equalization achieved by equalizing Y channel of YCrCb colorspace

```
In [157]: def clahe_contrast(X):
              X_clahe = np.copy(X)
              clahe = cv2.createCLAHE(tileGridSize=(4,4))
              for i in range(X.shape[0]):
```

```
                YCrCb = cv2.cvtColor(X[i], cv2.COLOR_RGB2YCrCb)
                Y, Cr, Cb = cv2.split(YCrCb)
                Y_clahe = clahe.apply(Y)
                YCrCb_clahe = cv2.merge((Y_clahe, Cr, Cb))
                X_clahe[i] = cv2.cvtColor(YCrCb_clahe, cv2.COLOR_YCrCb2RGB)
            print('Dataset histogram equalized clahe')
            return X_clahe
```

In [165]:
```
X_clahe = clahe_contrast(X_train)
X_train, y_train, X_clahe = shuffle(X_train, y_train, X_clahe)
fig = plt.figure(figsize=(8,8))
fig.suptitle('Increase contrast CLAHE')

ax1 = plt.subplot(221)
ax1.set_title(sign_names['SignName'][y_train[0]])
plt.imshow(X_train[0])

ax2 = plt.subplot(222)
ax2.set_title(sign_names['SignName'][y_train[0]])
plt.imshow(X_clahe[0])

ax3 = plt.subplot(223)
ax3.set_title(sign_names['SignName'][y_train[1]])
plt.imshow(X_train[1])

ax4 = plt.subplot(224)
ax4.set_title(sign_names['SignName'][y_train[1]])
plt.imshow(X_clahe[1])
plt.show()
```

```
Dataset histogram equalized clahe
```



2.4 Contrast Normalization

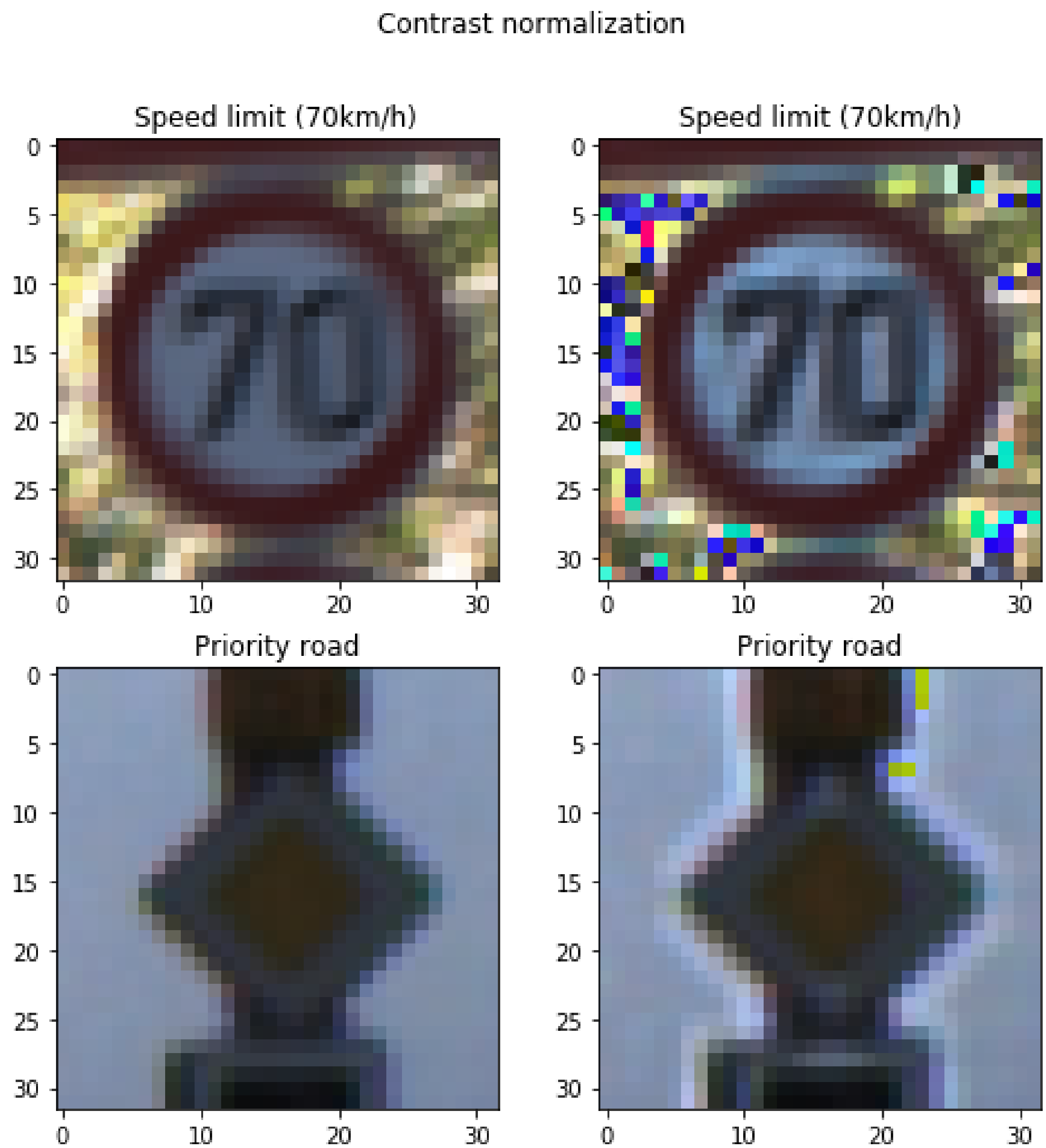
- Use a difference of gaussian to amplify edges
- Obtained by convolving a difference of gaussians on the image and adding that to the image
- Based on Sermanet Lecun 2011
- Can lead to artifacts in color images. I don't understand why that is, so I'm not including this algorithm

```
In [166]: def contrast_normalization(X):
              X_conorm = np.copy(X)
```

```
        gauss_1 = cv2.getGaussianKernel(5, 1) + np.transpose(cv2.getGaussianK
        gauss_2 = cv2.getGaussianKernel(5, 3) + np.transpose(cv2.getGaussianK
        diff_gauss = gauss_1 - gauss_2
        for i in range(X.shape[0]):
            X_conorm[i] = X[i] + cv2.filter2D(X[i], -1, diff_gauss)
        print('Contrast normalized')
        return X_conorm
```

In [183]:
```
X_conorm = contrast_normalization(X_train)
X_train, y_train, X_conorm = shuffle(X_train, y_train, X_conorm)
fig = plt.figure(figsize=(8,8))
fig.suptitle('Contrast normalization')

ax1 = plt.subplot(221)
ax1.set_title(sign_names['SignName'][y_train[0]])
plt.imshow(X_train[0])

ax2 = plt.subplot(222)
ax2.set_title(sign_names['SignName'][y_train[0]])
plt.imshow(X_conorm[0])

ax3 = plt.subplot(223)
ax3.set_title(sign_names['SignName'][y_train[1]])
plt.imshow(X_train[1])

ax4 = plt.subplot(224)
ax4.set_title(sign_names['SignName'][y_train[1]])
plt.imshow(X_conorm[1])
plt.show()
```

```
Contrast normalized
```



In [184]:
```
# Note contrast normalization removed. It doesn't look like it's working
def amplify_dataset(X, y):
    X_rot_pos, X_rot_neg = rotate_images(X, 5)
    X = np.concatenate((X, X_rot_neg, X_rot_pos), axis=0)
    y = np.concatenate((y, y, y), axis=0)

    X_histeq = amplify_contrast(X)
    X_clahe = clahe_contrast(X)
    X_conorm = contrast_normalization(X)
    X = np.concatenate((X, X_histeq, X_clahe), axis=0)
```

```
        y = np.concatenate((y, y, y), axis=0)
        print('Number of examples increased to {0}'.format(X.shape[0]))
        return X, y
```

```
In [185]: X_train, y_train = amplify_dataset(X_train, y_train)
```

```
Dataset rotated +/-5 degrees.
Dataset histogram equalized
Dataset histogram equalized clahe
Contrast normalized
Number of examples increased to 313191
```

3 Preprocess Data

- Performed on training, validation and test data.
- Grayscale images to reduce the number of parameters.
- Sermanet Lecun 2011 found color didn't improve accuracy a lot. Prior models run with color agreed with this.
- Data is normalized by subtracting the mean image and normalizing following common best practices in order to keep our features in a consistent range. This will reduce the likelihood of our gradients getting out of control through vanishing gradient / saturating neurons in the network

```
In [186]: def grayscale(X):
              X_gray = np.copy(X[:,:,:,0])
              for i in range(X.shape[0]):
                  X_gray[i] = cv2.cvtColor(X[i], cv2.COLOR_RGB2GRAY)
              return X_gray
```

```
In [187]: #Normalize the data
          def normalize(X):
              X = X.astype('float64') - np.mean(X, axis=0)
              X /= np.std(X, axis=0)
              return X
```

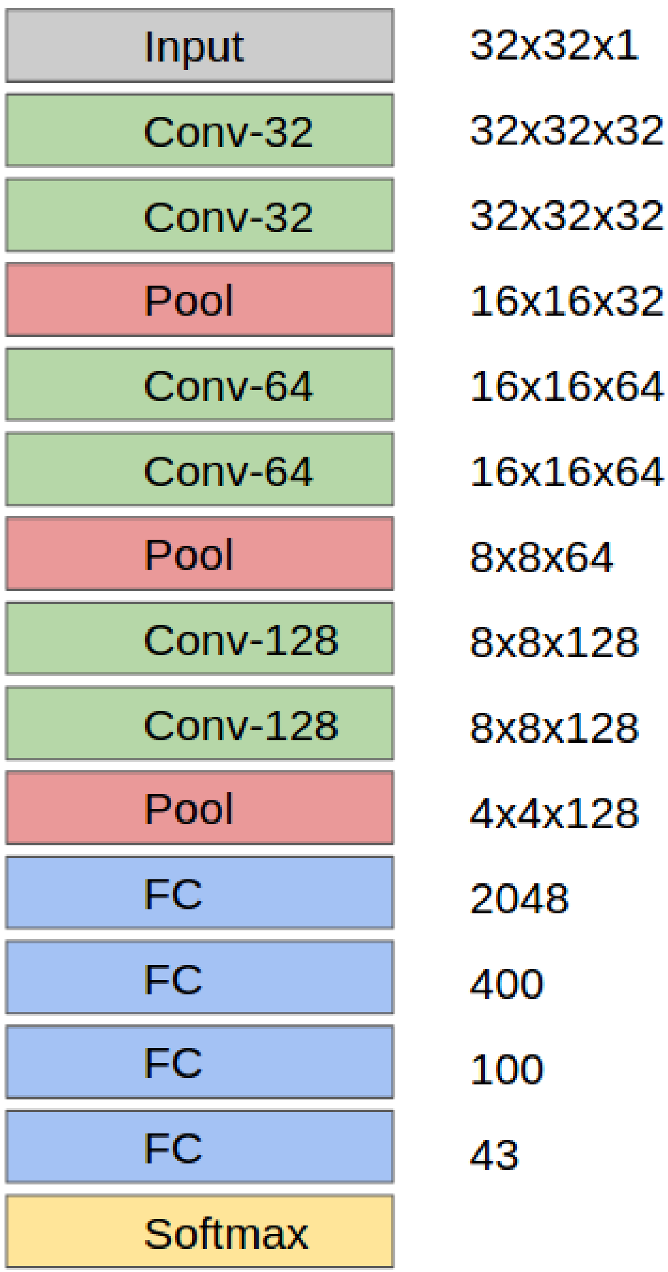
```
In [188]: def preprocess(X):
              X_gray = grayscale(X)
              X_norm = normalize(X_gray)
              return X_norm
```

```
In [189]: X_train = preprocess(X_train)
          X_valid = preprocess(X_valid)
          X_test = preprocess(X_test)
```

3.1 Model Architecture

1. Follows similar structure to Ciresan et al 2012

2. Consists of 3 sets of two convolutional layers with ReLU activation functions and a pooling layer
3. Same padding used to limit reduction in image size since starting image size was smaller than paper
4. A fully connected layer is followed by a dropout layer.
5. Dropout is used for regularization to reduce overfitting of the model.
6. Two more hidden layers are used before the final output layer
7. The exact shape of every layer is in the picture below



In [13]:
```
import tensorflow as tf
print(tf.__version__)
```

```
1.0.0
```

```
In [17]: def weight_variable(shape):
             return tf.Variable(tf.truncated_normal(shape, mean=0.01, stddev=0.1))
         def bias_variable(shape):
             return tf.Variable(tf.zeros(shape=shape))
```

```
In [18]: def conv2d(x, W):
             return tf.nn.conv2d(x, W, strides=[1,1,1,1], padding='VALID')
         def conv2d_same(x, W):
             return tf.nn.conv2d(x, W, strides=[1,1,1,1], padding='SAME')
         def max_pool(x):
             return tf.nn.max_pool(x, ksize=[1,2,2,1],strides=[1,2,2,1],
                                   padding='VALID')
```

3.2 Train, Validate and Test the Model

A validation set can be used to assess how well the model is performing. A low accuracy on the training and validation sets imply underfitting. A high accuracy on the training set but low accuracy on the validation set implies overfitting.

1. Learning rate set to 1e-4. The learning rate of Adam decays over time and adjusts based on the gradient of the variables with momentum.
2. Adam Optimizer adjusts the learning rate using the Adam algorithm This optimizer is derived from Adagrad an adaptive learning algorithm. The algorithm monotonically reduces its learning rate over time. RMSProp improved on this by using a moving average of gradients to reduce the aggressiveness of Adagrad. Adam improved on RMSProp by adding momentum. The default momentum and decay rate are used from tensorflow.
3. A batch size of 64 is a function of using a large VGG-like architecture and having an older GPU. The first LeNet-like architecture had a batch size of 512.
4. Dropout parameter of 0.5 is used as a default because it works Srivastava et al 2014 supposedly because it maximizes the regularization value of the dropout layer.
5. Based on VGGNet
6. The number of epochs was set to 1000 originally. This is because it was a large number at which point it seemed like the loss had reached a plateau. When training multiple networks 500 was used because it took a long time and graphs of validation accuracy of the prior run had plateued around then.

```
In [19]: def SketchNet(input_layer, dropout, num_classes=43):
             ''' Neural Network modeled on VGG Net and scaled down for my machine.
             Params: input_layer:  4D tensor holding 32x32 grayscale images
                     dropout:      Fraction of neurons to kill during training usi
                     num_classes:  Number of discrete classes this network will pre
             '''
         #     depth = [1, 6, 16, 400, 160, 96, num_classes]
             input_layer = tf.reshape(x, [-1,32,32, 1])
             print('Layer 0 Init: Shape {}'.format(input_layer.get_shape()))

             F_w_1 = weight_variable([5,5,1,32])
```

```
F_b_1 = bias_variable([32])
conv_1 = tf.nn.relu(conv2d_same(input_layer, F_w_1) + F_b_1)
print('Layer 1 Convolution: Shape {}'.format(conv_1.get_shape()))
F_w_2 = weight_variable([3,3,32,32])
F_b_2 = bias_variable([32])
conv_2 = tf.nn.relu(conv2d_same(conv_1, F_w_2) + F_b_2)
print('Layer 2 Convolution: Shape {}'.format(conv_2.get_shape()))
pool_1 = max_pool(conv_2)
print('Layer 3 Pooling: Shape {}'.format(pool_1.get_shape()))

F_w_3 = weight_variable([3,3,32,64])
F_b_3 = bias_variable([64])
conv_3 = tf.nn.relu(conv2d_same(pool_1, F_w_3) + F_b_3)
print('Layer 4 Convolution: Shape {}'.format(conv_3.get_shape()))
F_w_4 = weight_variable([3,3,64,64])
F_b_4 = bias_variable([64])
conv_4 = tf.nn.relu(conv2d_same(conv_3, F_w_4) + F_b_4)
print('Layer 5 Convolution: Shape {}'.format(conv_4.get_shape()))
pool_2 = max_pool(conv_4)
print('Layer 6 Pooling: Shape {}'.format(pool_2.get_shape()))

F_w_5 = weight_variable([3,3,64,128])
F_b_5 = bias_variable([128])
conv_5 = tf.nn.relu(conv2d_same(pool_2, F_w_5) + F_b_5)
print('Layer 7 Convolution: Shape {}'.format(conv_5.get_shape()))
F_w_6 = weight_variable([3,3,128,128])
F_b_6 = bias_variable([128])
conv_6 = tf.nn.relu(conv2d_same(conv_5, F_w_6) + F_b_6)
print('Layer 8 Convolution: Shape {}'.format(conv_6.get_shape()))
pool_3 = max_pool(conv_6)
print('Layer 9 Pooling: Shape {}'.format(pool_3.get_shape()))

dense_1 = tf.contrib.layers.flatten(pool_3)
print('Layer 10 Flatten: Shape {}'.format(dense_1.get_shape()))

drop_1 = tf.nn.dropout(dense_1, dropout)

F_w_7 = weight_variable([2048, 400])
F_b_7 = bias_variable([400])
dense_2 = tf.nn.relu(tf.matmul(drop_1, F_w_7) + F_b_7)
print('Layer 11 Matrix Multiplication: Shape {}'.format(dense_2.get_sh

F_w_8 = weight_variable([400, 100])
F_b_8 = bias_variable([100])
dense_3 = tf.nn.relu(tf.matmul(dense_2, F_w_8) + F_b_8)
print('Layer 12 Matrix Multiplication: Shape {}'.format(dense_3.get_sh

F_w_9 = weight_variable([100, n_classes])
```

```
        F_b_9 = bias_variable([n_classes])
        logits = tf.nn.relu(tf.matmul(dense_3, F_w_9) + F_b_9)
        print('Final Layer Matrix Multiplication: Shape {}'.format(logits.get_

        return logits
```

```
In [20]: tf.reset_default_graph()
         x = tf.placeholder(tf.float32, (None, 32, 32))
         y = tf.placeholder(tf.int32, (None))
         keep_prob = tf.placeholder(tf.float32)
         # x = tf.constant(X_train_rot_gray)
         one_hot_y = tf.one_hot(y, n_classes)

         rate = 0.0001
         pred = SketchNet(x, keep_prob)
         cross_entropy = tf.nn.softmax_cross_entropy_with_logits(logits= pred,
                                                                 labels= one_hot_y)


         loss_operation = tf.reduce_mean(cross_entropy)
         optimizer = tf.train.AdamOptimizer(learning_rate=rate)
         training_operation = optimizer.minimize(loss_operation)
         correct_pred = tf.equal(tf.argmax(pred, 1), tf.argmax(one_hot_y, 1))
         accuracy_op = tf.reduce_mean(tf.cast(correct_pred, tf.float32))
```

```
Layer 0 Init: Shape (?, 32, 32, 1)
Layer 1 Convolution: Shape (?, 32, 32, 32)
Layer 2 Convolution: Shape (?, 32, 32, 32)
Layer 3 Pooling: Shape (?, 16, 16, 32)
Layer 4 Convolution: Shape (?, 16, 16, 64)
Layer 5 Convolution: Shape (?, 16, 16, 64)
Layer 6 Pooling: Shape (?, 8, 8, 64)
Layer 7 Convolution: Shape (?, 8, 8, 128)
Layer 8 Convolution: Shape (?, 8, 8, 128)
Layer 9 Pooling: Shape (?, 4, 4, 128)
Layer 10 Flatten: Shape (?, 2048)
Layer 11 Matrix Multiplication: Shape (?, 400)
Layer 12 Matrix Multiplication: Shape (?, 100)
Final Layer Matrix Multiplication: Shape (?, 43)
```

```
In [89]: def evaluate(X_data, y_data, sess):
             num_examples = len(X_data)
             total_accuracy = 0
             for offset in range(0, num_examples, BATCH_SIZE):
                 batch_x = X_data[offset:offset+BATCH_SIZE]
                 batch_y = y_data[offset:offset+BATCH_SIZE]
                 accuracy = sess.run(accuracy_op, feed_dict={x: batch_x,
                                                             y: batch_y,
```

```
                                                    keep_prob: 1.0})
            total_accuracy += (accuracy * len(batch_x))
        return total_accuracy / num_examples
```

3.2.1 Training multiple networks

The below training sought to train multiple networks for testing an ensemble network. The same code works to train a single network.

```
In [30]: for i in range(7,10):
             tf.reset_default_graph()
             x = tf.placeholder(tf.float32, (None, 32, 32))
             y = tf.placeholder(tf.int32, (None))
             keep_prob = tf.placeholder(tf.float32)
             # x = tf.constant(X_train_rot_gray)
             one_hot_y = tf.one_hot(y, n_classes)

             rate = 0.0001
             pred = SketchNet(x, keep_prob)
             cross_entropy = tf.nn.softmax_cross_entropy_with_logits(logits= pred,
                                                                     labels= one_ho


             loss_operation = tf.reduce_mean(cross_entropy)
             optimizer = tf.train.AdamOptimizer(learning_rate=rate)
             training_operation = optimizer.minimize(loss_operation)
             correct_pred = tf.equal(tf.argmax(pred, 1), tf.argmax(one_hot_y, 1))
             accuracy_op = tf.reduce_mean(tf.cast(correct_pred, tf.float32))

             import time
             epoch_accuracy = []
             EPOCHS = 500
             BATCH_SIZE = 64
             save_file = './test_model{0}.ckpt'.format(i)
             saver = tf.train.Saver()
             # print('Saver successfully created')
             with tf.Session() as sess:
                 init = tf.global_variables_initializer()
                 sess.run(init)
                 cur_time = time.time()
                 for epoch in range(EPOCHS):
                     X_train, y_train = shuffle(X_train, y_train)
                     for offset in range(0, n_train, BATCH_SIZE):
                         images_feed= X_train[offset:offset+BATCH_SIZE]
                         labels_feed = y_train[offset:offset+BATCH_SIZE]
                         _, loss_value = sess.run([training_operation, loss_operati
                                                   feed_dict={x: images_feed, y: lab
                     if (epoch+1) % 10 == 0:
                         validation_accuracy = evaluate(X_valid, y_valid)
```

```
                    epoch_accuracy.append((validation_accuracy, loss_value))
                    prev_time = cur_time
                    cur_time = time.time()
                    print('EPOCH {}'.format(epoch+1))
                    print('Loss Value {}'.format(loss_value))
                    print('Validation Accuracy = {:.3f}'.format(validation_acc
                    print('Time/epoch {0} s\n'.format((cur_time - prev_time)/1
            saver.save(sess, save_file)
            print('Saved {0} successfully'.format(save_file))
        epoch_accuracy_loss = []
        epoch_accuracy_acc = []
        for epoch in epoch_accuracy:
            epoch_accuracy_acc.append(epoch[0])
            epoch_accuracy_loss.append(epoch[1])
        epochs = np.arange(10,EPOCHS+1,10)
        accuracy = pd.DataFrame({'Epoch': epochs,
                                 'Loss': epoch_accuracy_loss,
                                 'Accuracy': epoch_accuracy_acc})
        accuracy
        accuracy.to_csv('accuracy_testmodel{0}.csv'.format(i), index=False)
```

```
Layer 0 Init: Shape (?, 32, 32, 1)
Layer 1 Convolution: Shape (?, 32, 32, 32)
Layer 2 Convolution: Shape (?, 32, 32, 32)
Layer 3 Pooling: Shape (?, 16, 16, 32)
Layer 4 Convolution: Shape (?, 16, 16, 64)
Layer 5 Convolution: Shape (?, 16, 16, 64)
Layer 6 Pooling: Shape (?, 8, 8, 64)
Layer 7 Convolution: Shape (?, 8, 8, 128)
Layer 8 Convolution: Shape (?, 8, 8, 128)
Layer 9 Pooling: Shape (?, 4, 4, 128)
Layer 10 Flatten: Shape (?, 2048)
Layer 11 Matrix Multiplication: Shape (?, 400)
Layer 12 Matrix Multiplication: Shape (?, 100)
Final Layer Matrix Multiplication: Shape (?, 43)
EPOCH 10
Loss Value 3.490654468536377
Validation Accuracy = 0.084
Time/epoch 53.51769535541534 s

EPOCH 20
Loss Value 3.058199882507324
Validation Accuracy = 0.156
Time/epoch 53.209389090538025 s

EPOCH 30
Loss Value 1.5504026412963867
Validation Accuracy = 0.581
```

```
Time/epoch 53.21339662075043 s

EPOCH 40
Loss Value 0.39222604036331177
Validation Accuracy = 0.816
Time/epoch 53.20665421485901 s

EPOCH 50
Loss Value 0.36341074109077454
Validation Accuracy = 0.870
Time/epoch 53.194975233078004 s

EPOCH 60
Loss Value 0.22096551954746246
Validation Accuracy = 0.872
Time/epoch 53.15903890132904 s

EPOCH 70
Loss Value 0.25180310010910034
Validation Accuracy = 0.882
Time/epoch 53.149676012992856 s

EPOCH 80
Loss Value 0.19409331679344177
Validation Accuracy = 0.901
Time/epoch 53.07203860282898 s

EPOCH 90
Loss Value 0.1360066682100296
Validation Accuracy = 0.910
Time/epoch 53.068830490112305 s

EPOCH 100
Loss Value 0.11865735054016113
Validation Accuracy = 0.913
Time/epoch 53.064456129074095 s

EPOCH 110
Loss Value 0.005096019711345434
Validation Accuracy = 0.901
Time/epoch 53.062315058708194 s

EPOCH 120
Loss Value 0.07833929359912872
Validation Accuracy = 0.917
Time/epoch 53.14083995819092 s

EPOCH 130
```

```
Loss Value 0.000202967319637537
Validation Accuracy = 0.907
Time/epoch 53.05740141868591 s

EPOCH 140
Loss Value 0.2923966646194458
Validation Accuracy = 0.927
Time/epoch 53.066979217529294 s

EPOCH 150
Loss Value 0.2569212317466736
Validation Accuracy = 0.926
Time/epoch 53.062325620651244 s

EPOCH 160
Loss Value 0.07807845622301102
Validation Accuracy = 0.920
Time/epoch 53.06166276931763 s

EPOCH 170
Loss Value 0.1436450481414795
Validation Accuracy = 0.913
Time/epoch 53.054788041114804 s

EPOCH 180
Loss Value 0.17633110284805298
Validation Accuracy = 0.923
Time/epoch 53.064660000801084 s

EPOCH 190
Loss Value 0.059870388358831406
Validation Accuracy = 0.920
Time/epoch 53.06181490421295 s

EPOCH 200
Loss Value 0.00027461149147711694
Validation Accuracy = 0.930
Time/epoch 53.05368151664734 s

EPOCH 210
Loss Value 0.23646923899650574
Validation Accuracy = 0.922
Time/epoch 53.06076426506043 s

EPOCH 220
Loss Value 0.12256752699613571
Validation Accuracy = 0.927
Time/epoch 53.05485310554504 s
```

```
EPOCH 230
Loss Value 0.11755076050758362
Validation Accuracy = 0.928
Time/epoch 53.06219832897186 s

EPOCH 240
Loss Value 0.11759935319423676
Validation Accuracy = 0.927
Time/epoch 53.05841197967529 s

EPOCH 250
Loss Value 0.11766086518764496
Validation Accuracy = 0.932
Time/epoch 53.063020491600035 s

EPOCH 260
Loss Value 0.059147242456674576
Validation Accuracy = 0.932
Time/epoch 53.06206090450287 s

EPOCH 270
Loss Value 0.11871938407421112
Validation Accuracy = 0.937
Time/epoch 53.05417647361755 s

EPOCH 280
Loss Value 0.11754101514816284
Validation Accuracy = 0.931
Time/epoch 53.06199131011963 s

EPOCH 290
Loss Value 0.09802286326885223
Validation Accuracy = 0.937
Time/epoch 53.06087872982025 s

EPOCH 300
Loss Value 0.17670820653438568
Validation Accuracy = 0.938
Time/epoch 53.06172118186951 s

EPOCH 310
Loss Value 0.11756624281406403
Validation Accuracy = 0.926
Time/epoch 53.058766102790834 s

EPOCH 320
Loss Value 0.23521068692207336
```

```
Validation Accuracy = 0.926
Time/epoch 53.06044363975525 s

EPOCH 330
Loss Value 0.1778244972229004
Validation Accuracy = 0.940
Time/epoch 53.064014768600465 s

EPOCH 340
Loss Value 0.11777230352163315
Validation Accuracy = 0.935
Time/epoch 53.05599873065948 s

EPOCH 350
Loss Value 0.2350798398256302
Validation Accuracy = 0.916
Time/epoch 53.05869874954224 s

EPOCH 360
Loss Value 0.05903824046254158
Validation Accuracy = 0.937
Time/epoch 53.07547943592071 s

EPOCH 370
Loss Value 0.05878651514649391
Validation Accuracy = 0.936
Time/epoch 53.063064742088315 s

EPOCH 380
Loss Value 1.2647128642129246e-06
Validation Accuracy = 0.937
Time/epoch 53.05747218132019 s

EPOCH 390
Loss Value 0.059153106063604355
Validation Accuracy = 0.937
Time/epoch 53.087419271469116 s

EPOCH 400
Loss Value 0.1763305962085724
Validation Accuracy = 0.925
Time/epoch 54.170326948165894 s

EPOCH 410
Loss Value 0.11753951758146286
Validation Accuracy = 0.929
Time/epoch 54.043428134918216 s
```

```
EPOCH 420
Loss Value 0.41183745861053467
Validation Accuracy = 0.924
Time/epoch 53.63017358779907 s

EPOCH 430
Loss Value 3.4654676710488275e-05
Validation Accuracy = 0.936
Time/epoch 53.38587491512298 s

EPOCH 440
Loss Value 0.1791813224554062
Validation Accuracy = 0.937
Time/epoch 54.32847898006439 s

EPOCH 450
Loss Value 0.23517253994941711
Validation Accuracy = 0.935
Time/epoch 55.025445222854614 s

EPOCH 460
Loss Value 0.12134981155395508
Validation Accuracy = 0.943
Time/epoch 54.64195365905762 s

EPOCH 470
Loss Value 0.1175454631447792
Validation Accuracy = 0.944
Time/epoch 56.21623985767364 s

EPOCH 480
Loss Value 0.004683051258325577
Validation Accuracy = 0.932
Time/epoch 54.38817734718323 s

EPOCH 490
Loss Value 0.05979417636990547
Validation Accuracy = 0.934
Time/epoch 54.567841219902036 s

EPOCH 500
Loss Value 0.05877096578478813
Validation Accuracy = 0.931
Time/epoch 54.53912818431854 s

Saved ./test_model7.ckpt successfully
Layer 0 Init: Shape (?, 32, 32, 1)
Layer 1 Convolution: Shape (?, 32, 32, 32)
```

```
Layer 2 Convolution: Shape (?, 32, 32, 32)
Layer 3 Pooling: Shape (?, 16, 16, 32)
Layer 4 Convolution: Shape (?, 16, 16, 64)
Layer 5 Convolution: Shape (?, 16, 16, 64)
Layer 6 Pooling: Shape (?, 8, 8, 64)
Layer 7 Convolution: Shape (?, 8, 8, 128)
Layer 8 Convolution: Shape (?, 8, 8, 128)
Layer 9 Pooling: Shape (?, 4, 4, 128)
Layer 10 Flatten: Shape (?, 2048)
Layer 11 Matrix Multiplication: Shape (?, 400)
Layer 12 Matrix Multiplication: Shape (?, 100)
Final Layer Matrix Multiplication: Shape (?, 43)
EPOCH 10
Loss Value 3.5030837059020996
Validation Accuracy = 0.062
Time/epoch 54.39298417568207 s

EPOCH 20
Loss Value 3.3996071815490723
Validation Accuracy = 0.069
Time/epoch 54.2818205833435 s

EPOCH 30
Loss Value 1.8172221183776855
Validation Accuracy = 0.437
Time/epoch 54.44207174777985 s

EPOCH 40
Loss Value 0.5546555519104004
Validation Accuracy = 0.685
Time/epoch 54.010689401626585 s

EPOCH 50
Loss Value 0.5299626588821411
Validation Accuracy = 0.768
Time/epoch 53.23627066612244 s

EPOCH 60
Loss Value 0.528257429599762
Validation Accuracy = 0.800
Time/epoch 53.74606647491455 s

EPOCH 70
Loss Value 0.381015419960022
Validation Accuracy = 0.819
Time/epoch 55.319636654853824 s

EPOCH 80
```

```
Loss Value 0.37777870893478394
Validation Accuracy = 0.830
Time/epoch 55.099873065948486 s

EPOCH 90
Loss Value 0.29659515619277954
Validation Accuracy = 0.835
Time/epoch 54.47803463935852 s

EPOCH 100
Loss Value 0.19498413801193237
Validation Accuracy = 0.836
Time/epoch 54.02949392795563 s

EPOCH 110
Loss Value 0.41443532705307007
Validation Accuracy = 0.842
Time/epoch 54.18805747032165 s

EPOCH 120
Loss Value 0.6127446889877319
Validation Accuracy = 0.867
Time/epoch 53.72728931903839 s

EPOCH 130
Loss Value 0.418956995010376
Validation Accuracy = 0.855
Time/epoch 53.66988160610199 s

EPOCH 140
Loss Value 0.0687803104519844
Validation Accuracy = 0.851
Time/epoch 53.85901670455932 s

EPOCH 150
Loss Value 0.24131038784980774
Validation Accuracy = 0.852
Time/epoch 55.64516479969025 s

EPOCH 160
Loss Value 0.3192443251609802
Validation Accuracy = 0.866
Time/epoch 53.648840475082395 s

EPOCH 170
Loss Value 0.37455615401268005
Validation Accuracy = 0.860
Time/epoch 54.411151719093326 s
```

```
EPOCH 180
Loss Value 0.1807766854763031
Validation Accuracy = 0.862
Time/epoch 53.55290441513061 s

EPOCH 190
Loss Value 0.2940000891685486
Validation Accuracy = 0.868
Time/epoch 54.41455183029175 s

EPOCH 200
Loss Value 0.11767612397670746
Validation Accuracy = 0.861
Time/epoch 53.81856007575989 s

EPOCH 210
Loss Value 0.2563493251800537
Validation Accuracy = 0.863
Time/epoch 54.628816628456114 s

EPOCH 220
Loss Value 0.18293353915214539
Validation Accuracy = 0.867
Time/epoch 56.88869185447693 s

EPOCH 230
Loss Value 0.3303506374359131
Validation Accuracy = 0.866
Time/epoch 54.76349241733551 s

EPOCH 240
Loss Value 0.06321946531534195
Validation Accuracy = 0.867
Time/epoch 55.17261061668396 s

EPOCH 250
Loss Value 0.17795386910438538
Validation Accuracy = 0.873
Time/epoch 56.41953554153442 s

EPOCH 260
Loss Value 0.2940717041492462
Validation Accuracy = 0.881
Time/epoch 55.66902503967285 s

EPOCH 270
Loss Value 0.6465493440628052
```

```
Validation Accuracy = 0.882
Time/epoch 56.59350936412811 s

EPOCH 280
Loss Value 0.15138055384159088
Validation Accuracy = 0.861
Time/epoch 56.29117460250855 s

EPOCH 290
Loss Value 0.36115971207618713
Validation Accuracy = 0.872
Time/epoch 56.34417695999146 s

EPOCH 300
Loss Value 0.2579424977302551
Validation Accuracy = 0.878
Time/epoch 55.05306560993195 s

EPOCH 310
Loss Value 0.17779144644737244
Validation Accuracy = 0.880
Time/epoch 55.75719492435455 s

EPOCH 320
Loss Value 0.41795089840888977
Validation Accuracy = 0.879
Time/epoch 55.80955755710602 s

EPOCH 330
Loss Value 0.5322633981704712
Validation Accuracy = 0.887
Time/epoch 56.92654228210449 s

EPOCH 340
Loss Value 0.117564857006073
Validation Accuracy = 0.878
Time/epoch 56.66927878856659 s

EPOCH 350
Loss Value 0.2940155267715454
Validation Accuracy = 0.885
Time/epoch 54.7671293258667 s

EPOCH 360
Loss Value 0.23586395382881165
Validation Accuracy = 0.879
Time/epoch 56.00897183418274 s
```

```
EPOCH 370
Loss Value 0.23537227511405945
Validation Accuracy = 0.883
Time/epoch 56.41729147434235 s

EPOCH 380
Loss Value 0.1763276308774948
Validation Accuracy = 0.883
Time/epoch 55.15845437049866 s

EPOCH 390
Loss Value 0.11897905170917511
Validation Accuracy = 0.883
Time/epoch 53.79849669933319 s

EPOCH 400
Loss Value 0.23510581254959106
Validation Accuracy = 0.880
Time/epoch 53.63479323387146 s

EPOCH 410
Loss Value 0.4709963798522949
Validation Accuracy = 0.872
Time/epoch 53.64160153865814 s

EPOCH 420
Loss Value 0.13514569401741028
Validation Accuracy = 0.881
Time/epoch 53.6414767742157 s

EPOCH 430
Loss Value 0.29384535551071167
Validation Accuracy = 0.888
Time/epoch 53.710523867607115 s

EPOCH 440
Loss Value 0.1773061901330948
Validation Accuracy = 0.888
Time/epoch 53.762827491760255 s

EPOCH 450
Loss Value 0.4126024842262268
Validation Accuracy = 0.893
Time/epoch 53.76892328262329 s

EPOCH 460
Loss Value 0.2502591013908386
Validation Accuracy = 0.889
```

```
Time/epoch 53.76353361606598 s

EPOCH 470
Loss Value 0.3526131510734558
Validation Accuracy = 0.875
Time/epoch 53.763596415519714 s

EPOCH 480
Loss Value 0.05878424644470215
Validation Accuracy = 0.889
Time/epoch 53.77308981418609 s

EPOCH 490
Loss Value 0.35280948877334595
Validation Accuracy = 0.886
Time/epoch 53.780203628540036 s

EPOCH 500
Loss Value 0.11754566431045532
Validation Accuracy = 0.884
Time/epoch 53.77831091880798 s

Saved ./test_model8.ckpt successfully
Layer 0 Init: Shape (?, 32, 32, 1)
Layer 1 Convolution: Shape (?, 32, 32, 32)
Layer 2 Convolution: Shape (?, 32, 32, 32)
Layer 3 Pooling: Shape (?, 16, 16, 32)
Layer 4 Convolution: Shape (?, 16, 16, 64)
Layer 5 Convolution: Shape (?, 16, 16, 64)
Layer 6 Pooling: Shape (?, 8, 8, 64)
Layer 7 Convolution: Shape (?, 8, 8, 128)
Layer 8 Convolution: Shape (?, 8, 8, 128)
Layer 9 Pooling: Shape (?, 4, 4, 128)
Layer 10 Flatten: Shape (?, 2048)
Layer 11 Matrix Multiplication: Shape (?, 400)
Layer 12 Matrix Multiplication: Shape (?, 100)
Final Layer Matrix Multiplication: Shape (?, 43)
EPOCH 10
Loss Value 3.419048309326172
Validation Accuracy = 0.068
Time/epoch 53.90260796546936 s

EPOCH 20
Loss Value 3.2160818576812744
Validation Accuracy = 0.143
Time/epoch 53.934254217147824 s

EPOCH 30
```

```
Loss Value 2.082726001739502
Validation Accuracy = 0.492
Time/epoch 53.949260401725766 s

EPOCH 40
Loss Value 1.035753846168518
Validation Accuracy = 0.744
Time/epoch 53.93984503746033 s

EPOCH 50
Loss Value 0.24839964509010315
Validation Accuracy = 0.840
Time/epoch 53.9347419500351 s

EPOCH 60
Loss Value 0.35652652382850647
Validation Accuracy = 0.873
Time/epoch 53.929841947555545 s

EPOCH 70
Loss Value 0.21008503437042236
Validation Accuracy = 0.889
Time/epoch 53.938786792755124 s

EPOCH 80
Loss Value 0.19954434037208557
Validation Accuracy = 0.900
Time/epoch 53.919185638427734 s

EPOCH 90
Loss Value 0.1241820827126503
Validation Accuracy = 0.914
Time/epoch 53.92304522991181 s

EPOCH 100
Loss Value 0.18549934029579163
Validation Accuracy = 0.909
Time/epoch 53.95525679588318 s

EPOCH 110
Loss Value 0.19092458486557007
Validation Accuracy = 0.920
Time/epoch 53.95475780963898 s

EPOCH 120
Loss Value 0.1275901049375534
Validation Accuracy = 0.924
Time/epoch 53.96477575302124 s
```

```
EPOCH 130
Loss Value 0.07133034616708755
Validation Accuracy = 0.924
Time/epoch 53.9582515001297 s

EPOCH 140
Loss Value 0.19048258662223816
Validation Accuracy = 0.917
Time/epoch 53.96227235794068 s

EPOCH 150
Loss Value 0.059184327721595764
Validation Accuracy = 0.920
Time/epoch 53.965414667129515 s

EPOCH 160
Loss Value 0.19404970109462738
Validation Accuracy = 0.924
Time/epoch 53.97174198627472 s

EPOCH 170
Loss Value 0.12498500943183899
Validation Accuracy = 0.931
Time/epoch 53.965019297599795 s

EPOCH 180
Loss Value 0.18354877829551697
Validation Accuracy = 0.927
Time/epoch 53.97208001613617 s

EPOCH 190
Loss Value 0.1763223558664322
Validation Accuracy = 0.935
Time/epoch 53.98572678565979 s

EPOCH 200
Loss Value 0.1852569878101349
Validation Accuracy = 0.932
Time/epoch 53.989094376564026 s

EPOCH 210
Loss Value 0.0007359905284829438
Validation Accuracy = 0.932
Time/epoch 53.99215724468231 s

EPOCH 220
Loss Value 0.26579487323760986
```

```
Validation Accuracy = 0.933
Time/epoch 53.99198596477508 s

EPOCH 230
Loss Value 0.0007353522232733667
Validation Accuracy = 0.939
Time/epoch 53.99026136398315 s

EPOCH 240
Loss Value 0.17665749788284302
Validation Accuracy = 0.935
Time/epoch 54.006837940216066 s

EPOCH 250
Loss Value 0.0001312726817559451
Validation Accuracy = 0.930
Time/epoch 53.998423194885255 s

EPOCH 260
Loss Value 0.0627204030752182
Validation Accuracy = 0.924
Time/epoch 53.994708156585695 s

EPOCH 270
Loss Value 0.17631518840789795
Validation Accuracy = 0.929
Time/epoch 54.04091284275055 s

EPOCH 280
Loss Value 0.17656394839286804
Validation Accuracy = 0.931
Time/epoch 54.04328784942627 s

EPOCH 290
Loss Value 0.12049417197704315
Validation Accuracy = 0.935
Time/epoch 54.05194664001465 s

EPOCH 300
Loss Value 0.17631638050079346
Validation Accuracy = 0.927
Time/epoch 54.03776979446411 s

EPOCH 310
Loss Value 0.17631463706493378
Validation Accuracy = 0.936
Time/epoch 54.04577875137329 s
```

```
EPOCH 320
Loss Value 0.11758115887641907
Validation Accuracy = 0.936
Time/epoch 54.044568634033205 s

EPOCH 330
Loss Value 0.1763652265071869
Validation Accuracy = 0.930
Time/epoch 54.050613379478456 s

EPOCH 340
Loss Value 0.35262590646743774
Validation Accuracy = 0.933
Time/epoch 54.04581396579742 s

EPOCH 350
Loss Value 0.11753824353218079
Validation Accuracy = 0.939
Time/epoch 54.06279170513153 s

EPOCH 360
Loss Value 0.05877010524272919
Validation Accuracy = 0.943
Time/epoch 54.07713875770569 s

EPOCH 370
Loss Value 0.05882471054792404
Validation Accuracy = 0.934
Time/epoch 54.081227922439574 s

EPOCH 380
Loss Value 0.21368181705474854
Validation Accuracy = 0.928
Time/epoch 54.08398704528808 s

EPOCH 390
Loss Value 0.17630665004253387
Validation Accuracy = 0.932
Time/epoch 54.082628560066226 s

EPOCH 400
Loss Value 0.17663967609405518
Validation Accuracy = 0.932
Time/epoch 54.081160116195676 s

EPOCH 410
Loss Value 0.1763269454240799
Validation Accuracy = 0.943
```

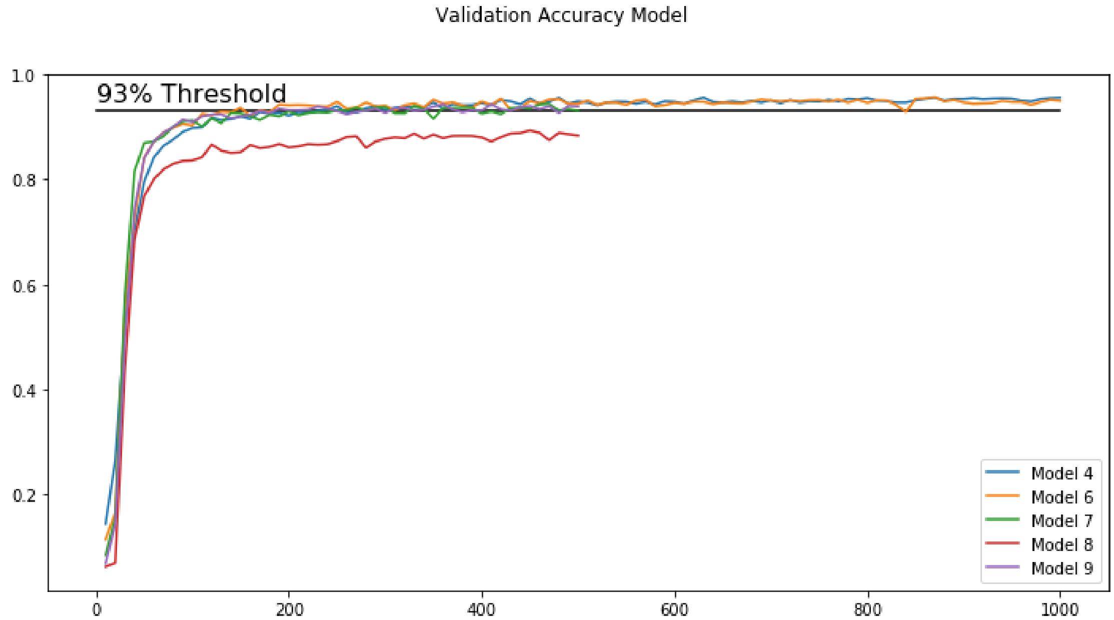
```
Time/epoch 54.087117075920105 s

EPOCH 420
Loss Value 0.1763089895248413
Validation Accuracy = 0.934
Time/epoch 54.0866712808609 s

EPOCH 430
Loss Value 0.1201428472995758
Validation Accuracy = 0.931
Time/epoch 54.080964183807374 s

EPOCH 440
Loss Value 0.1763075590133667
Validation Accuracy = 0.938
Time/epoch 53.98373551368714 s

EPOCH 450
Loss Value 0.1763285994529724
Validation Accuracy = 0.940
Time/epoch 53.47293472290039 s

EPOCH 460
Loss Value 0.11759638786315918
Validation Accuracy = 0.934
Time/epoch 53.47245950698853 s

EPOCH 470
Loss Value 0.23507526516914368
Validation Accuracy = 0.940
Time/epoch 53.468425846099855 s

EPOCH 480
Loss Value 0.0005968312034383416
Validation Accuracy = 0.927
Time/epoch 53.46960098743439 s

EPOCH 490
Loss Value 0.14574527740478516
Validation Accuracy = 0.940
Time/epoch 53.471102714538574 s

EPOCH 500
Loss Value 0.2350994348526001
Validation Accuracy = 0.939
Time/epoch 53.47247228622437 s

Saved ./test_model9.ckpt successfully
```

```
In [28]: epoch_accuracy_loss = []
         epoch_accuracy_acc = []
         for epoch in epoch_accuracy:
             epoch_accuracy_acc.append(epoch[0])
             epoch_accuracy_loss.append(epoch[1])
         epochs = np.arange(10,1001,10)
         accuracy = pd.DataFrame({'Epoch': epochs,
                                  'Loss': epoch_accuracy_loss,
                                  'Accuracy': epoch_accuracy_acc})
         accuracy
         accuracy.to_csv('accuracy_testmodel6.csv', index=False)
```

3.3 Validation Accuracy

- All networks but one achieved the accuracy threshold.
- The inaccurate network (8) was trained exactly the same as other networks (7&9)
- A prior model (4) with an architecture CPCPCPFFF was just as accurate as VGGs CCPC-CPCCCPFFF architecture

```
In [133]: # Models 6-9 trained with VGG-like net
          fig = plt.figure(figsize=(12,6))
          fig.suptitle('Validation Accuracy Model'.format(i))
          ax1.set_xlim(left=0, right=1000)
          ax1.set_ylim(top=1.0, bottom=0.0)
          ax1 = plt.subplot(111)
          plt.text(0,.95, '93% Threshold', fontsize=16)
          ax1.plot((0,1000),(.93,.93), 'k-')
          for i in range(4,10):
              if i != 5:
                  accuracy = pd.read_csv('accuracy_testmodel{0}.csv'.format(i))
                  ax1.plot(accuracy['Epoch'], accuracy['Accuracy'], label='Model {0
          legend = ax1.legend()
          plt.show()
```



3.4 Ensemble

Ensemble bagging across 4 networks was carried out. It didn't have any impact. This is probably because usually 10 networks are used in ensemble learning and the networks are only different in their initialization and EPOCH numbers. ## Restoring models * Major lesson learned. restore expects a path so use ./ if in root directory… * Test set accuracy is similar to validation set accuracy so overfitting to the validation set is not an issue.

```
In [97]: with tf.Session() as sess:
             BATCH_SIZE = 64
             num_examples = len(X_valid)
             saver = tf.train.Saver()

             sess.run(tf.global_variables_initializer())
             saver.restore(sess, './test_model6.ckpt')
             print('Model 6 Validation Accuracy: {}'.format(evaluate(X_valid, y_val
             print('Model 6 Test Accuracy: {}'.format(evaluate(X_test, y_test, sess
             pred_valid_6 = predict_labels(X_valid)
             pred_test_6 = predict_labels(X_test)

             sess2 = tf.Session()
             saver.restore(sess2, './test_model7.ckpt')
             print('Model 7 Validation Accuracy: {}'.format(evaluate(X_valid, y_val
             print('Model 7 Test Accuracy: {}'.format(evaluate(X_test, y_test, sess
             pred_valid_7 = predict_labels(X_valid)
             pred_test_7 = predict_labels(X_test)
```

```
            sess3 = tf.Session()
            saver.restore(sess3, './test_model9.ckpt')
            print('Model 9 Validation Accuracy: {}'.format(evaluate(X_valid, y_val
            print('Model 9 Test Accuracy: {}'.format(evaluate(X_test, y_test, sess
            pred_valid_9 = predict_labels(X_valid)
            pred_test_9 = predict_labels(X_test)

            sess4 = tf.Session()
            saver.restore(sess4, './test_model8.ckpt')
            print('Model 8 Validation Accuracy: {}'.format(evaluate(X_valid, y_val
            print('Model 8 Test Accuracy: {}'.format(evaluate(X_test, y_test, sess
            pred_valid_8 = predict_labels(X_valid)
            pred_test_8 = predict_labels(X_test)

            ensemble_pred = tf.divide(tf.add_n([pred_valid_6, pred_valid_7, pred_v
            ensemble_x_entropy = sess.run(tf.nn.softmax_cross_entropy_with_logits

                                          feed_dict={y: y_valid})
            ensemble_loss = sess.run(tf.reduce_mean(ensemble_x_entropy))
            ensemble_correct_pred = sess.run(tf.equal(tf.argmax(ensemble_pred, 1),
                                             feed_dict={y: y_valid})
            ensemble_accuracy= sess.run(tf.reduce_mean(tf.cast(ensemble_correct_pr
            print('Ensemble Accuracy: {0}'.format(ensemble_accuracy))

            ensemble_test = tf.divide(tf.add_n([pred_test_6, pred_test_7, pred_tes
            ensemble_x_entropy = sess.run(tf.nn.softmax_cross_entropy_with_logits

                                          feed_dict={y: y_test})
            ensemble_loss = sess.run(tf.reduce_mean(ensemble_x_entropy))
            ensemble_correct_pred = sess.run(tf.equal(tf.argmax(ensemble_test, 1),
                                             feed_dict={y: y_test})
            ensemble_accuracy= sess.run(tf.reduce_mean(tf.cast(ensemble_correct_pr
            print('Ensemble Accuracy Test: {0}'.format(ensemble_accuracy))
        #     loss_operation = tf.reduce_mean(cross_entropy)
        #     optimizer = tf.train.AdamOptimizer(learning_rate=rate)
        #     training_operation = optimizer.minimize(loss_operation)
        #     correct_pred = tf.equal(tf.argmax(pred, 1), tf.argmax(one_hot_y, 1))
        #     accuracy_op = tf.reduce_mean(tf.cast(correct_pred, tf.float32))
```

```
Model 6 Validation Accuracy: 0.9498866210719085
Model 6 Test Accuracy: 0.9447347585303578
Model 7 Validation Accuracy: 0.93129251679055
Model 7 Test Accuracy: 0.9383214568959657
Model 9 Validation Accuracy: 0.9394557815560408
Model 9 Test Accuracy: 0.9279493270652783
Model 8 Validation Accuracy: 0.8836734694688498
Model 8 Test Accuracy: 0.8868566904573901
Ensemble Accuracy: 0.9498866200447083
```

```
Ensemble Accuracy Test: 0.9447347521781921
```

```
In [105]: def predict_labels(X_data):
              num_examples = len(X_data)
              total_accuracy = 0
              sess = tf.get_default_session()
              all_predictions = sess.run(pred, feed_dict={x: X_data[0:BATCH_SIZE],
              for offset in range(BATCH_SIZE, num_examples, BATCH_SIZE):
                  batch_x = X_data[offset:offset+BATCH_SIZE]
                  batch_predictions = sess.run(pred, feed_dict={x: batch_x, keep_pr
                  all_predictions = tf.concat([all_predictions, batch_predictions],
              return all_predictions
```

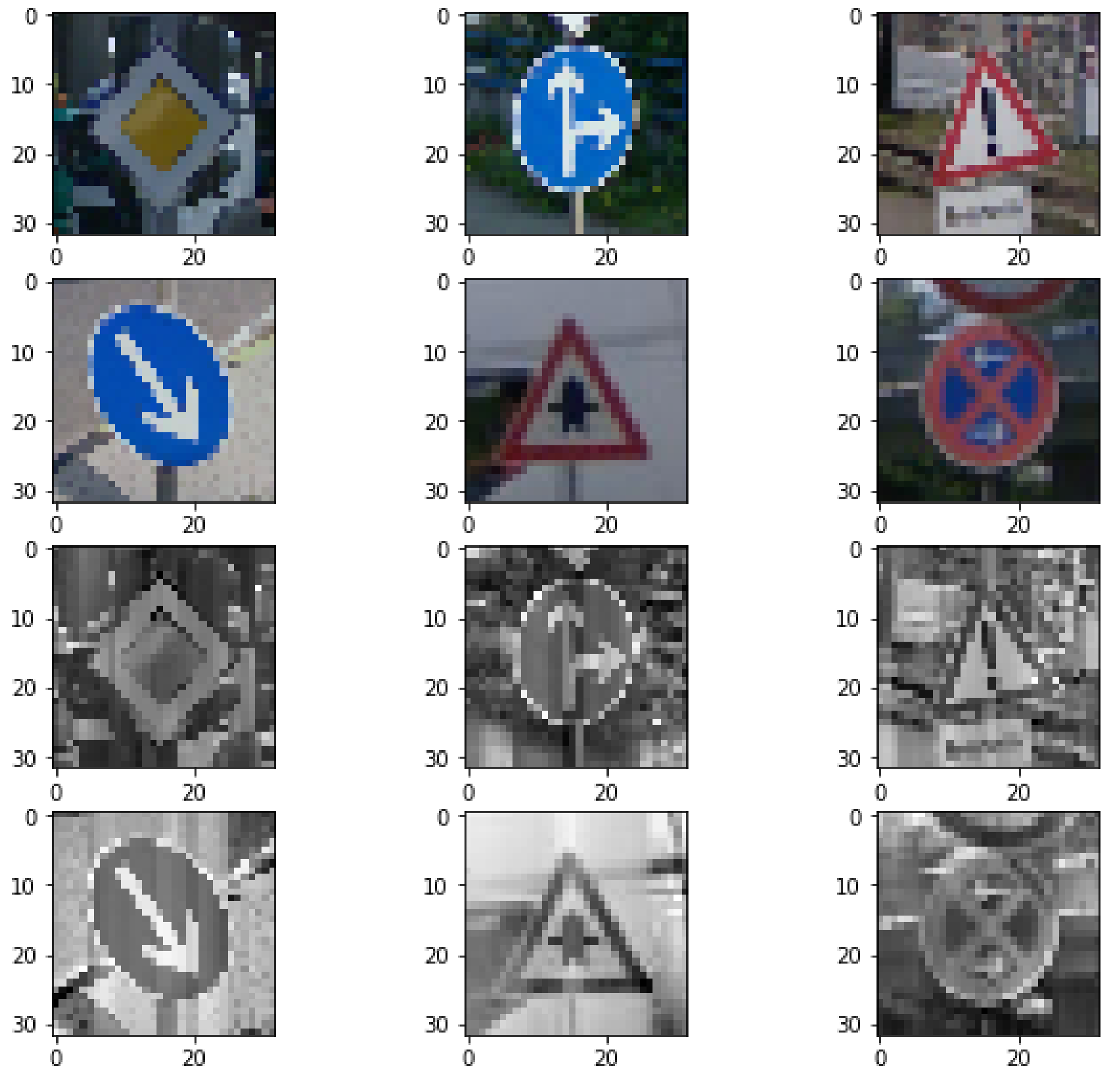
3.5 Acquiring New Images

- Images were found by driving around with Google streetview in Hamburg.
- The images from streetview were skewed from looking at signs from angle
- The fourth image is close to the ground and is more skewed than the others.
- The background of the fifth image is a truck cabin.
- These images should be easy for the model to predict
- In order to be tested the images needed to be resized to 32x32 and normalized

```
In [103]: from PIL import Image
```

```
In [123]: for i in range(9,15):
              img = cv2.imread('./examples/Selection_{0:03d}.png'.format(i))
              resized = cv2.resize(img, (32,32), 0, 0, cv2.INTER_CUBIC)
              cv2.imwrite('./examples/Resized_{0:03d}.png'.format(i), resized)
          #     resized = cv2.cvtColor(resized, cv2.COLOR_BGR2RGB)
          #     plt.subplot(230+i)
          #     plt.imshow(resized)
          images = np.zeros((6,32,32))
          fig = plt.figure(figsize=(10,9))
          fig.suptitle('Extra images')
          for i in range(6):
              img = mpimg.imread('./examples/Resized_{0:03d}.png'.format(i+9))
              ax = plt.subplot(4,3,i+1)
              plt.imshow(img)
              gray = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)
              norm = normalize(gray)
              axn = plt.subplot(4,3,i+7)
              plt.imshow(norm, cmap='gray')
              images[i] = norm
          plt.show()
```

Extra images



```
In [132]: a = []
          with tf.Session() as sess:
              saver = tf.train.Saver()
              sess.run(tf.global_variables_initializer())
              saver.restore(sess, './test_model6.ckpt')
              test_accuracy = evaluate(X_test, y_test, sess)
              print('Test Accuracy is {:.2f}%'.format(test_accuracy*100))
              guess = sess.run(pred, feed_dict={x: images, keep_prob: 1.0})
              smax = tf.nn.softmax(guess)
              top_5 = sess.run(tf.nn.top_k(smax, k=5, sorted=True))
```

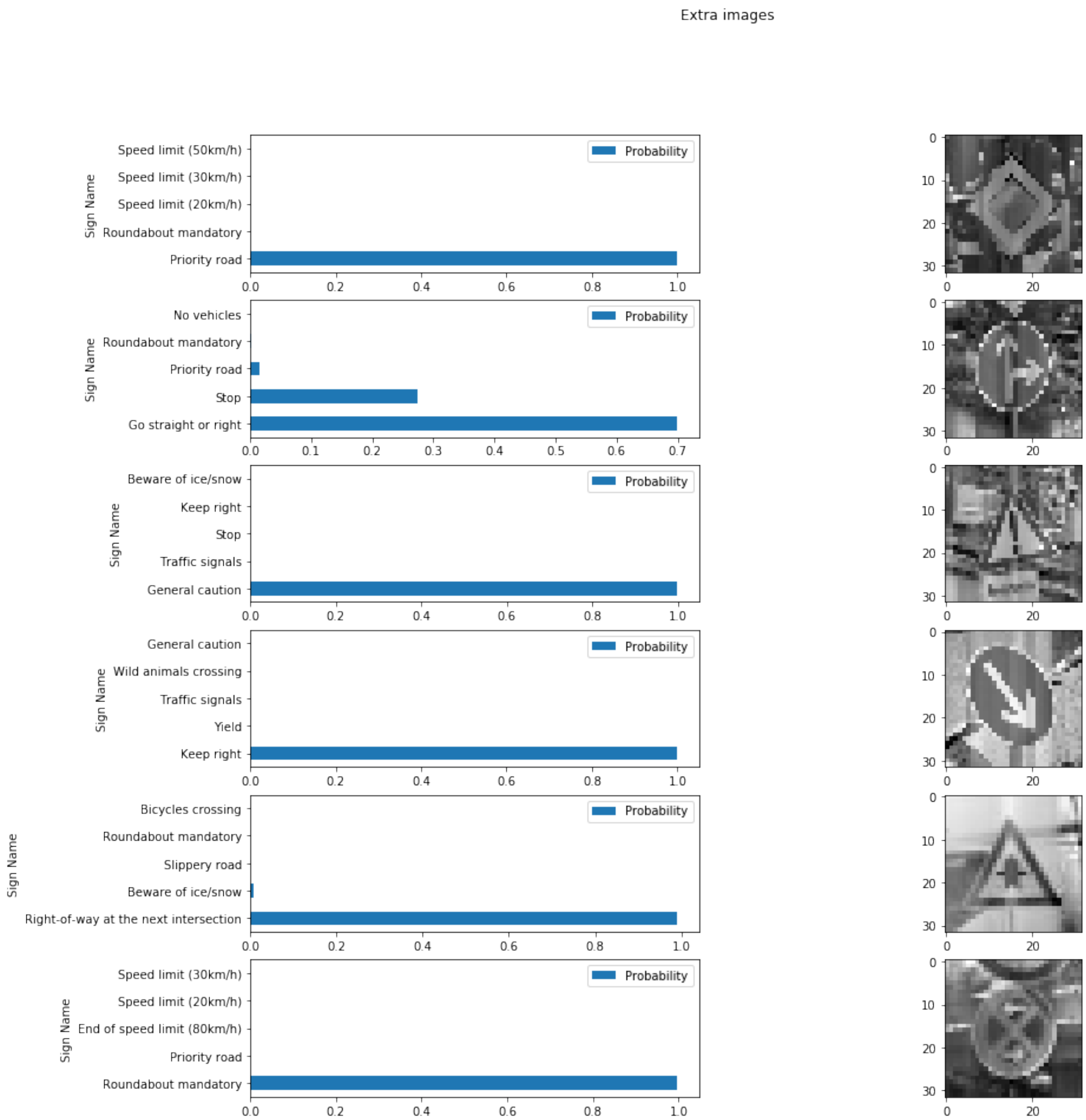
```python
            fig = plt.figure(figsize=(15,15))
            fig.suptitle('Extra images')
            for i in range(6):
                df5 = pd.DataFrame({'Probability': top_5.values[i],
                                    'Sign Name': sign_names['SignName'][top_5.inc
                df5 = df5.set_index('Sign Name')
                print(df5, '\n')
                ax1 = plt.subplot(6,2,i*2+2)
                ax2 = plt.subplot(6,2,i*2+1)
                ax1.imshow(images[i], cmap='gray')
                df5.plot.barh(ax=ax2)
            plt.show()
#       print(pd.DataFrame({'a': top_5.indices, 'b': top_5.values}))
#       df5 = pd.DataFrame({'SignIndex': top_5.indices,
#                           'Probabilities': top_5.values})
#       for i in range(images.shape[0]):
#           print(guess[i])
#           print(sign_names['SignName'][guess[i].argsort()[0:5]])
```

```
Test Accuracy is 94.47%
                      Probability
Sign Name
Priority road         1.000000e+00
Roundabout mandatory  1.093382e-10
Speed limit (20km/h)  1.289648e-12
Speed limit (30km/h)  1.289648e-12
Speed limit (50km/h)  1.289648e-12

                      Probability
Sign Name
Go straight or right     0.699499
Stop                     0.273761
Priority road            0.014698
Roundabout mandatory     0.002172
No vehicles              0.000299

                     Probability
Sign Name
General caution     9.987790e-01
Traffic signals     1.165736e-03
Stop                3.694654e-05
Keep right          1.032009e-06
Beware of ice/snow  8.811696e-07

                       Probability
Sign Name
Keep right            1.000000e+00
Yield                 1.143891e-26
```

Traffic signals	1.324083e-29
Wild animals crossing	3.446154e-30
General caution	1.264167e-30

Sign Name	Probability
Right-of-way at the next intersection	9.911767e-01
Beware of ice/snow	8.823336e-03
Slippery road	2.569768e-09
Roundabout mandatory	7.904444e-20
Bicycles crossing	2.305340e-20

Sign Name	Probability
Roundabout mandatory	0.997253
Priority road	0.000694
End of speed limit (80km/h)	0.000371
Speed limit (20km/h)	0.000042
Speed limit (30km/h)	0.000042



Successfully classified 6/6 images