# Classify\_Traffic\_Sign\_Images\_Using\_LeNet

#### October 18, 2019

#### 1 PROBLEM STATEMENT

In this case study, we have been provided with images of traffic signs and the goal is to train a Deep Network to classify them

Figure 1. Traffic Sign Classification-

- The dataset contains 43 different classes of images.
- Classes are as listed below:
  - (0, 'Speed limit (20km/h)')
  - (1, 'Speed limit (30km/h)')
  - (2, 'Speed limit (50km/h)')
  - (3, 'Speed limit (60km/h)')
  - (4, 'Speed limit (70km/h)')
  - (5, 'Speed limit (80km/h)')
  - (6, 'End of speed limit (80km/h)')
  - (7, 'Speed limit (100km/h)')
  - (8, 'Speed limit (120km/h)')
  - (9, 'No passing')
  - (10, 'No passing for vehicles over 3.5 metric tons')
  - (11, 'Right-of-way at the next intersection')
  - (12, 'Priority road')
  - (13, 'Yield') (14, b'Stop')
  - (15, 'No vehicles')
  - (16, 'Vehicles over 3.5 metric tons prohibited')
  - (17, 'No entry')
  - (18, 'General caution')
  - (19, 'Dangerous curve to the left')
  - (20, 'Dangerous curve to the right')
  - (21, 'Double curve')
  - (22, 'Bumpy road')
  - (23, 'Slippery road')
  - (24, 'Road narrows on the right')
  - (25, 'Road work')
  - (26, 'Traffic signals')
  - (27, 'Pedestrians')
  - (28, 'Children crossing')

- (29, 'Bicycles crossing')
- (30, 'Beware of ice/snow')
- (31, 'Wild animals crossing')
- (32, 'End of all speed and passing limits')
- (33, 'Turn right ahead')
- (34, 'Turn left ahead')
- (35, 'Ahead only')
- (36, 'Go straight or right')
- (37, 'Go straight or left')
- (38, 'Keep right')
- (39, 'Keep left')
- (40, 'Roundabout mandatory')
- (41, 'End of no passing')
- (42, 'End of no passing by vehicles over 3.5 metric tons')
- The network used is called LeNet that was presented by Yann LeCun http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf
- Citation: J. Stallkamp, M. Schlipsing, J. Salmen, and C. Igel. The German Traffic Sign Recognition Benchmark: A multi-class classification competition. In Proceedings of the IEEE International Joint Conference on Neural Networks, pages 1453–1460. 2011. @inproceedings{Stallkamp-IJCNN-2011, author = {Johannes Stallkamp and Marc Schlipsing and Jan Salmen and Christian Igel}, booktitle = {IEEE International Joint Conference on Neural Networks}, title = {The {G}erman {T}raffic {S}ign {R}ecognition {B}enchmark: A multi-class classification competition}, year = {2011}, pages = {1453–1460}}

#### 2 IMPORT LIBRARIES

```
[1]: import matplotlib.pyplot as plt
import numpy as np
import os

[2]: import pickle
import pandas as pd
import seaborn as sns
import PIL

[3]: from tensorflow.keras import layers
import tensorflow as tf
```

### 3 IMPORT DATASETS AND NORMALIZE IT

```
[5]: X_train, y_train = train['features'], train['labels']
    X_validation, y_validation = valid['features'], valid['labels']
    X_test, y_test = test['features'], test['labels']

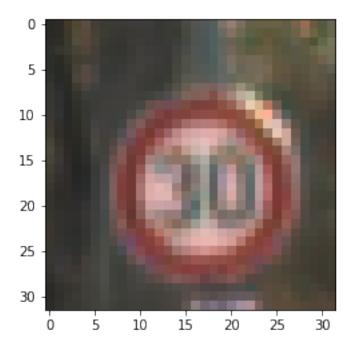
[6]: X_train.shape
[6]: (34799, 32, 32, 3)

[7]: y_train.shape
[7]: (34799,)
```

# 4 VISUALIZE DATASET

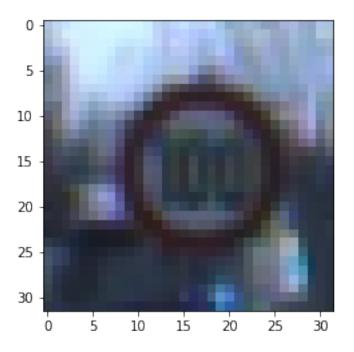
```
[8]: i = 3100
plt.imshow(X_train[i])
y_train[i]
```

[8]: 1



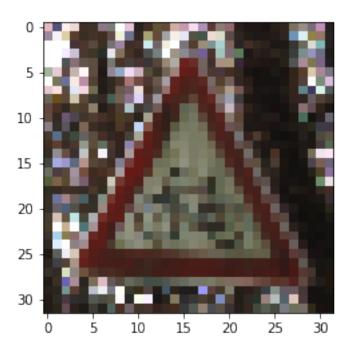
```
[9]: i = 3001
plt.imshow(X_validation[i])
y_validation[i]
```

[9]: 7



```
[10]: i = 2100
plt.imshow(X_test[i])
y_test[i]
```

[10]: 29



#### 5 DATA PREPARATION

```
[11]: from sklearn.utils import shuffle
     X_train, y_train = shuffle(X_train, y_train)
[12]: X_train_gray = np.sum(X_train/3, axis = 3, keepdims = True)
     X_test_gray = np.sum(X_test/3, axis = 3, keepdims = True)
     X_validation_gray = np.sum(X_validation/3, axis = 3, keepdims = True)
[13]: X_train_gray.shape
[13]: (34799, 32, 32, 1)
[14]: X_test_gray.shape
[14]: (12630, 32, 32, 1)
[15]: X_validation_gray.shape
[15]: (4410, 32, 32, 1)
[16]: X_train_gray_norm = (X_train_gray - 128)/128
     X_test_gray_norm = (X_test_gray - 128)/128
     X_validation_gray_norm = (X_validation_gray - 128)/128
[17]: X_train_gray_norm
[17]: array([[[[-0.7890625],
              [-0.78125
                          ],
              [-0.76822917],
              [-0.76041667],
              [-0.77083333],
              [-0.78385417]],
             Γ[-0.78125
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              [-0.77604167],
              [-0.765625],
              [-0.76302083],
              [-0.77864583]],
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              [-0.77604167],
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              [-0.77083333],
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             . . . ,
```

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 [ 0.9921875 ],
 [ 0.98958333],
```

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 [-0.734375],
 [-0.72135417]],
```

[[-0.6953125],

```
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[[ 0.6796875 ],
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```
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```

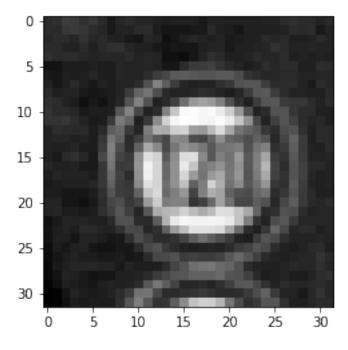
[-0.55729167],

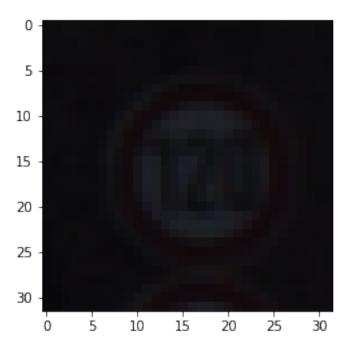
```
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              ],
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 [ 0.33333333],
 [ 0.3333333],
 . . . ,
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```

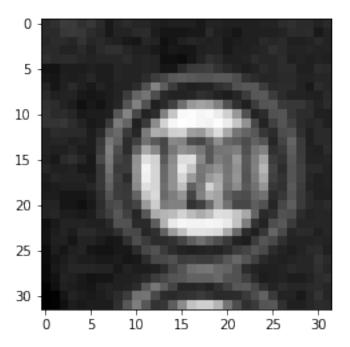
```
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 . . . ,
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 [-0.65364583],
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[[-0.59895833],
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 [-0.57552083],
 [-0.65104167],
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 [-0.63020833]],
[[-0.56510417],
 [-0.57552083],
 [-0.58333333],
 [-0.6484375],
 [-0.59895833],
 [-0.60416667]]])
```

```
[18]: i = 60
plt.imshow(X_train_gray[i].squeeze(), cmap = 'gray')
plt.figure()
plt.imshow(X_train[i])
plt.figure()
plt.imshow(X_train_gray_norm[i].squeeze(), cmap = 'gray')
```

[18]: <matplotlib.image.AxesImage at 0x1c70007fcf8>



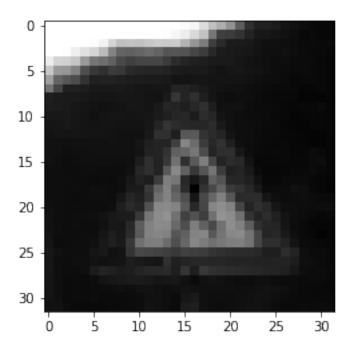


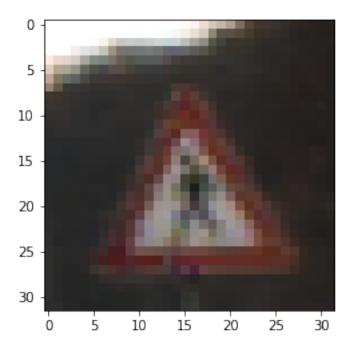


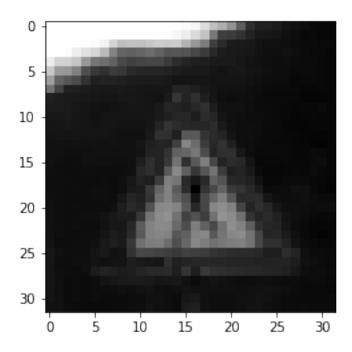
```
[19]: i = 610
plt.imshow(X_test_gray[i].squeeze(), cmap = 'gray')
plt.figure()
plt.imshow(X_test[i])
plt.figure()
```

```
plt.imshow(X_test_gray_norm[i].squeeze(), cmap = 'gray')
```

[19]: <matplotlib.image.AxesImage at 0x1c7001b34e0>

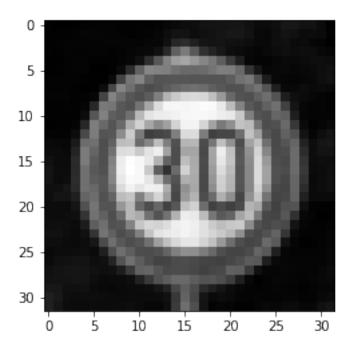


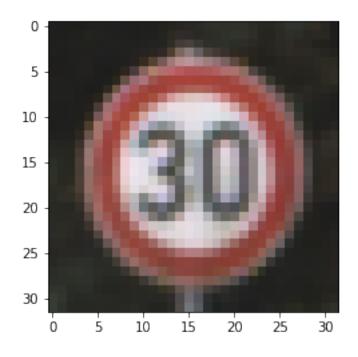


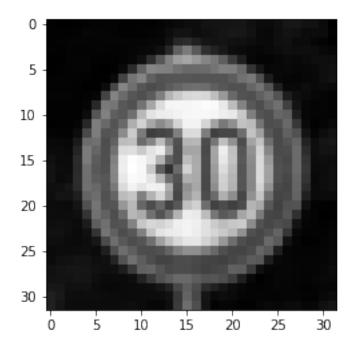


```
[20]: i = 500
plt.imshow(X_validation_gray[i].squeeze(), cmap = 'gray')
plt.figure()
plt.imshow(X_validation[i])
plt.figure()
plt.imshow(X_validation_gray_norm[i].squeeze(), cmap = 'gray')
```

[20]: <matplotlib.image.AxesImage at 0x1c75bb52f28>







#### 6 MODEL TRAINING

The model consists of the following layers:

- STEP 1: THE FIRST CONVOLUTIONAL LAYER #1
  - Input = 32x32x1
  - Output = 28x28x6
  - Output =  $(Input-filter+1)/Stride^* => (32-5+1)/1=28$
  - Used a 5x5 Filter with input depth of 3 and output depth of 6
  - Apply a RELU Activation function to the output
  - pooling for input, Input = 28x28x6 and Output = 14x14x6
  - Stride is the amount by which the kernel is shifted when the kernel is passed over the image.
- STEP 2: THE SECOND CONVOLUTIONAL LAYER #2
  - Input = 14x14x6
  - Output = 10x10x16
  - Layer 2: Convolutional layer with Output = 10x10x16
  - Output = (Input-filter+1)/strides => 10 = 14-5+1/1
  - Apply a RELU Activation function to the output
  - Pooling with Input = 10x10x16 and Output = 5x5x16
- STEP 3: FLATTENING THE NETWORK
  - Flatten the network with Input = 5x5x16 and Output = 400
- STEP 4: FULLY CONNECTED LAYER
  - Layer 3: Fully Connected layer with Input = 400 and Output = 120
  - Apply a RELU Activation function to the output
- STEP 5: ANOTHER FULLY CONNECTED LAYER
  - Layer 4: Fully Connected Layer with Input = 120 and Output = 84
  - Apply a RELU Activation function to the output
- STEP 6: FULLY CONNECTED LAYER
  - Layer 5: Fully Connected layer with Input = 84 and Output = 43

```
[21]: from tensorflow.keras import datasets, layers, models

LeNet = models.Sequential()

LeNet.add(layers.Conv2D(6, (5,5), activation = 'relu', input_shape = (32,32,1)))
LeNet.add(layers.AveragePooling2D())

LeNet.add(layers.Conv2D(16, (5,5), activation = 'relu'))
```

```
LeNet.add(layers.AveragePooling2D())

LeNet.add(layers.Flatten())

LeNet.add(layers.Dense(120, activation = 'relu'))

LeNet.add(layers.Dense(84, activation = 'relu'))

LeNet.add(layers.Dense(43, activation = 'softmax'))
LeNet.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 6)	156
average_pooling2d (AveragePo	(None, 14, 14, 6)	0
conv2d_1 (Conv2D)	(None, 10, 10, 16)	2416
average_pooling2d_1 (Average	(None, 5, 5, 16)	0
flatten (Flatten)	(None, 400)	0
dense (Dense)	(None, 120)	48120
dense_1 (Dense)	(None, 84)	10164
dense_2 (Dense)	(None, 43)	3655 ========
Total params: 64,511		

Trainable params: 64,511
Non-trainable params: 0

\_\_\_\_\_\_

```
[22]: LeNet.compile(optimizer = 'Adam', loss = 'sparse_categorical_crossentropy', use metrics = ['accuracy'])

[23]: history = LeNet.fit(X_train_gray_norm, y_train, batch_size = 500, nb_epoch = 50, verbose = 1, validation_data = (X_validation_gray_norm, y_validation))
```

WARNING: Logging before flag parsing goes to stderr.

W1018 22:13:07.586207 16828 training.py:701] The `nb\_epoch` argument in `fit` has been renamed `epochs`.

```
Train on 34799 samples, validate on 4410 samples
Epoch 1/50
accuracy: 0.1815 - val_loss: 2.6016 - val_accuracy: 0.3184
Epoch 2/50
accuracy: 0.5693 - val_loss: 1.2840 - val_accuracy: 0.6236
Epoch 3/50
34799/34799 [============== ] - 15s 438us/sample - loss: 0.8503 -
accuracy: 0.7624 - val_loss: 0.9664 - val_accuracy: 0.7333
Epoch 4/50
accuracy: 0.8341 - val_loss: 0.8458 - val_accuracy: 0.7651
Epoch 5/50
accuracy: 0.8687 - val_loss: 0.7665 - val_accuracy: 0.7871
Epoch 6/50
accuracy: 0.8903 - val_loss: 0.7181 - val_accuracy: 0.8111
Epoch 7/50
34799/34799 [============== ] - 16s 454us/sample - loss: 0.3481 -
accuracy: 0.9082 - val_loss: 0.6641 - val_accuracy: 0.8234
34799/34799 [============== ] - 16s 460us/sample - loss: 0.3001 -
accuracy: 0.9228 - val_loss: 0.6393 - val_accuracy: 0.8297
accuracy: 0.9324 - val_loss: 0.6417 - val_accuracy: 0.8363
Epoch 10/50
accuracy: 0.9404 - val_loss: 0.6282 - val_accuracy: 0.8433
Epoch 11/50
accuracy: 0.9467 - val_loss: 0.6213 - val_accuracy: 0.8422
Epoch 12/50
accuracy: 0.9499 - val_loss: 0.6205 - val_accuracy: 0.8531
Epoch 13/50
accuracy: 0.9571 - val_loss: 0.5958 - val_accuracy: 0.8524
Epoch 14/50
accuracy: 0.9620 - val_loss: 0.5945 - val_accuracy: 0.8522
Epoch 15/50
```

```
accuracy: 0.9648 - val_loss: 0.5730 - val_accuracy: 0.8574
Epoch 16/50
accuracy: 0.9685 - val_loss: 0.6105 - val_accuracy: 0.8587
Epoch 17/50
accuracy: 0.9700 - val_loss: 0.5860 - val_accuracy: 0.8583
Epoch 18/50
34799/34799 [============== ] - 15s 436us/sample - loss: 0.1098 -
accuracy: 0.9734 - val_loss: 0.6329 - val_accuracy: 0.8533
Epoch 19/50
34799/34799 [============== ] - 15s 423us/sample - loss: 0.1020 -
accuracy: 0.9741 - val_loss: 0.6231 - val_accuracy: 0.8617
Epoch 20/50
accuracy: 0.9774 - val_loss: 0.5986 - val_accuracy: 0.8719
Epoch 21/50
34799/34799 [============== ] - 18s 508us/sample - loss: 0.0858 -
accuracy: 0.9791 - val_loss: 0.6339 - val_accuracy: 0.8637
Epoch 22/50
accuracy: 0.9814 - val_loss: 0.6581 - val_accuracy: 0.8649
Epoch 23/50
accuracy: 0.9818 - val_loss: 0.6833 - val_accuracy: 0.8553
Epoch 24/50
34799/34799 [============== ] - 14s 401us/sample - loss: 0.0673 -
accuracy: 0.9833 - val_loss: 0.6759 - val_accuracy: 0.8667
accuracy: 0.9856 - val_loss: 0.6929 - val_accuracy: 0.8628
Epoch 26/50
accuracy: 0.9866 - val_loss: 0.7099 - val_accuracy: 0.8594
Epoch 27/50
accuracy: 0.9874 - val_loss: 0.6834 - val_accuracy: 0.8692
Epoch 28/50
accuracy: 0.9879 - val_loss: 0.7080 - val_accuracy: 0.8696
Epoch 29/50
accuracy: 0.9887 - val_loss: 0.7828 - val_accuracy: 0.8660
Epoch 30/50
accuracy: 0.9895 - val_loss: 0.7569 - val_accuracy: 0.8612
Epoch 31/50
```

```
accuracy: 0.9905 - val_loss: 0.7930 - val_accuracy: 0.8669
Epoch 32/50
accuracy: 0.9915 - val_loss: 0.7902 - val_accuracy: 0.8669
Epoch 33/50
accuracy: 0.9905 - val_loss: 0.7467 - val_accuracy: 0.8669
Epoch 34/50
34799/34799 [============= ] - 12s 342us/sample - loss: 0.0344 -
accuracy: 0.9917 - val_loss: 0.7562 - val_accuracy: 0.8660
Epoch 35/50
34799/34799 [============= ] - 12s 334us/sample - loss: 0.0303 -
accuracy: 0.9933 - val_loss: 0.7618 - val_accuracy: 0.8728
Epoch 36/50
accuracy: 0.9919 - val_loss: 0.7860 - val_accuracy: 0.8735
Epoch 37/50
34799/34799 [============= ] - 13s 386us/sample - loss: 0.0318 -
accuracy: 0.9919 - val_loss: 0.8505 - val_accuracy: 0.8680
Epoch 38/50
accuracy: 0.9916 - val_loss: 0.6967 - val_accuracy: 0.8739
Epoch 39/50
accuracy: 0.9937 - val_loss: 0.6780 - val_accuracy: 0.8900
Epoch 40/50
34799/34799 [============= ] - 12s 338us/sample - loss: 0.0235 -
accuracy: 0.9942 - val_loss: 0.8278 - val_accuracy: 0.8671
accuracy: 0.9948 - val_loss: 0.7804 - val_accuracy: 0.8741
accuracy: 0.9966 - val_loss: 0.7662 - val_accuracy: 0.8748
Epoch 43/50
accuracy: 0.9957 - val_loss: 0.7943 - val_accuracy: 0.8680
Epoch 44/50
accuracy: 0.9957 - val_loss: 0.7970 - val_accuracy: 0.8710
Epoch 45/50
accuracy: 0.9951 - val_loss: 0.9367 - val_accuracy: 0.8499
Epoch 46/50
accuracy: 0.9932 - val_loss: 0.9788 - val_accuracy: 0.8578
Epoch 47/50
```

# 7 MODEL EVALUATION

[24]:	<pre>score = LeNet.evaluate(X_test_gray_norm, y_test)</pre>
	<pre>print('Test Accuracy: {}'.format(score[1]))</pre>

12630/1 [====================================
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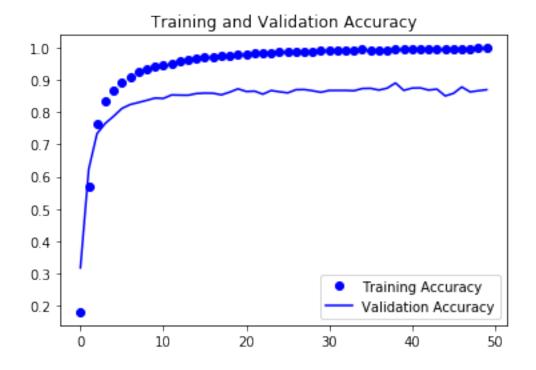
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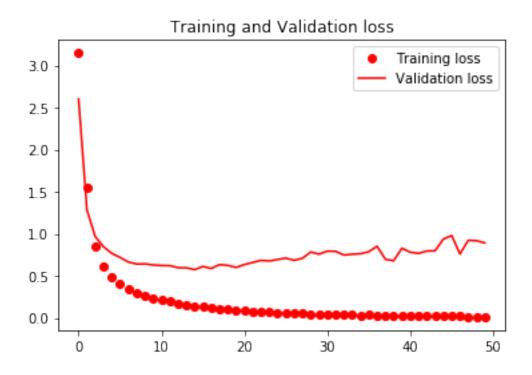
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[27]: <matplotlib.legend.Legend at 0x1c701a50be0>



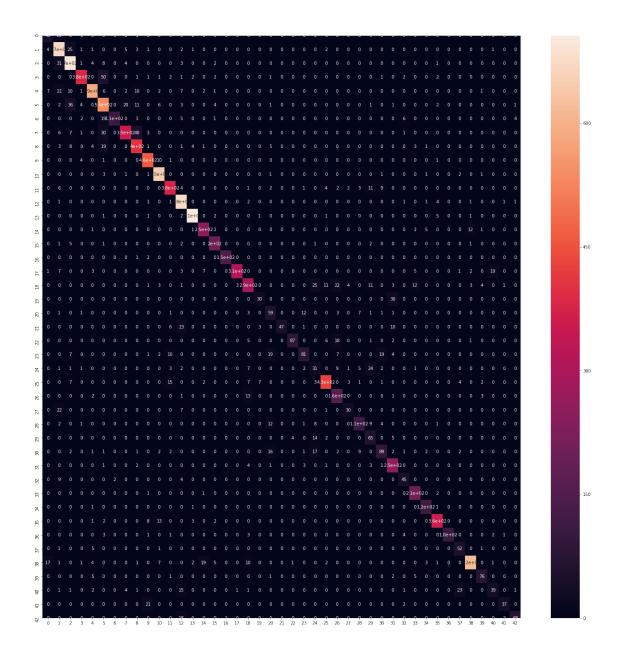
```
[28]: plt.plot(epochs, loss, 'ro', label='Training loss')
  plt.plot(epochs, val_loss, 'r', label='Validation loss')
  plt.title('Training and Validation loss')
  plt.legend()
```

[28]: <matplotlib.legend.Legend at 0x1c70013bbe0>



```
[29]: predicted_classes = LeNet.predict_classes(X_test_gray_norm)
    y_true = y_test
[30]: from sklearn.metrics import confusion_matrix
    cm = confusion_matrix(y_true, predicted_classes)
    plt.figure(figsize = (25, 25))
    sns.heatmap(cm, annot = True)
```

[30]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1c74d768780>

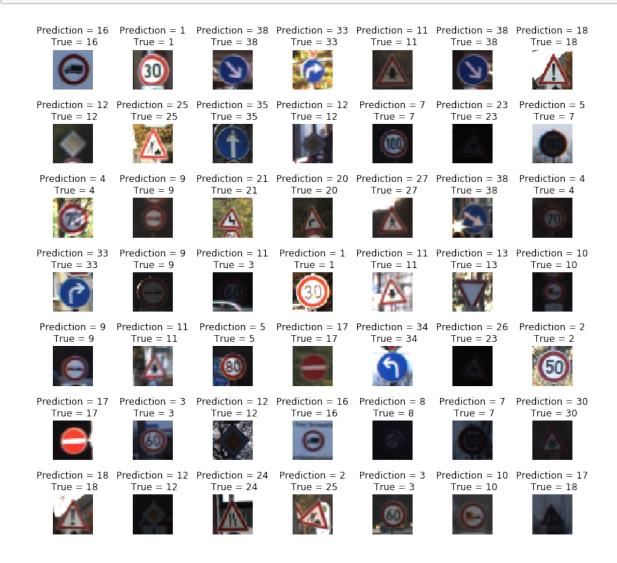


```
[31]: L = 7
W = 7

fig, axes = plt.subplots(L, W, figsize = (12, 12))
axes = axes.ravel()

for i in np.arange(0, L*W):
    axes[i].imshow(X_test[i])
    axes[i].set_title('Prediction = {}\n True = {}'.format(predicted_classes[i], \n \dots \d
```

## plt.subplots\_adjust(wspace = 1)



## 8 Skills Utilized:

- 1. Convolutional NN
- 2. LeNet
- 3. RELU

## 9 Interesting Links:

- http://setosa.io/ev/image-kernels/
- http://scs.ryerson.ca/~aharley/vis/conv/flat.html

## 10 Notes:

- RELU layers are used to add non-linearity in the feature map.
- Pooling or down sampling layers are placed after convolutional layers to reduce feature map dimensionality.
- This improves the computational efficiency while preserving the features.
- Pooling helps the model to generalize by avoiding overfitting.
- Improve accuracy by adding more feature detectors/filters or adding a dropout.
- Dropout refers to dropping out units in a neural network
- Dropout is a regularization technique for reducing overfitting in neural networks.
- Dropout enalbes training to occur on several architectures of the neural network.
- Neurons develop co-dependency amongst each other during training