Traffic Sign Classification

I. Exploratory Data Analysis

The data set used for the final project is *German Traffic Sign Recognition Benchmark (GTSRB)* from Kaggle (*https://www.kaggle.com/datasets/meowmeowmeowmeowmeow/gtsrb-german-traffic-sign*). There are 39219 images in training set and 12630 images in test set. The location of the bounding box is given by the coordinates of its upper left and lower right corners within an image. The goal is to classify images into 43 classes of traffic signs. Some sample images from the data set are shown in Fig. 1.

Fig. 1. sample images from the data set

II. Template Matching

In addition to the training images and the test images, templates for each class are as well provided in the data set. Some sample templates are shown in Fig. 2.

Fig. 2. sample templates from the data set

With the templates provided, Sum-of-Absolute Differences (SAD), Sum-of-Squared Differences (SSD) and Normalized Cross-Correlation (NCC) are used to classify the test images.

The test results for SAD are shown in Fig. 3, along with the classes best and worst classified in terms of accuracy. An overall test accuracy of 0.1652 is achieved. 16 classes are not recognized at all (zero accuracy).

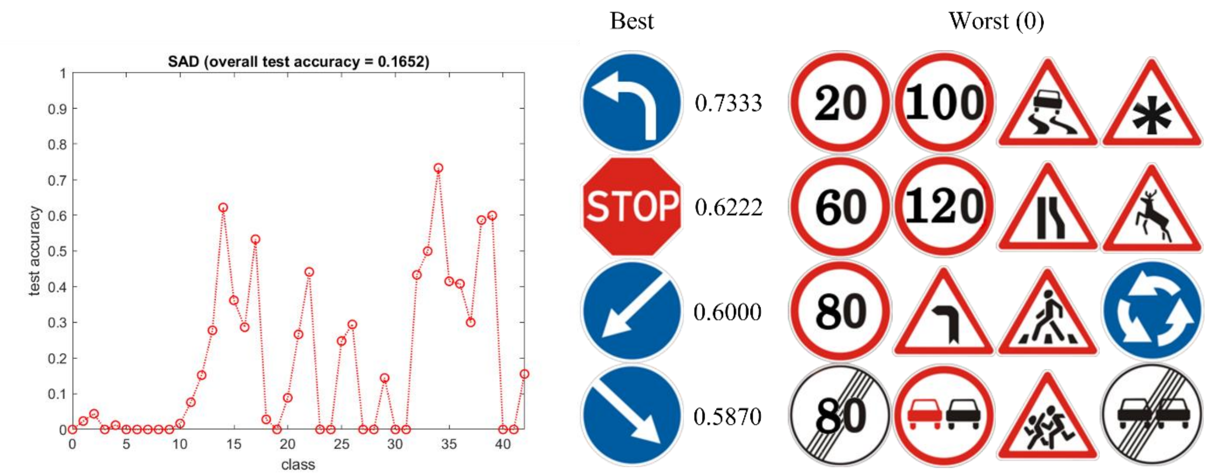

Fig. 3. test results for SAD

The test results for SSD are shown in Fig. 4, along with the classes best and worst classified in terms of accuracy. An overall test accuracy of 0.1804 is achieved. 13 classes are not recognized at all (zero accuracy).

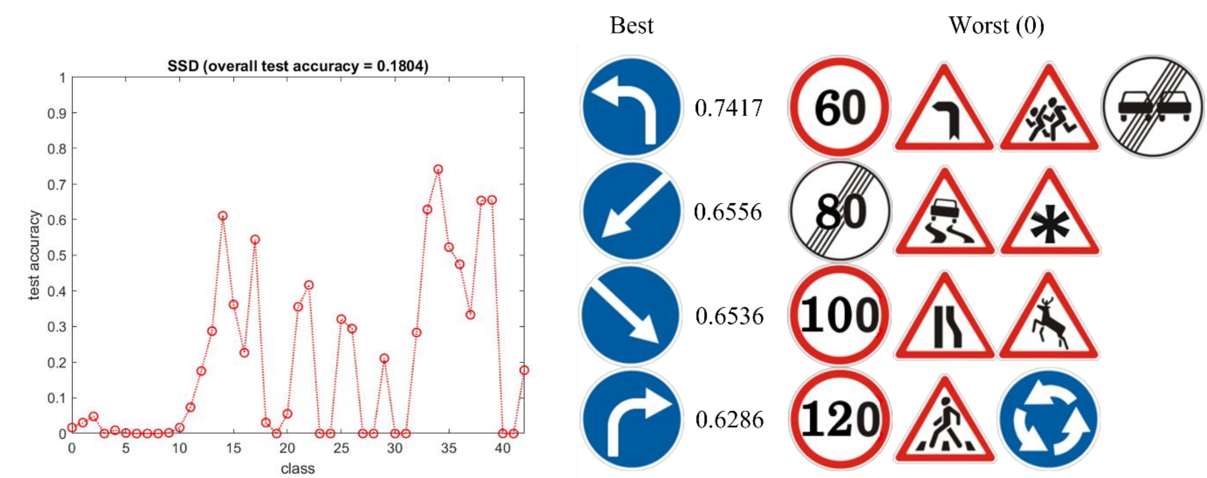

Fig. 4. test results for SSD

The test results for NCC are shown in Fig. 5, along with the classes best and worst classified in terms of accuracy. An overall test accuracy of 0.3116 is achieved. 8 classes are not recognized at all (zero accuracy).

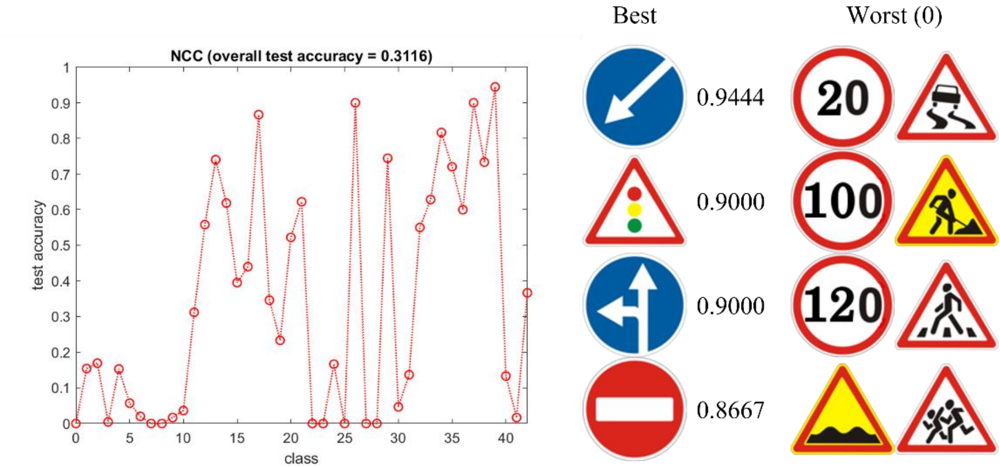

Fig. 5. test results for NCC

III. Histogram of Oriented Gradients (HOG)

Gaussian derivative masks are used to find gradients where the optimal standard deviation *sigma* is determined in the validation process. The whole image is divided into *patchNum* * *patchNum* patches. For each patch, the orientations of the gradients are put into a histogram with *oriNum* bins based on either being signed (two orientations differing by 180 degrees are considered different) or unsigned (two orientations differing by 180 degrees are considered the same). The histogram describing each patch can be considered a vector, from which there are two ways to represent the whole image: (1) a covariance matrix where the minimum Riemannian Manifold with the mean covariance matrices is used to classify images; (2) a rasterized vector from all the patches where the minimum Euclidean distance to the mean vectors is used to classify images. 20% of training images from each class together form a validation set which is used to tune the *parameters (sigma, patchNum, oriNum, signed/unsigned)*.

For preliminary model selection, images are divided into 8*8 patches and there are 9 bins in the histogram. Models are built upon both grayscale images and RGB images. Performance of each model is evaluated upon the validation accuracy with different standard deviations (*sigma = 0.25, 0.5, 0.75 and 1*), where the optimal *sigma* is determined in the validation process.

The validation results from grayscale images are shown in Fig. 6. A best validation accuracy of 0.3059 is achieved in the covariance models and a best validation accuracy of 0.8020 is achieved in the vector models.

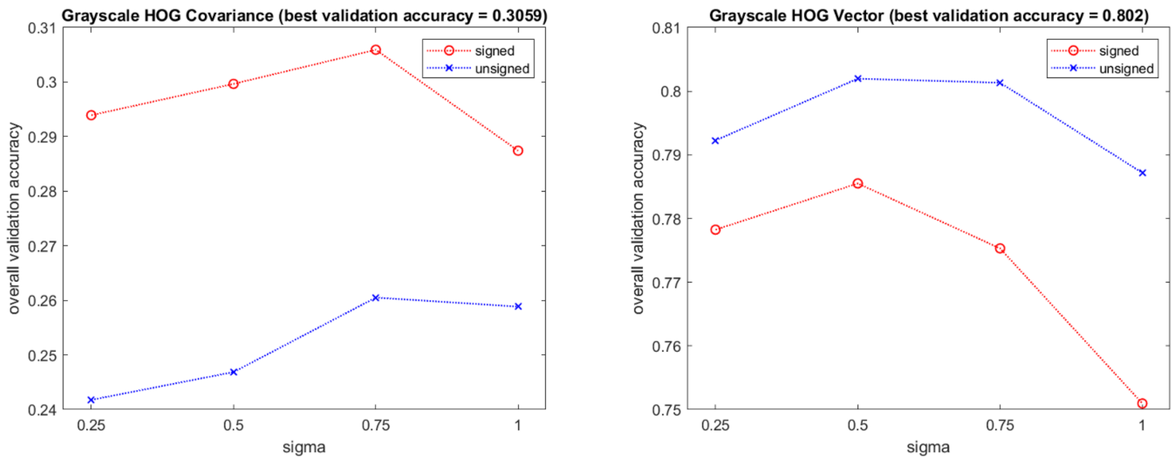

Fig. 6. validation results for grayscale images

The validation results from RGB images using the RGB voting method are shown in Fig. 7, where the classification is determined by the majority of the three channels and, if there is a tie, by the green channel. A best validation accuracy of 0.3063 is achieved in the covariance models and a best validation accuracy of 0.7972 is achieved in the vector models.

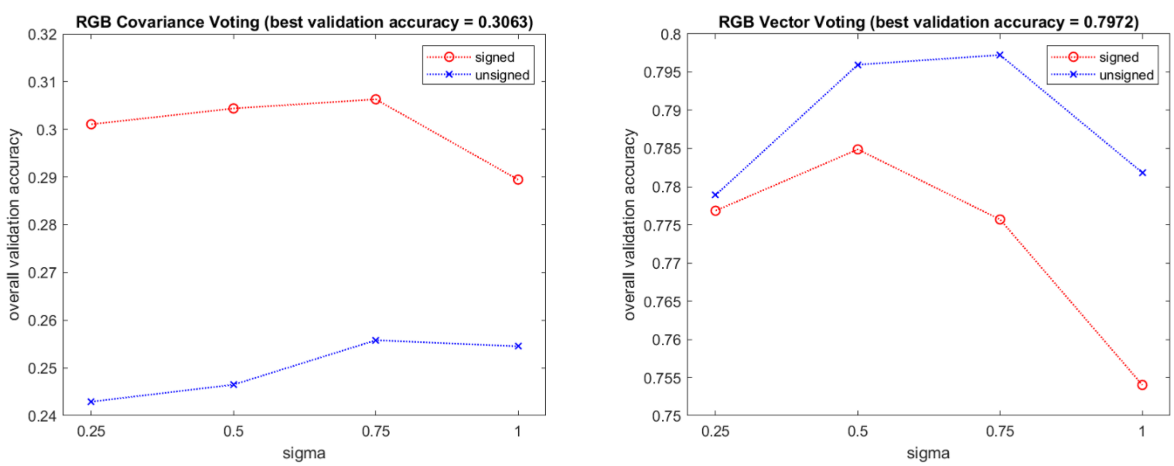

Fig. 7. validation results from RGB images classified using the RGB voting method

The validation results from RGB images using the RGB minimum method are shown in Fig. 8, where the classification is determined by the channel with the minimum measure. A best validation accuracy of 0.2867 is achieved in the covariance models and a best validation accuracy of 0.8011 is achieved in the vector models.

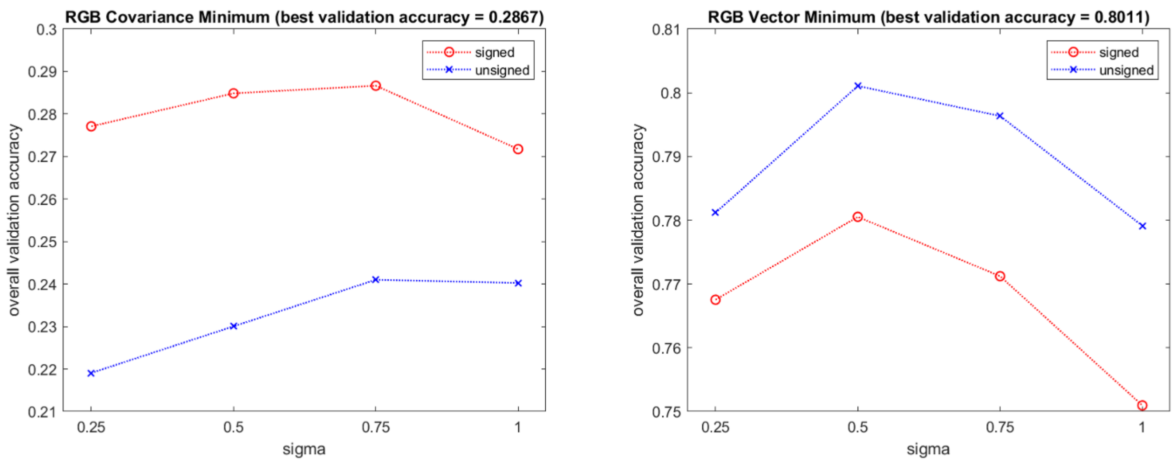

Fig. 8. Validation results from RGB images classified using the RGB minimum method

The validation results from RGB images using the RGB vector total method are shown in Fig. 9, where the classification is determined by the total Euclidean distance in RGB space. A best validation accuracy of 0.8122 is achieved.

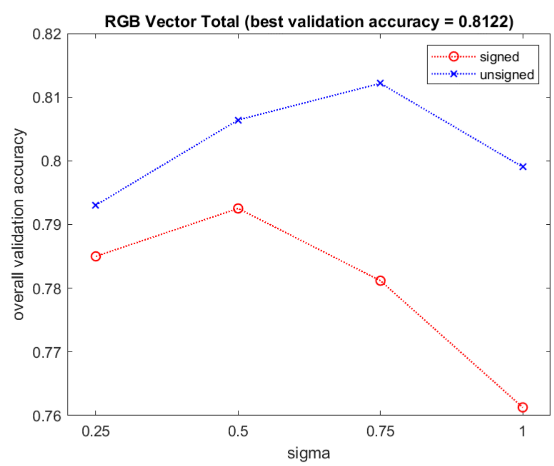

Fig. 9. validation results from RGB images classified using the RGB vector total method

The best validation accuracy achieved from RGB images is 0.8122, which is slightly higher than the best validation accuracy of 0.8020 achieved from grayscale images. The comparison among the RGB images, grayscale images and three channels is shown in Fig. 10. In terms of orientations of gradients, grayscale images have captured most of the information, and, if each channel is treated independently, some information may be lost, which could be the reason why the best validation accuracy achieved from the RGB minimum method is slightly lower than that from the grayscale images. Grayscale images are good enough to build models on.

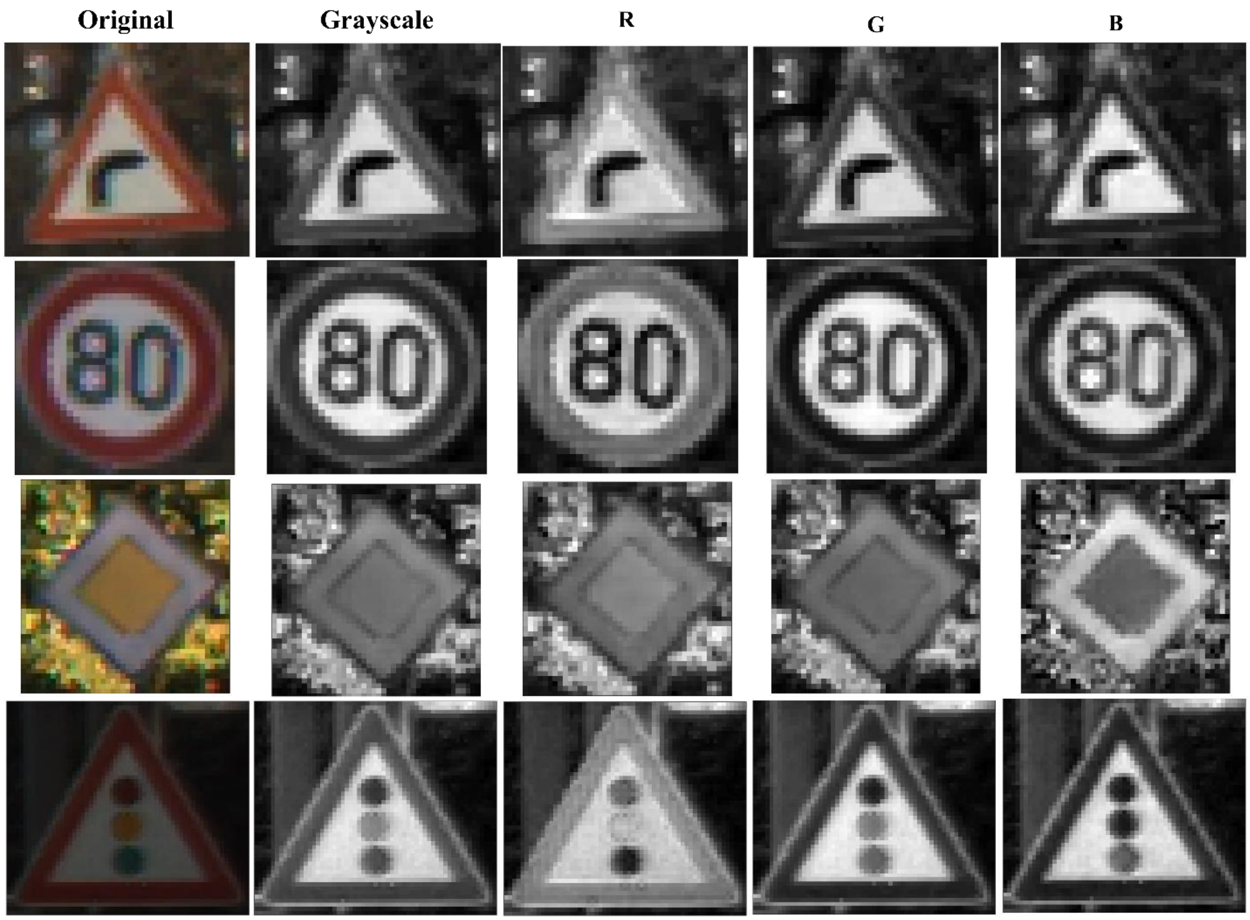

Fig. 10. comparison among the RGB images, grayscale images and three channels

The best performing signed HOG covariance model and unsigned HOG vector model from preliminary model selection are then refined using grayscale images. The optimal number of patches and the optimal number of bins in the histogram are determined in the validation process. The validation results for the signed HOG covariance model and the unsigned HOG vector model are shown in Fig. 11.

A best validation accuracy of 0.3484 is achieved for the signed HOG covariance model and a best validation accuracy of 0.8323 is achieved for the unsigned HOG vector model.

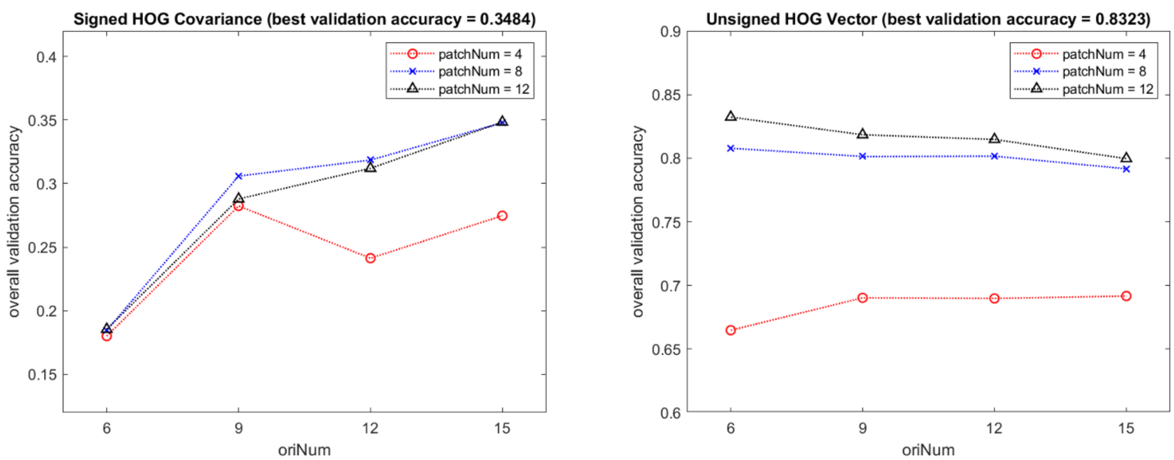

Fig. 11. validation results from the signed HOG covariance model and the unsigned HOG vector model

The test results for the signed HOG covariance model are shown in Fig. 12, along with the classes best and worst classified in terms of accuracy. An overall test accuracy of 0.3146 is achieved. The best test accuracy among classes is 0.8565 and the worst test accuracy among classes is 0.0111.

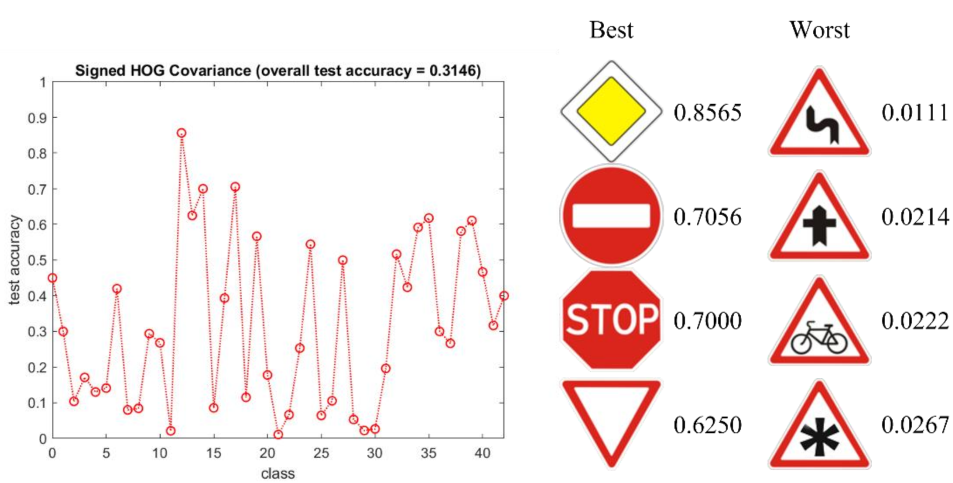

Fig. 12. test results for the signed HOG covariance model

The test results for the unsigned HOG vector model are shown in Fig. 13, along with the classes best and worst classified in terms of accuracy. An overall test accuracy of 0.7788 is achieved. The best test accuracy among classes is 1.000 and the worst test accuracy among classes is 0.0444. The test accuracies for all the classes other than class 29 are above 0.45.

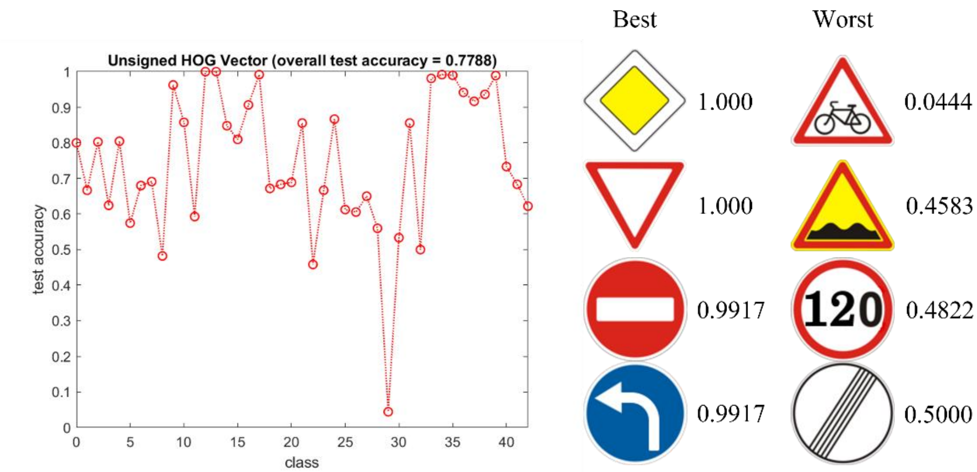

Fig. 13. test results for the unsigned HOG vector model