Proceedings of the
2007 IEEE Intelligent Vehicles Symposium
Istanbul, Turkey, June 13-15, 2007



# Road-Sign Identification Using Ensemble Learning

Abbas Z. Kouzani

*Abstract*— **Ensemble learning that combines the decisions of multiple weak classifiers to from an output, has recently emerged as an effective identification method. This paper presents a road-sign identification system based upon the ensemble learning approach. The system identifies the regions of interest that are extracted from the scene into the road-sign groups that they belong to. A large road-sign image dataset is formed and used to train and test the system. Fifteen groups of road signs are chosen for identification. Five experiments are performed and the results are presented and discussed.**

## I. INTRODUCTION

Road signs guide drivers and warn them of road conditions. A driver, however, may not notice a road sign or may choose to disregard it. Failure to notice or obey critical road signs at the crucial moments may indirectly contribute to road accidents. An automatic road sign recognition system identifies road signs within live colour images captured by a camera. The system alerts the driver of the road signs. Developing a reliable road sign recognition system is considered a challenging task [1]. There are a number of issues that need to be considered. These issues are listed below:

- The direction of road-signs face is not always ideal. Thus, road-sign shapes and patterns can be affected .
- The strength of the light depends on the time of the day and season, and also on the weather conditions. In addition, road sign patterns within images can be affected by shadows from surrounding objects.
- Road signs get bigger as the vehicle moves towards them.
- Road signs can be confused with several other shapes such as commercial signs and building windows.
- Obstacles, such as tree, buildings, vehicles, and pedestrians, may partially occlude road signs.
- Images of road signs often suffer from blurring due to vibration when the imaging sensor is mounted on a moving vehicle.
- The paint on signs also deteriorates with time. Colours on road sign may fade after a long exposure to the sun and rain. Paint on signs may even flake or peel off.
- Multiple road signs may appear one over/beside the other.
- The characteristics of the image acquisition system can affect the quality of images captured.

Fig. 1 displays examples of road-sign images containing variations.

A.Z. Kouzani is with the School of Engineering and Information Technology, Deakin University, Geelong, Victoria 3217, Australia kouzani@deakin.edu.au

A road sign is distinct in its shape and colour that form the sign's appearance. Therefore, most of the existing methods rely heavily on these features of road signs.

Shape is an attribute of road signs that can be used to recognise them. Shape-based methods can detect the relevant shapes of road signs. Several techniques on shape-based identification have been developed. These include: hierarchical spatial feature matching [2], Hough transform [3], [4], shape templates [5], distance transform matching [6], shape support vector machine [7], etc.

On the other hand, colours are used in road signs and often include primary colours (red, green, or blue) with yellow as a secondary colour. Colour-based methods segment the image to extract regions of interest for identification. These include: colour thresholding segmentation [8], hue-saturation-intensity (HSI) transformation [9], dynamic pixel aggregation [10], region growing [11], Laplace kernel [9], colour neural network [1], ring partitioned [12], trainable similarity measure [13], fuzzy ARTMAP [14], colour support vector machine [15], etc.

The shape-based methods face more limitations than colour-based ones. Issues such as road signs in cluttered scene, imperfect shapes, as well as variations in scale and orientation make the recognition challenging. On the other hand, the colour-based methods are sensitive to the lighting conditions which can affect the colour acquired by the imaging sensor. But the colour-based methods can operate in a considerably fast speed. Majority of the existing methods can perform well on images containing standard imaging conditions (e.g., front-lit and front view road signs). Their performances reduce when they are presented with the road-sign image contains imaging variations.

Fig. 1. Examples of road-sign images containing variations.

Ensemble learning [16] which combines the decisions of multiple classifiers to from an integrated output has recently emerged as an effective identification method. The variety of the members of an ensemble is known to be an important factor in specifying its generalisation capability. Using ensemble learning, a complex problem can be decomposed into multiple subproblems that are easier to solve. A random forest [17] is an ensemble learning method that grows many identification trees. To identify an object from an input vector, the input vector is put down each of the trees in the forest. Each tree gives an identification. The forest selects the identification that has most votes. This paper presents an identification system that employs the random forest method to identify road-sign images.

The paper is organised as follows. Section II reviews the random forest method. Section III presents the experimental results. Section IV discusses the performance of the developed system as well as some existing counterparts. Finally, concluding remarks are given in Section V.

## II. Random Forest

Ensemble learning [16] refers to the algorithms that produce collections or ensembles of classifiers which learn to identify by training individual learners and fusing their predictions. Growing an ensemble of trees and getting them vote for the most popular class has provided a good enhancement in the accuracy of identification. Often, random vectors are built that control the growth of each tree in the ensemble. The ensemble learning methods can be divided into two main groups: bagging and boosting. In bagging, models are fit in parallel where successive trees do not depend on previous trees. Each tree is independently built using bootstrap sample of the dataset. A majority vote determines prediction. In boosting, models are fit sequentially where successive trees assign additional weight to those observations poorly predicted by previous model. A weighted vote specifies prediction.

A random forest [18] adds an additional degree of randomness to bagging. Although each tree is constructed using a different bootstrap sample of the dataset, the method by which the identification trees ate built is improved. A random forest predictor is an ensemble of individual identification tree predictors. For each observation, each individual tree votes for one class and the forest predicts the class that has the plurality of votes. The user has to specify the number of randomly selected variables ($m_{\text{try}}$) to be searched through for the best split at each node.

Whilst a node is split using the best split among all variables in standard trees, in a random forest the node is split using the best among a subset of predictors randomly chosen at that node. The largest tree possible is grown and is not pruned. The root node of each tree in the forest contains a bootstrap sample from the original data as the training set. The observations that are not in the training set, are referred to as “out-of-bag” observations.

Since an individual tree is unpruned, the terminal nodes can contain only a small number of observations. The training data are run down each tree. If observations $i$ and $j$ both end up in the same terminal node, the similarity between $i$ and $j$ is increased by one. At the end of the forest construction, the similarities are symmetrised and divided by the number of trees. The similarity between an observation and itself is set to one. The similarities between objects form a matrix which is symmetric, and each entry lies in the unit interval $[0, 1]$. Breiman defines the random forest as [18]:

> A random forest is a classifier consisting of a collection of tree-structured classifiers $\{h(\mathbf{x}, \Theta_k), k = 1, \ldots\}$ where $\{\Theta_k\}$ are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input **x.**

A summary of the random forest algorithm for identification is given below [19]:

- Draw $n_{\text{tree}}$ bootstrap samples from the original data.
- For each of the bootstrap samples, grow an unpruned identification tree, with the following modification: at each node, rather than choosing the best split among all predictors, randomly sample $m_{\text{try}}$ of the predictors and choose the best split from among those variables. Bagging can be thought of as the special case of the random forest obtained when $m_{\text{try}} = p$, the number of predictors.
- Predict new data by aggregating the predictions of the $n_{\text{tree}}$ trees, i.e., majority votes for identification, average for regression.

The generalisation error of a forest of tree classifiers depends on the strength of the individual trees in the forest and the correlation between them. Using a random selection of features to split each node yields error rates that compare to AdaBoost [20]. An estimate of the error rate can be obtained, based on the training data, by the following [19]:

- At each bootstrap iteration, predict the data that is not in the bootstrap sample, called “out-of-bag” data, using the tree which is grown with the bootstrap sample.
- Aggregate the out-of-bag predictions. On the average, each data point would be out-of-bag around 36% of the times, so aggregate these predictions. Calculate the error rate, and call it the “out-of-bag” estimate of error rate.

The random forest performs well compared to several other popular classifiers, including discriminant analysis, support vector machine, and neural networks. In addition, it is user-friendly as it has only two parameters: (i) the number of variables in the random subset at each node, and (ii) the number of trees in the forest. The random forest is not usually very sensitive to the values of these parameters.

Some of the advantages of the random forest are listed in the following [17]: (i) for many data sets, it produces an accurate classifier; (ii) it handles a large number of input variables; (iii) it predicts the importance of variables; (iv) it generates an internal unbiased estimate of the generalisation error; (v) it provides an experimental way to detect variable interactions; (vi) it learns fast.

The random forest algorithm is employed to form the proposed road sign identification system. The system classifies the regions of interest that are extracted from the scene into the proper road-sign categories they belongs to.

We have constructed large training and test datasets and used them in developing the road sign identification system. The total number of road sign images used for training and testing of the system is close to 2500. The size of each image is $30 \times 30$. The training and test datasets include not only road-sign images, but also non-road-sign images that are needed to enhance the rejection capability of the system.

Fifteen categories of road signs have been selected for identification in this work. The fifteen categories are stop, give way, no entry, no left turn, no right turn, speed limit 10, speed limit 20, speed limit 30, speed limit 40, speed limit 50, speed limit 60, speed limit 70, speed limit 80, speed limit 90, and speed limit 100 signs. These categories have been chosen based on an observation made by the authors on about 80 images captured on Singapore's roads. Those signs that demonstrated a higher chance of occurrence were selected. In addition, we included another category named 'others' consisting of the images that do not belong to the above-mentioned fifteen road sign categories such as non-road-sign images. Fig. 2 illustrates one example image from each road-sign category.

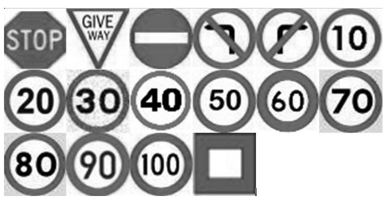


Fig. 2. Example images from the selected categories of road signs.

It has been observed that variations between images of the same road sign that are due to changes in imaging conditions are sometimes larger than the variations due to change in road sign identity. Little attempts have been made to incorporate invariance to a combination of imaging variations. In order to reduce the system's sensitivity to such variations as illumination, scale, orientation, motion-degradation, images of road signs containing possible variations are used in the training of the proposed system. In the training and test datasets, each of the fifteen road sign categories contains many images of the associated road sign incorporating the indicated variations. The number of images in each road sign category is as follows: 215 stop, 193 give way, 80 no entry, 134 no left turn, 140 no right turn, 117 speed limit 10, 125 speed limit 20, 126 speed limit 30, 123 speed limit 40, 217 speed limit 50, 192 speed limit 60, 126 speed limit 70, 124 speed limit 80, 248 speed limit 90, 120 speed limit 100, and 211 others. Fig. 3 displays example stop sign images containing different imaging variations.

## III. Experimental Results

This section presents the evaluation results of the developed road sign identification system. The obtained results are compared against those support vector machine [21], bagging support vector machine [22], and AdaBoost naive Bayes [23] approaches. Using these classifiers, a number of experiments were performed. With regard to the random forest classifier, we explored: (i) different number of trees to grow, and (ii) different number of variables that are randomly sampled as candidates at each split. Concerning the support vector machine classifier, we used the support vector machine with the polynomial kernel. About the bagging support vector machine, we used ten iterations of bagging and polynomial kernel. Finally, with regard to the AdaBoost naive Bayes we used ten iterations of AdaBoost.

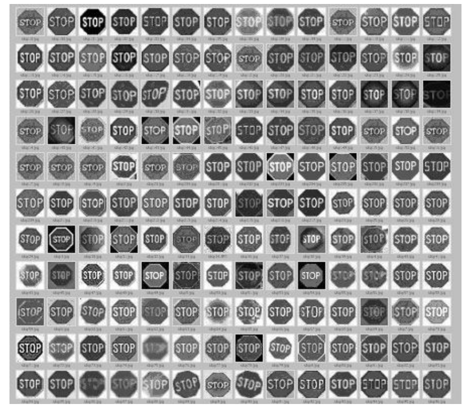

Fig. 3. Example stop sign images containing different imaging variations.

Confusion matrices were first calculated for each test. Then identification errors for each class were worked out. Finally, the overall identification error for each test was found. In our experiments with the random forest, we employed Ting Wang's interface [24] to the random forest algorithm that is developed by Leo Breiman and Adele Cutler [25]. Also, in our experiments with the support vector machine, the bagging support vector machine, and the AdaBoost naive Bayes, we utilised Rong Yan's MatlabArsenal [26] that encapsulates a number of popular identification algorithms.

### A. Experiment 1: Grayscale 50/50

The constructed road sign images were used to training and test the tested systems. The images were grouped into 16 classes. The number of images in each class is as follows: (1,215) (2,193) (3,80) (4,134) (5,140) (6,117) (7,125) (8,126) (9,123) (10,217) (11,192) (12,126) (13,124) (14,248) (15,120) (16,211). The colour images were all converted to grayscale images. All images were resized to $30 \times 30$. The pixel intensities were directly used as features for identification. Therefore, the number of samples and features were 2491 and 900, respectively. Two datasets were created: training and test. 50% of the images of each class were used to form the training dataset, and the other 50% of the images were used to form the test dataset. Therefore, overall 1246 road-sign images were used for training and 1245 road-sign images were used for testing.

With regard to the random forest-based system, the experiments were performed in two steps. First, the two parameters of the random forest were varied coarsely from 5 to 900 with an increment of 50 for no-of-trees-grown, and from 5 to 900 with an increment of 50 for no-of-variables-at-each-split. Fig. 4 (top) shows a graph representation of the obtained identification errors.

Second, using the results achieved in Step 1, we varied the two parameters finely from 305 to 405 with an increment

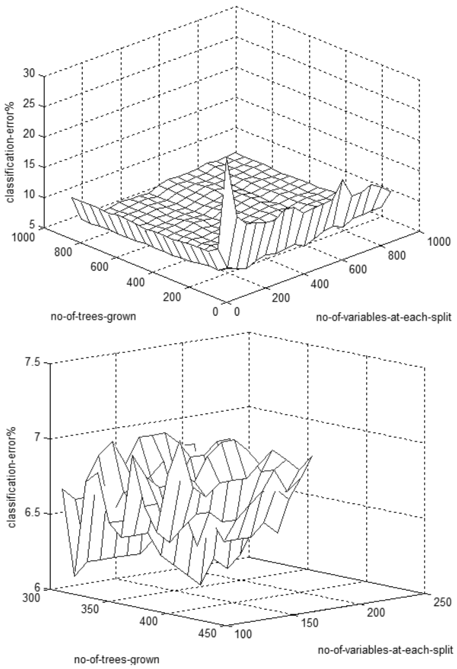


Fig. 4. Identification errors for the random forest-based classifiers created in the first step (top), and the second step (bottom).

of 10 for no-of-trees-grown, and from 105 to 205 with an increment of 10 for no-of-variables-at-each-split. Fig. 4 (bottom) illustrates a graph representation of the computed identification errors.

In addition, several support vector machine-based classifiers with the polynomial kernel of different parameters were developed. The classifier's kernel parameter was changed from 0.05 to 0.95. The same training and test data were employed. The identification results of some support vector machine-based classifiers as well as random forest-based classifiers are presented in Table I.

TABLE I
SAMPLE IDENTIFICATION ERRORS FOR GRAYSCALE 50/50.

| classifier | parameters | error % |
|---|---|---|
| support vector machine | polynomial kernel, 0.05 | 26.3 |
| | polynomial kernel, 0.20 | 8.0 |
| | polynomial kernel, 0.63 | 6.5 |
| | polynomial kernel, 0.75 | 7.5 |
| | polynomial kernel, 0.95 | 7.5 |
| random forest | 5 trees, 5 variables | 27.5 |
| | 305 trees, 105 variables | 6.6 |
| | 365 trees, 155 variables | 6.1 |
| | 405 trees, 205 variables | 6.9 |
| | 855 trees, 855 variables | 8.1 |

The table shows that the lowest identification errors for the support vector machine-based and the random forest-based systems were 6.5% and 6.1% respectively. These identification errors were obtained for the support vector machine classifier using polynomial kernel of parameter 0.63, and the random forest-based classifier employing 365 trees and 155 variables sampled at each split.

### *B. Experiment 2: PCA-Grayscale 50/50*

In the first experiment, the image pixel intensities were directly used as features for identification. Therefore, the number of features used for $30 \times 30$ road-sin images was 900. In this experiment, however, the principal components analysis (PCA) [27] is employed first to extract the significant features out of the road-sign image dataset reducing the multidimensional dataset to a lower dimension for faster identification. The PCA builds a low-dimensional road-sign space from a high-dimensional image space using example road-sign images. All road-sign images were transformed using the PCA, and 2491 road-sign basis were computed. Then each road-sign image was separately projected into the road-sign space, and 2491 coefficients were calculated. Out of these coefficients, those associated with the top 1% of the best road-sign basis were kept as features representing the particular road-sign image. Therefore, each road-sign was represented by 24 features instead of 900.

The two parameters of the random forest were varied from 1 to 200 with an increment of 4 for no-of-trees-grown, and from 1 to 24 with an increment of 1 for no-of-variables-at-each-split. The support vector machine classifier's polynomial kernel parameter was varied from 0.05 to 0.95. The identification results of some support vector machine-based classifiers as well as random forest-based classifiers are given in Table II.

TABLE II
SAMPLE IDENTIFICATION ERRORS FOR PCA-GRAYSCALE 50/50.

| classifier | parameters | error % |
|---|---|---|
| support vector machine | polynomial kernel, 0.05 | 37.2 |
| | polynomial kernel, 0.57 | 13.4 |
| | polynomial kernel, 0.95 | 20.0 |
| random forest | 1 trees, 1 variables | 35.9 |
| | 185 trees, 6 variables | 8.1 |
| | 197 trees, 24 variables | 11.5 |

The lowest identification error for the support vector machine-based and the random forest-based systems were 13.4% and 8.1% respectively. These identification errors were achieved for the support vector machine classifier employing polynomial kernel of parameter 0.57, and the random forest-based classifier employing 185 trees and 6 variables sampled at each split.

### *C. Experiment 3: Colour 50/50*

In this experiment, the road-sign images were used in their original colour mode. The colour road-sign images were transformed from the RGB colour space into the HSI colour space [4]. The HSI representation encodes colour information by separating out an overall intensity value from two values to encode hue and saturation making it more immune to changes in illumination. The pixel intensities were directly used as features for identification. Therefore, the number of samples and features were 2491 and 2700, respectively.

With regard to the proposed random forest-based system, the experiments were performed in two steps. First, the two parameters of the random forest were varied coarsely from 5 to 2700 with an increment of 300 for no-of-trees-grown, and from 5 to 2700 with an increment of 300 for no-of-variables-at-each-split. Second, using the results achieved in Step 1, we varied the two parameters finely from 855 to 925 with an increment of 10 for no-of-trees-grown, and from 285 to 325 with an increment of 10 for no-of-variables-at-each-split.

In addition, several support vector machine-based classifiers with the polynomial kernel of different parameters were developed. The classifier's kernel parameter was changed from 0.05 to 0.95. The same training and test data were employed. The identification results of some support vector machine-based classifiers as well as random forest-based classifiers are presented in Table III.

TABLE III
SAMPLE IDENTIFICATION ERRORS FOR COLOUR 50/50.

| classifier | parameters | error % |
|---|---|---|
| support vector machine | polynomial kernel, 0.05 | 43.5 |
| | polynomial kernel, 0.63 | 9.8 |
| | polynomial kernel, 0.95 | 10.4 |
| random forest | 5 trees, 5 variables | 38.5 |
| | 855 trees, 455 variables | 6.58 |
| | 2405 trees, 2405 variables | 8.3 |

It can be seen that the lowest identification error for the support vector machine-based and the random forest-based systems were 9.8% and 6.58% respectively. These identification errors were obtained for the support vector machine classifier using polynomial kernel of parameter 0.63, and the random forest-based classifier employing 855 trees and 455 variables sampled at each split.

### D. Experiment 4: PCA-Colour 50/50

In this experiment, first the significant features of the road-sign image dataset were extracted using the PCA. All colour road-sign images were transformed using the PCA, and 2491 road-sign basis were computed. Then each road-sign image was projected into the road-sign space, and 2491 coefficients were computed. Those coefficients that were associated with the top 1% of the best road-sign basis were kept as features. Each image was represented by a set of 24 features. The two parameters of the random forest were varied from 1 to 200 with an increment of 10 for no-of-trees-grown, and from 1 to 24 with an increment of 1 for no-of-variables-at-each-split. In addition, the support vector machine classifier's polynomial kernel parameter was varied from 0.05 to 0.95. The identification results of some support vector machine-based classifiers as well as random forest-based classifiers are given in Table IV.

The lowest identification error for the support vector machine-based and the random forest-based systems were 14.1% and 11.4% respectively. These identification errors were achieved for the support vector machine classifier employing polynomial kernel of parameter 0.72, and the random forest-based classifier employing 191 trees and 4 variables sampled at each split.

TABLE IV
SAMPLE IDENTIFICATION ERRORS FOR PCA-COLOUR 50/50.

| classifier | parameters | error % |
|---|---|---|
| support vector machine | polynomial kernel, 0.05 | 37.7 |
| | polynomial kernel, 0.72 | 14.1 |
| | polynomial kernel, 0.95 | 20.8 |
| random forest | 1 trees, 1 variables | 44.2 |
| | 191 trees, 4 variables | 11.4 |
| | 191 trees, 24 variables | 15.5 |

### E. Experiment 5: Bagging SVM and AdaBoost Naive Bayes

In order to perform a comparison of the performance of proposed random forest-based system against those of some other ensemble-based approaches, two ensemble classifiers were trained and tested using the road-sign image dataset: bagging support vector machine and AdaBoost naive Bayes. The first approach used the support vector machine ensemble with bagging (bootstrap aggregating) [28]. In bagging, each individual support vector machine is trained independently using the training samples randomly chosen through a bootstrap technique. Then the trained individual support vector machines are aggregated to make a collective decision.

The second approach used the classical naive Bayes ensemble boosted with the AdaBoost [20]. Multiple classifiers in sequential trials are formed by adaptively changing the distribution of the training set based upon the performance of the previously created classifiers. Individual classifiers are merged via weighted voting to form a composite classifier. We did not use the support vector machine as component classifiers for AdaBoost because AdaBoost does not perform well with strong component classifiers such as the support vector machine.

The PCA-extracted 24 features were employed to represent each road-sign image. The identification results are given in Table V.

TABLE V
IDENTIFICATION ERRORS FOR PCA-COLOUR 50/50 BAGGING SVM AND ADABOOST NAIVE BAYES.

| classifier | parameters | error % |
|---|---|---|
| support vector machine | polynomial kernel, 0.72 | 14.1 |
| bagging support vector machine | polynomial kernel, 0.72<br>10 iterations for bagging | 13.8 |
| naive Bayes | | 21.1 |
| AdaBoost naive Bayes | 10 iterations for AdaBoost | 17.2 |

As can be seen in the table, the identification error for the bagging support vector machine and the AdaBoost naive Bayes classifiers were 13.8% and 17.2% respectively. These identification errors were achieved for 10 iterations of both bagging as well as Adaboost larners.

## IV. DISCUSSIONS

This study was motivated by emergence of ensemble-based identification approaches, and also importance of robust automated road-sign recognition. The results demonstrate that the proposed random forest-based system performs better than the support vector machine as well as the bagging support vector machine and the AdaBoost naive Bayes approaches in all experiments. The lowest identification error (6.1%) was produced by the random forest-based system with 365 no-of-trees-grown and 165 no-of-variables-at-each-split for grayscale road-sign images.

It is surprising that the utilisation of road-sign images in colour mode did not improve the performance of the tested systems. Comparing the identification errors achieved for the grayscale 50/50 against those of the colour 50/50 experiments, it can be seen that for a fixed number of available images (2491), the specific datasets used, and the particular experiments conducted, using images in grayscale mode produces slightly lower identification error (6.1%) than the colour mode (6.5%). This is also true for the PCA transformed images.

While the two ensemble learning approaches, the bagging support vector machine and the AdaBoost naive Bayes improved the performance of their non-ensemble version, the support vector machine and the naive Bayes, in the experiment performed, they were not able to beat the random forest-based system.

The random forest-based system, that is an ensemble learning method which grows many identification trees, has shown to be an accurate classifier as it has performed very well for the road-sign identification problem considered in this work. The system has produced the lowest identification error amongst the system tested in our experiments.

Further experiments will be carried out to devise a proper explanation for why the utilisation of colour features did not reduce the identification errors. Also, different number of PCA coefficients will be employed to find out if some other projections could do better.

## V. Conclusions

We presented a road-sign identification system employing random forest. Five experimenters were carried out. In the first two experiments, the colour images were converted to grayscale, while in the last three experiment, images were used in the HSI colour space. In the second, fourth, and fifth experiments, the road-sign images were transformed using the PCA, and the top 1% of the best coefficients were kept as features. The random forest-based system together with the support vector machine, the bagging support vector machine, and the AdaBoost naive Bayes approaches were trained and tested using the same datasets. The lowest identification error (6.1%) was produced by the random forest-based system for the grayscale images. For the specific datasets used and the particular experiments conducted, utilisation of road-sign images in colour mode did not improve the performance of the tested systems. While the bagging support vector machine and the AdaBoost naive Bayes improved the performance of their non-ensemble versions, they were not able to do better than the random forest-based system. The random forest-based system proved that it is an accurate classifier as it performed well for the road-sign identification problem.

## References


[1] W. Wu, X. Chen, and J. Yang, "Detection of text on road signs from video," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, no. 4, p. 378390, 2005.

[2] Road Sign Recognition Group, "The road sign recognition system," 1999. [Online]. Available: http://euler.fd.cvut.cz/research/rs2

[3] G. Loy and N. Barnes, "Fast shape-based road sign detection for a driver assistance system," in *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, vol. 1, 2004, pp. 70–75.

[4] R. C. Gonzalez and R. E. Woods, *Digital Image Processing (2nd edition)*. Prentice Hall, 2002.

[5] J. Torresen, J. Bakke, and L. Sekanina, "Efficient recognition of speed limit signs," in *Proc. of the 7th Int. IEEE Conf. on Intelligent Transportation Systems*, 2004, p. 652656.

[6] D. Gavrila and V. Philomin, "Real-time object detection for smart vehicles," in *Proc. of IEEE Int. Conf. on Computer Vision*, 1999, p. 8793.

[7] P. Gil-Jimenez, S. Lafuente-Arroyo, S. Maldonado-Bascon1, and H. Gomez-Moreno, "Shape classification algorithm using support vector machines for traffic sign recognition," *Lecture Notes in Computer Science*, vol. 3512, pp. 873–880, 2005.

[8] A. de la Escalera, J. M. Armingol, , and M. Mata, "Traffic sign recognition and analysis for intelligent vehicles," *Image Vision Computing*, vol. 21, p. 247258, 2003.

[9] P. Paclik, J. Novovicova, P. Pudil, and O. Somol, "Road sign classification using the Laplace kernel classifier," *Pattern Recognition Letters*, vol. 21, pp. 1165–1173, 2000.

[10] S. Vitabile, G. Pollaccia, G. Pilato, and F.Sorbello, "Road signs recognition using a dynamic pixel aggregation technique in the hsv colour space," in *Proc. Int. Conf. on Image Analysis and Processing*, 2001, p. 572577.

[11] P. Paclik, "Road sign recognition survey," 1999. [Online]. Available: http://euler.fd.cvut.cz/research/rs2/files/skoda-rs-survey.html

[12] A. Soetedjo and K. Yamada, "Traffic sign classification using ring partitioned method," *IEICE Trans. Fumdamentals*, vol. E88A, no. 9, pp. 166 – 178, Sep 2005.

[13] P. Paclik, J. Novovicova, and R. Duin, "Building road-sign classifiers using a trainable similarity measure," *IEEE Trans. on Intelligent Transportation Systems*, vol. 7, no. 3, pp. 309–321, Sep 2006.

[14] H. Fleyeh, S. Gilani, and M. Dougherty, "Road sign detection and recognition using Fuzzy ARTMAP: A case study swedish speed-limit signs," in *Proc. of Artificial Intelligence and Soft Computing*, 2006.

[15] P. Silapachote, A. Hanson, and R. Weiss, "A hierarchical approach to sign recognition," in *Proc. of the Seventh IEEE Workshops on Application of Computer Vision*, 2005, pp. 22–28.

[16] J. Lu, K. Plataniotis, A. Venetsanopoulos, and S. Li, "Ensemble-based discriminant learning with boosting for face recognition," *IEEE Trans. on Neural Networks*, vol. 17, no. 1, pp. 166 – 178, Jan 2006.

[17] Wikipedia, "Random Forests." [Online]. Available: http://en.wikipedia.org/wiki/Random_forests

[18] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, p. 532, 2001.

[19] A. Liaw and M. Wiener, "Classification and regression by randomForest," *R News*, vol. 2, no. 3, p. 1820, 2002.

[20] Y. Freund and R. Schapire, "A short introduction to boosting," *Journ. of Jap. Soc. for Artificial Intelligence*, vol. 14(5), pp. 771–780, 1999.

[21] V. Vapnik, *The Nature of Statistical Learning Theory*. Springer-Verlag, 1999.

[22] H. Kim, S. Pang, H. Je, D. Kim, and S. Ban, *Pattern Recognition with Support Vector Machines: First International Workshop, SVM 2002 Proceedings*. Springer Berlin/Heidelberg, 2002, ch. Support Vector Machine Ensemble with Bagging.

[23] K. Ting and Z. Zheng, "A study of adaboost with naive bayesian classifiers: Weakness and improvement," *Computational Intelligence*, vol. 19(2), pp. 873–880, 2003.

[24] T. Wang, "Random Forests." [Online]. Available: Available: http://lib.stat.cmu.edu/matlab/RandomForest.zip

[25] L. Breiman and A. Cutler, "Random forests." [Online]. Available: www.stat.berkeley.edu/users/breiman/RandomForests/cc_home.htm

[26] R. Yan, "MatlabArsenal." [Online]. Available: http://finalfantasyxi.inf.cs.cmu.edu/MATLABArsenal/MATLABArsenal.htm

[27] K. Fukunaga, *Introduction to Statistical Pattern Recognition*. Elsevier, 1990.

[28] L. Breiman, "Bagging predictors," *Machine Learning*, vol. 24(2), 1996.