JOURNAL OF CRITICAL REVIEWS

ISSN- 2394-5125 VOL 07, ISSUE 09, 2020

INDIAN TRAFFIC ROAD SIGN RECOGNITION FOR INTELLIGENCE DRIVER ASSISTANCE SYSTEM USING SVM

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Received:26 January 2020 Revised and Accepted: 11 April 2020

ABSTRACT: This research work proposes a vision based approach for autonomous vehicle drivers through safety warning messages during critical situation. The proposed system indicates four main phases: background subtraction, sign extraction, feature extraction and recognition. First, it detects the traffic sign, if it has sufficient contrast from the background then it use HSV color detection and morphological erosion and dilation operation. Second, extract the detected traffic sign from the background using ROI. A novel and efficient method for organizing Sign Block Intensity Vector (SBIV) is proposed. Third, to extract the features form extracted sign using SBIV. Finally, recognition are performed through Support Vector Machine (SVM). The performance of traffic sign recognition is estimated for Traffic Sign board image and the system achieves a recognition rate of 93.5% using SBIV features and SVM. System is employed in real time environment and tested on national highway and intend to help autonomous vehicle driver to have safer and pleasant driving thereby focusing on his valid workload.

I. INTRODUCTION

Intelligent Driver Assistant System (IDAS) is a system that builds a secure, efficient and integrated transportation environment based on advanced technologies. Road signs extraction and recognition is an important part of IDAS, which offer ways to collect the real time traffic data for processing at a central facility. Although the first works in this area date back to the 1960s, significant progress has been made during the last years.

The principle classifies the road signs into three categories: (a). Mandatory road signs as shown in the figure 1, (b). Cautionary road signs as shown in the figure 2. Informatory road signs as shown in the figure 3. However, major differences still exist among different categories, which may not be important to humans, but are a major challenge for computer vision algorithms.

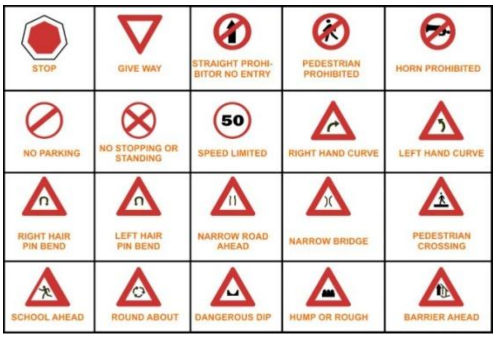

Figure 1. Mandatory Road Signs.

Figure 2. Cautionary Road Signs.

Calculations state that approximately 50% of traffic accidents could be prevented by reducing forward inattention among the drivers [1]. It is possible that accidents can be prevented by utilizing an automatic road sign recognition system to provide traffic information to the driver, including information about the road in front of the vehicle. This paper concentrates on Indian traffic road sign recognition system in complex environment scene.

Figure 3. Informatory Road Signs.

1.1 Related work:

The proposed work is to implement the traffic road sign recognition model based on Artificial Intelligence (AI) and image processing technologies, which applies a machine learning method, Support Vector Machines, to recognize road signs. Many systems aiming in enhancing drivers comfort and safety are in computer vision research. Road lane departing warning system [2], Road pedestrian detection system [3], drowsiness detection system [4], and traffic road sign recognition [5], traffic hand signal recognition system [6] and [7], road hazard warning system [8] and vehicle light recognition system [9] are few of them. In most of the past traffic sign recognition techniques [10] the first step is to detect the location of each traffic sign in an image. In [12] a comparison was discussed among HSV/HSI, RGB, TSL and YCbCr color space performances. Cumulative Block Intensity Vector (CBIV) as feature is proposed [13].

The rest of this paper is organized as follows. Section 2 discusses the overview of the proposed approach. Section 3 describes feature extraction procedure. Section 4 describes Support Vector Machine (SVM). Experimental analyses are discussed in Section 5. Finally, Section 6 concludes the paper.

Proposed Approach

The overview of the proposed sign recognition approach is shown in Figure 4. The proposed approach is evaluated using Indian traffic road sign images. Road sign image is subtracted by using HSV color detection from the input image. Sign information is extracted by identifying the Region of Interest (ROI). The extracted sign images are used for further analysis. Sign Block Intensity Vector (SBIV) are extracted as feature. The extracted features are fed to the SVM classifier and to recognize the traffic road sign.

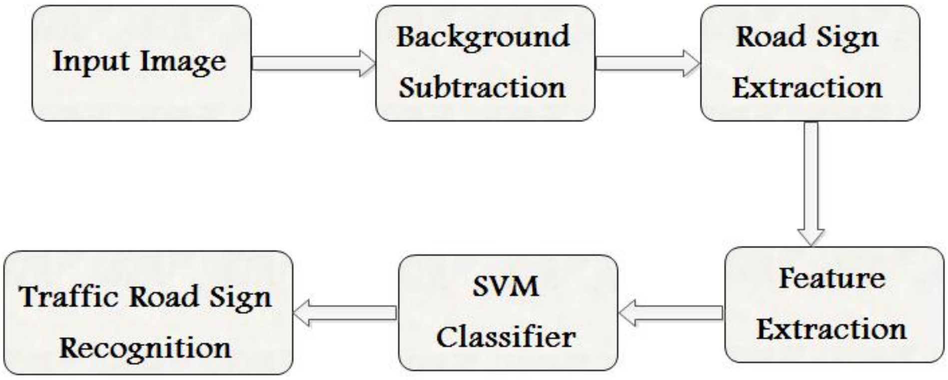

Figure 4. Proposed Approach for Road Sign Recognition.

2.1. Background Subtraction:

The workflow of the proposed Background subtraction and road sign extraction is shown in Figur 5. Background subtraction of traffic road sign is divided into three steps: Color conversion of traffic image, Hsv color detection and detection of region shape.

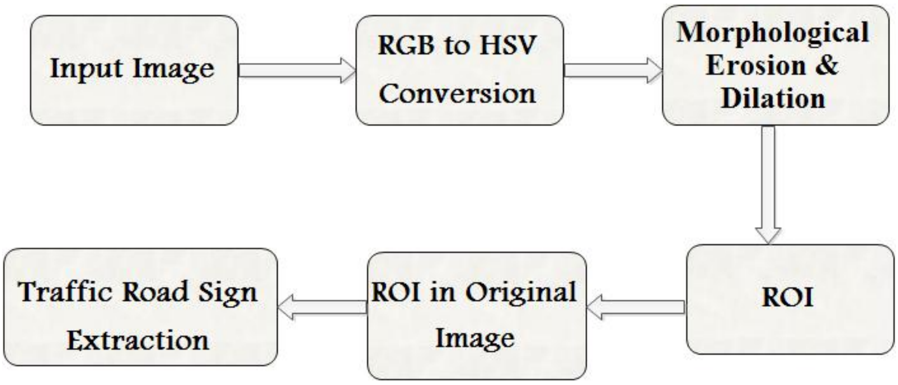

Figure 5. Background subtraction and Extraction.

The first step in the Background subtraction stage is the color thresholding. The original RGB frames are converted into HSV color feature. The second step in the background subtraction stage is the HSV color detection. A more natural and realistic color space for this problem is the HSV color space, which is more representative of the way of humans observe color. Three main color space in H, S, V color component threshold range is shown in Table 1: (H, S, V color values were normalized to [0, 255]).

Table 1. The H, S, V color component threshold range of the main color of road traffic.

Color	**H**	**S**	**V**
Red	$H \geq 238 or H \leq 11$	$S \geq 41$	$V \geq 28$
Green	$20 \leq H \leq 47$	$S \geq 146$	$V \geq 64$
Blue	$125 \leq H \leq 170$	$S \geq 124.5$	$V \geq 22$

The third step in the Background subtraction stage is morphological operations. Morphological erosion and delusion operation is to remove noisy pixels and the road sign regions are subtracted as shown in the Figure 6.

ISSN- 2394-5125 VOL 07, ISSUE 09, 2020

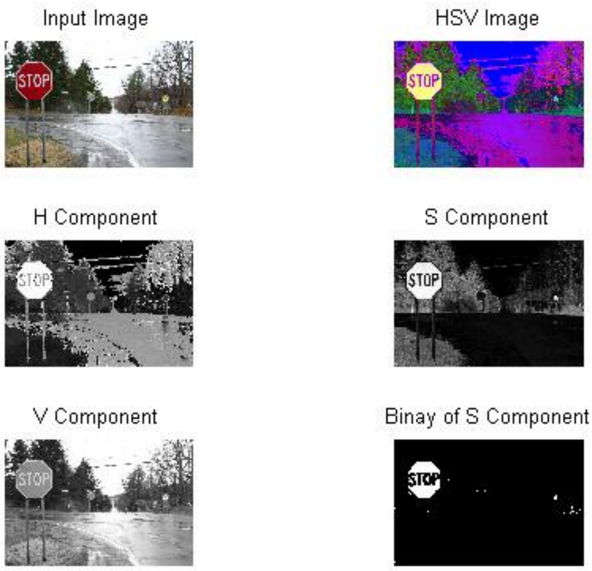

Figure 6. Traffic road sign detection.

2.2. Road Sign Extraction:

The prevalence of traffic road sign extraction systems for intelligent driver assistance system using road scene information is expanding rapidly in recent trends. Region of Interest (ROI) is used to extract the road sign. Once the foreground image is extracted, the next step is to identify the ROI for further analysis. For ROI extraction, the approach used in [14] is utilized.

The height of the bounding box $SH_{(St)}$ for ROI extraction is calculated using Sign $Height_{(St)}=SH_{(St)}/SH_{(max)}$, where $SH_{(St)}$ is the height of the bounding box in the video frame at time 'St', $SH_{(max)}$ is the maximum value that $SH_{(St)}$ has for the entire video sequence. Width of the bounding box is fixed similarity using $SWidth_{(st)} = SW_{(St)} / SW_{(max)}$. Finally, ROI is extracted as

Sign ROI = $SHeight_{(St)} / SWidth_{(St)}$.

The bounding boxes extracted for various frames in the road traffic sequence is shown in Figure 7. For the purpose of the uniformity, the ROI region is considered to be of size 60 X 60 for all signs without any loss in information.

Figure 7. Road Sign Extraction using ROI.

Feature Extraction

A novel and efficient feature called Sign Block Intensity Vector (SBIV) is proposed in this work.

3.1. Sign Block Intensity Vector (SBIV):
The extracted ROI as discussed in Section 2.3 is identified as traffic road sign regions. The road traffic sign image is size of 640 X 480.The proposed approach uses ROI of size 60 X 60. The sign region is divided into many blocks for recognition. In order to minimize the computation, extraction of SBIV features as 5 X 5, 5 X 6, 6 X 6, 6 X 10 10 X 10 blocks and each Block of size is 20 X 20, 12 X 12, 12 X 10, 10 X 10, 10 X 6 and 6 X 6. The average intensity value of pixels in each block is calculated as Sign Block Intensity Vector (SBIV). In this work 9, 25, 30, 36, 60 and 100 dimension SBIV features are extracted.

Support Vector Machine (SVM)
Support Vector Machine (SVM) is a popular technique for classification in visual pattern recognition [15], [16] and [17]. The SVM is most widely used in kernel learning algorithm. It achieves reasonably vital pattern recognition performance in optimization theory [18] and [19]. Classification tasks are typically involved with training and testing data. The training data are separated by $(x_1,y_1),(x_2,y_2),....(x_m,y_m)$ into two classes, where $\mathbf{x}_{\mathbf{i}=\mathfrak{R}^{\mathbf{n}}}$ contains n-dimensional feature vector and y_i∈{+1,-1} are the class labels. The aim of SVM is to generate a model which predicts the target value from testing set. In binary classification the hyper plane w.x + b = 0, where $\mathbf{w}_{\mathbf{i}=\mathfrak{R}^{\mathbf{n}}}$ is used to separate the two classes in some space Z [20] The maximum margin is given by M= 2⁄(‖w‖) as shown in Figure 8.

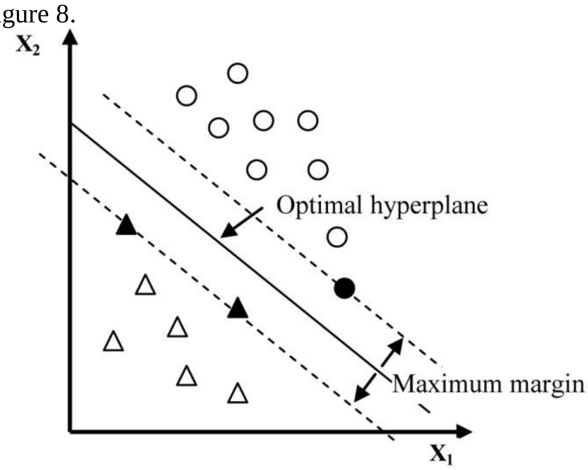

Figure. 8. Repesentation of Hyperplane.

The minimization problem is solved by using Lagrange multipliers $\boldsymbol{\alpha}_{\mathbf{i}}(\mathbf{i} = \mathbf{1}, \ldots \mathbf{m})$ where w and b are optimal values obtained from Eq. 1.

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{m} a_i y_i \, K(x_i, x) + b\right) \qquad (1)$$

The non-negative slack variables $\boldsymbol{\xi}_{\mathbf{i}}$ are used to maximize margin and minimize the training error. The soft margin classifier obtained by optimizing the Eq. 2 and Eq. 3.

$$\min_{w,b,\xi} \frac{1}{2} \, w^T w + C \sum_{i-1}^{l} \xi_i \qquad (2)$$

$$y_i(w^T \phi(x_i) + b \geq 1 - \xi_i, \xi_i \geq 0 \qquad (3)$$

If the training data is not linearly separable, the input space mapped into high dimensional space with kernel function K(x, y) =x.y is explained in 19. There are several SVM kernel functions as given in Table 2.

Table 2. Types of SVM kernels.

Name of the Kernel	Mathematical Formula
Linear	$k(x, y) = x^T .y$
Polynomial	$k(x, y) = (x^T , y)^P \, or \, k(x, y) = (x^T .y+1)^p$ where p is the polynomial degree
RBF(Gaussian)	$\phi(x) = \exp(-\frac{x^2}{2\sigma^2}), \sigma > 0$

Experimental Analysis

In this section, describe the Indian traffic road sign dataset and performance evaluation results, and the present experimental environments for the proposed sign block intensity vector (SBIV) with SVM classifier. The experiments carried out in C++ with OpenCV 2.2 in Ubuntu 12.04 operating system on a computer with Intel CORE^{TM} I5 Processor 2.30 GHz with 4 GB RAM. WEKA [21] tool to develop the model for each action and these models are used to test the performance of the proposed features.

5.1 Dataset:

Nowadays automation technologies struggle for designing smarter and intelligent vehicles, intend to minimize the number of industrial accident due to drivers inattention or wrong-decision. These road traffic sign detection systems enhances the safety by informing road regulation and immediate danger like blind turn, school ahead, railway crossing, road work progress etc. The proposed approaches concentrate on mandatory road signs and it is as discussed in figure 1. The datasets are created during daylight in real road environment and it is used for experimental purpose. The image size is 240 X 240.

The collected dataset is listed in Table 3. In this work, the images are taken into a training set at 175 images in each traffic road mandatory sign and testing set at 50 images in each traffic road mandatory sign.

Table 3. Description of the traffic road sign dataset.

Traffic Road Sign	Sign Type	Collections of Images
TRS1	Stop	250
TRS2	Right Hand Turn	270
TRS3	Left Hand Turn	275
TRS4	Speed Limit	240
TRS5	No Parking	225
TRS6	Pedestrian Crossing	250
TRS7	Left Reverse Bend	270
TRS8	Narrow Bridge	230
TRS9	School Ahead	235
TRS10	Give Way	245

5.2 Performance Evaluation:

The evaluation of detection level performance is of two metrics such as True Positive Rate (TPR) and False Positive Rate (FPR) and are defined as 4 and 5.

TPR = TP/(TP + FP) X 100 (4)
FPR = TP/(TP + FN) X 100 (5)

Where, TP and FP are True Positive and False Positive. To compute accuracy is defined as 6.

Accuracy = 2PR / (P+R) (6)

Where, P and R are Precision and Recall. Precision (P) or TPR is defined as 7 and 8.

$$Precision = TP / (TP + FP) \qquad (7)$$

Recall (R) is defined as,

$$Recall = TP / (TP + FN) \qquad (8)$$

Where, FN is False Negative represents the false alarms.

5.3 Performance Evaluation with SVM :

The performance of the recognition approach is evaluated using precision, recall and F-measure as discussed in Section 5.2 and these measures are obtained for ten types of traffic road signs (TRS). The proposed approach utilized SVM with polynomial and RBF kernels. Figure 9 shows the performance measure of precision and recall value of 36-dimentional SBIV using SVM with polynomial kernel and it gives 92.59% accuracy. Figure 10 shows the performance measure of precision and recall value of 36-dimentional SBIV using SVM with RBF kernel and it gives 93.5% accuracy.

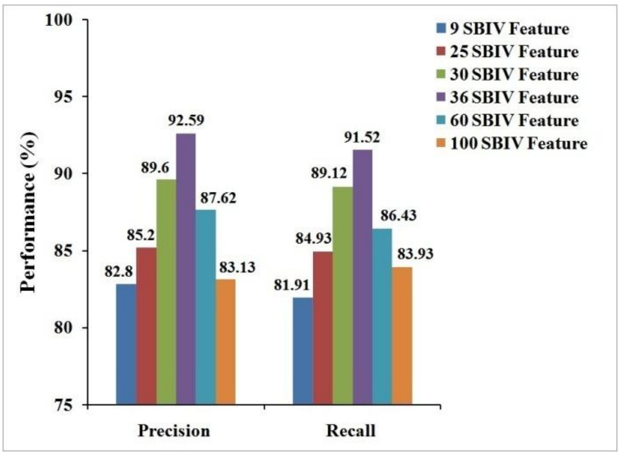

Figure 9. Precision-recall obtained with SVM (Polynomial) and 36 dimensional SBIV feature for all Traffic Road Signs (TRS).

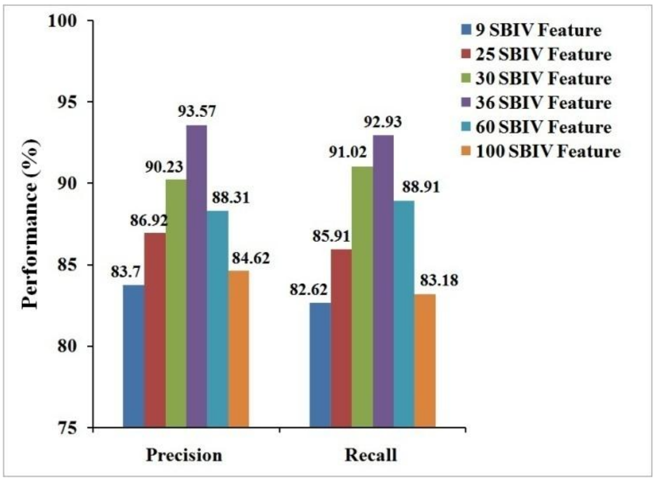

Fig. 10. Precision-recall obtained with SVM (RBF) and 36 dimensional

SBIV feature for all Traffic Road Signs (TRS).

From the Figures a and 10, it is seen that the 36-dimensional SBIV feature gives higher precision and recall value for traffic road sign recognition when compared with other SBIV features. The accuracy results obtained with 36-dimensional SBIV feature using SVM polynomial and RBF kernel for each individual traffic signs are presented in Tables 4 and 5 respectively.

Table 4. Accuracy obtained with proposed SBIV features for all Traffic Road Signs (TRS) using SVM (Polynomial). (in%)

SBIV Dimensions	TRS1	TRS2	TRS3	TRS4	TRS5	TRS6	TRS7	TRS8	TRS9	TRS10
9	83.91	82.45	81.09	85.91	80.61	81.52	83.14	82.92	80.53	80.95
25	86.21	84.52	83.42	84.78	84.12	86.04	83.92	85.27	86.92	86.08
30	90.52	89.45	89.15	91.06	90.43	87.52	91.52	89.62	91.52	87.21
36	93.15	91.78	89.42	93.72	95.34	94.51	92.73	92.09	93.81	90.43
60	88.51	89.56	90.12	89.54	88.03	89.53	88.47	85.74	85.49	81.53
100	84.92	82.92	81.95	85.46	81.27	86.29	84.21	83.75	85.49	82.79

Table 5. Accuracy obtained with proposed SBIV features for all Traffic Road Signs (TRS) using SVM (RBF). (in%)

SBIV Dimensions	TRS1	TRS2	TRS3	TRS4	TRS5	TRS6	TRS7	TRS8	TRS9	TRS10
9	87.62	84.23	86.48	87.29	81.59	83.72	81.08	81.92	82.74	80.24
25	85.62	87.25	87.24	85.74	88.24	83.78	89.45	84.92	86.48	83.72
30	89.68	88.27	92.58	94.29	89.73	89.04	88.93	87.06	89.45	94.23
36	92.52	96.21	93.58	92.52	95.29	91.73	93.03	93.12	94.92	92.03
60	85.45	87.52	86.72	91.58	94.52	89.73	86.72	89.07	84.21	86.73
100	82.81	89.54	86.41	90.8	82.14	80.7	81.42	82.58	81.93	82.73

Table 4 shows the accuracy result for proposed SBIV feature using SVM polynomial kernel. Table 5 shows the accuracy result for proposed SBIV feature using SVM RBF kernel. It is observed that the 36-dimensional SBIV feature for each traffic road sign yielded good recognition accuracy with both polynomial and RBF kernel of support vector machine. It is evident from the experimental results that 36-dimensional SBIV feature with SVM RBF produced good recognition accuracy for each traffic road sign.

Table 6. Confusion matrix obtained with 36 dimensional SBIV feature for all Traffic Road Signs (TRS) using SVM (RBF). (in%)

	TRS1	TRS2	TRS3	TRS4	TRS5	TRS6	TRS7	TRS8	TRS9	TRS10
TRS1	**92.64**	0.47	1.08	0.59	1.45	1.9	1.42	0.45	0	0
TRS2	0.23	**93.48**	0.96	0.46	0	0.84	0.18	1.45	2.4	0
TRS3	1.5	0.5	**94.5**	0.21	0.75	0.97	0.46	0.09	0.84	0.18
TRS4	0.75	0.97	1.4	**93.5**	0.45	0.21	0.75	0.97	0.49	0.51
TRS5	0.75	0.97	0.46	0.09	**92.48**	1.45	1.85	1.92	0.03	0
TRS6	1.52	0.86	1.92	0.03	0.25	**93.41**	0.71	0.52	0	0.78
TRS7	0	0.78	0.15	1.45	1.52	1.84	**92.47**	1.06	0.41	0.32
TRS8	0.75	0.64	0.52	0.75	0.97	0.46	0.09	**94.13**	1.49	0.2
TRS9	0.15	0.28	0.15	0.84	0.18	1.45	0.72	1.09	**94.67**	0.47
TRS10	0.45	0.21	0.75	0.97	1.54	0.84	0.18	1.45	0.19	**93.42**

Among the various proposed SBIV feature considered, 36-dimensional SBIV feature with support vector machine RBF kernel provides higher accuracy of 93.5%. Table 6 gives the confusion matrix of 36-dimensional SBIV using support vector machine with RBF kernel.

5.4 Conclusions and Future Work :

In this paper a real time system for traffic road sign recognition by using SVM for the autonomous vehicle driving system. The Traffic Road Signs (TRS) was implemented on a real time traffic sign image that manages and controls all the vehicle driver action. The proposed SBIV feature performed well in recognizing the traffic road sig. SVM RBF kernel gives higher accuracy compared to SVM polynomial kernel. Projected SBIV features showed satisfactory performance in recognizing all the traffic road signs.
The present work considered only daytime information for detection and recognition system and hence the future efforts can be focused on developing a system that handles nighttime environment which is still a challenging problem for the research community. Nonetheless, a lot of work remains to be done until a completely robust and reliable automated driver assistance system can be fully deployed in real conditions. In modern society, to avoid accident and to have a smooth drive, a real time intelligent driver assistance system (IDAS) will be very efficient.

II. REFERENCES

[1] Long chen Traffic sign detection and recognition for intelligent vehicle, IEEE Intelligent Vehicles Symposium, June 5-9, (2011).

[2] G. Taubel and J.-S. Yang, A lane departure warning system based on the integration of the optical flow and hough transform methods, in IEEE International Conference on Control and Automation (ICCA), 2013.

[3] B. Li, Q. Yao, and K. Wang, A Review on Vision-based Pedestrian Detection in Intelligent Transportation Systems, pp. 393398, 2012.

[4] N. J. Uke, R. C. Thool, and P. S. Dhotre, Drowsiness Detection A Visual System for Driver Support, Int. J. Electron. Commun. Comput. Eng., vol. 3, no. 2, pp. 2933, 2012.

[5] G. A. Tagunde, N. J. Uke, and C. Banchhor, Detection, classification and recognition of road traffic signs using color and shape Features, Int. J. Adv. Technol. Eng. Res., vol. 2, no. 4, pp. 202-206, 2012.

[6] R. Sathya, and M. Kalaiselvi Geetha. ”Vision Based Traffic Personnel Hand Gesture Recognition Using Tree Based Classifiers.” In Computational Intelligence in Data Mining, Springer India, Volume 2, pp. 187-200. 2015.

[7] R Sathya and M Kalaiselvi Geetha, Vision based traffic police hand signal recognition in surveillance video-a survey, International Journal of Computer Applications, vol. 81, no. 9, 2013.

[8] S. G. Charlton, Conspicuity , memorability , comprehension, and priming in road hazard warning signs, Accident Analysis and Prevention, vol. 38, pp. 496506, 2006.

[9] S. Hsu and C. Huang, Road sign detection and recognition using matching pursuit method, Image Vis. Comput. 19, vol. 19, pp. 119129, 2001.

[10] Cheol-Hwon Kim and June-Ho Yi, An optimal chrominance plane in the rgb color space for skin color segmentation, International Journal of Information Technology, vol. 12, no. 7, pp. 7381, 2006.

[11] Leila Sabeti and QM Jonathan Wu, High-speed skin color segmentation for real-time human tracking, in Systems, Man and Cybernetics, 2007. ISIC. IEEE, 2007, pp. 23782382.

[12] R. Sathya, M. Kalaiselvi Geetha, Framework for Traffic Personnel Gesture Recognition, Procedia Computer Science, 46, pp. 1700 1707, 2015.

[13] Qiong Liu, Jiajun Zhuang and Jun Ma.:, ‘‘Robust and fast pedestrian detection method for far-infrared automotive driving assistance systems,” Infrared Physics and Technology, pp. 288–299, (2013).

[14] Wallraven, C., Caputo, B. and Graf, A.: Recognition with local features: Kernel receipe, In Proceedings of ICCV, pp. 257–246, (2003).

[15] Wolf, L. and Shashua, A.: Kernel Principal angles for classification machines with applications to image sequences interpretation, In Proceedings of CVPR, pp. 635–640, (2003).

[16] Cristianini, N. and Shawe-Taylor, J.: An Introduction to Support Vector Machines and Other Kernel-based Learning Methods, Cambridge University Press, (2000).

[17] Vapnik, V.: Statistical Learning Theory, Wiley, NY, (1998).

[18] Lewis,J. P.: Tutorial on SVM, CGIT Lab, USC, (2004).

[19] Chang, C.-C. and Lin, C.J.: LIBSVM: A library for support vector machines, ACM Transactions on Intelligent Systems and Technology 2, pp. 1–27, (2011).

[20] Ian H.Witten, and Frank. E.: Data mining: Practical Machine Learning Tools and Techniques with Java Implementations, (1999).