Review of Computer Engineering Research
2022 Vol. 9, No. 3, pp. 135-149.
ISSN(e): 2410-9142
ISSN(p): 2412-4281
DOI: 10.18488/76.v9i3.3109

DETECTION AND RECOGNITION OF TRAFFIC SIGN BOARDS USING RANDOM FOREST CLASSIFIER

B. Jagadeesh[1+]
D. V. Vidhya Sree[2]

[1,2]*Gayatri Vidya Parishad College of Engineering (A), Visakhapatnam, A.P., India.*
[1]*Email: bjagadeesh76@gmail.com Tel: +919440043096*
[2]*Email: vidhyasreedukka24@gmail.com Tel: +919866199532*

(+ Corresponding author)

Article History
Received: 16 May 2022
Revised: 12 July 2022
Accepted: 29 July 2022
Published: 26 August 2022

Keywords
Advanced driver assistance system
Traffic sign detection
Color thresholding
HOG
Random forest classifier
Traffic sign recognition.

ABSTRACT

The traffic sign recognition system is a vital aspect of an intelligent transportation system since it provides information to drivers to help them drive more safely and effectively. This paper addresses some of these concerns, which will be accomplished in two steps. The first is the detection of traffic signs, which is divided into two stages. After a picture has been preprocessed to emphasize relevant information, signs are segmented based on color thresholding, shape-based detection. The second task is the recognition of traffic signs. There are two steps involved in this method. In this study, Histogram of Oriented Gradient is utilized as a feature extractor, and Random Forest Classifier is used in the recognition stage. The findings of the experiment show that utilizing Random Forest Classifier resulted in an accuracy score of 95.59 %, precision of 97.55 %, recall of 95.37% in the recognition process and 90.34 % accuracy in the detection process.

Contribution/Originality: In this research work, detection and recognition of traffic sign boards a related research question is formulated using Random Forest Classifier, created the models, implemented the codes, conducted research experiments for evidence collection, preparation and presentation of the published work, and coordination of research activities lead to this publication.

1. INTRODUCTION

Traffic signboards are essential for regulating traffic and preventing accidents. They're made to be one-of-a-kind, sturdy, and easily noticeable to drivers, with little variation in design. As a result, automatic traffic sign detection and identification have become crucial features for adaptive cruise control. These road signs detecting and identification systems are crucial not just for advanced driver assistance systems but also for other practical systems like metropolitan scenario interpretation, self-drive vehicles, and even signs surveillance for maintenance. Detecting and recognizing traffic signs, on the other hand, is difficult due to a number of issues, including:

- A wide range of illumination conditions.
- Obstacles, like trees, pedestrians, and vehicles.
- Motion blur caused by vehicle speed and friction.
- Vandalism.
- The current meteorological conditions.
- Historical context (for example, the existence of skyscrapers, roadways and signboards).

The purpose of signboard detection is to figure out where potential traffic signs are located, whereas the goal of sign recognition is to figure out what class the traffic sign belongs to. The visual features of traffic signs encode the information they provide: color, shape, and pictogram. Figure 1 shows different traffic signs.

Figure 1. Different traffic signs.

The color and shape are essential traits which can aid drivers to understand road conditions; traffic signs have some consistent attributes that can be used to detect and classify them. The color of traffic signs in each country is essentially identical, with basic colors like red, blue, yellow, etc., as well as standardized shapes like circles, triangles, rectangles, etc. External elements, such as weather, frequently impact the appearance of traffic signs. As a result, traffic-sign recognition is both a challenging and crucial topic in traffic engineering research. Based on the detection, feature extraction, and machine learning approach, this study proposes a traffic sign detection and recognition system [1-3]. Detection and recognition are the two main techniques. The first technique involves detection, which is split into two stages. The detection of signs is segmented based on color thresholding and shape-based detection after a picture is preprocessed to emphasize relevant information. There are two steps involved in the recognition stage. The first is feature extraction, in which HOG is utilized as a feature extractor. With HOG features extracted and input into a model using a Random Forest Classifier to categorize traffic signs into 43 categories.

This paper is divided into five modules. Module II contains information on related works. Module III displays the proposed method. Module IV describes our research's experiments and findings. Module V sets out our conclusion and issues for further research.

2. RELATED WORK

Various approaches to traffic sign recognition have been presented, and because they are based on different data, it is difficult to compare them. Different approaches to the detection and recognition challenges have been offered.

Ying-Chi, et al. [4] devised a detecting technique that uses different resolutions. In this method, the network training and testing are evaluated by comparing different input image resolutions and ROIs. Hemadri and Kulkarni [5] presented traffic sign identification with a 98 percent accuracy utilizing the dense scale-invariant feature transform (DSIFT) approach for feature extraction and SVM for classification. Cahya, et al. [6] proposed a technique that divides traffic sign detection into two stages. After segmenting the image using RGBN (Normalized RGB), the blobs are processed to recognize traffic signs. The process of recognizing traffic signs is broken into two parts. In this study, a combination of some feature extraction methods such as HOG, Gabor, LBP, and HSV color space is used, and certain classifiers such as SVM, KNN, Random Forest, and Naïve Bayes are compared in the recognition stage. The RGBN method had precision and recall of about 98.7% and 95.1 percent in detecting traffic signs, and 100% precision and 86.7 percent recall in recognizing processes using SVM Classifier, according to the results of the experimental work.

Tarequl [7] suggested a method in which the signs are not limited to a few and in which 28 signs are used for classification and two independent classifiers are used. These photos were analyzed to identify the region of interest, which is subsequently classified using two CNN classifiers. Pranjali and Ramesh [8] proposed TSDR for recognizing traffic signs positioned alongside the road using the template-matching approach. The template-matching approach was utilized in this study to identify accurately, eliminating false positive detection and loss of detection and to recognize road signs in low-light conditions. Adonis, et al. [9] before detection, a method is proposed in which the bilateral filtering pre-processing technique is used. Color thresholding in HSV color space, followed by segmentation of the region of interest using the Hough transform. A Histogram of Oriented Gradients is extracted from candidate traffic signs as the essential feature in classification in the recognition phase, and MLP is employed as a classifier. For traffic sign recognition, the Multilayer Perceptron Classifier has the best accuracy. Immawan, et al. [10] proposed using Gabor Wavelet and Principle Component Analysis to recognize traffic signs. On the traffic sign picture database, Gabor wavelet feature extractors paired with PCA showed higher recognition performance. Wang [11] provided a brief explanation of TSDR utilizing deep learning, stating that the model can learn the deep characteristics within the image independently from the training samples. It emphasizes the accuracy and efficiency of detection and recognition. Deep Learning dramatically reduces the time and cost of training negative samples, as well as improves the accuracy of the SoftMax classifier. Ivona, et al. [12] used Support Vector Machines (SVMs) with Gaussian and median filters to eliminate noise, Hough Transformation in the detection phase, and a Histogram of the Oriented Gradient descriptor for feature extraction in the classification phase.

Finally, traditional methods, such as machine learning, are seen to be more robust than neural networks [13, 14]. This study describes the classification and recognition of German traffic signs by combining numerous methodologies and features, which are explained in the next section.

3. PROPOSED METHOD

The proposed method is accomplished in three major steps, as shown in Figure 2. First, a pre-processing approach based on RGB to HSV color space conversion and the median filtering methodology is proposed [15-18]. Next, it is proposed that a detection technique based on color thresholding and shape detection be used. Lastly, it is suggested a recognition strategy based on a histogram of oriented gradients (HOG) and a Random Forest Classifier. HOG is utilized for feature extraction, and RF is used for recognition.

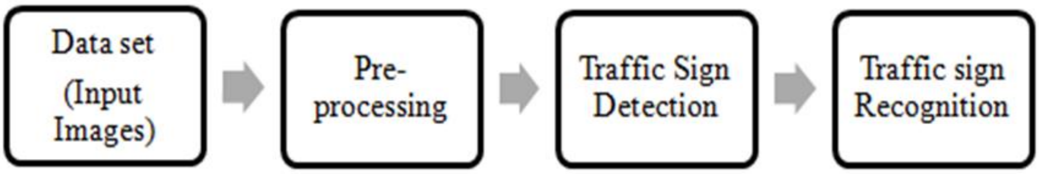

Figure 2. Proposed algorithm flow diagram.

3.1. Pre-Processing Stage

The goal of pre-processing is to remove useless data from photographs and restore useful information. This technique improves the accuracy of the detection. For picture pre-processing, this article primarily employs image enhancement and color space conversion [19].

3.1.1. Image Enhancement

The fundamental aspect of image pre-processing is image enhancement. The goal of image enhancement technology is to make confusing messages in an image clear so that the relevant messages can be extracted from the image. Median filtering is one of the most often used methods in image enhancement technologies to remove noise from images. It is a nonlinear filtering technique. When a sliding window has an odd number of points, the value of the window's center point is replaced with the median value of the window. The image's details can be protected by using median filtering. Figure 3 shows a comparison of before and after median filtering.

Figure 3. Before and after median filtering comparison.

3.1.2. Color Space Conversion

The RGB color space is widely used [20]. The color values of the image are represented by the red, green, and blue components. RGB space is described in terms of three fundamental colors; the components (R, G, B) are highly correlated to one another; any transformation in the element will lead to improvements in the image's pixel color value; this change is ineffective for distinguishing road signs. Using RGB to assess the image will not aid later operations because traffic signs are exposed to the elements year after year and can fade or be destroyed as a consequence of the weather's influence. The HSV color scheme is used in this study, and its three components demonstrate the image's brilliance: Hue, Saturation, and Value.

The Equation 1. gives the formula for converting RGB to HSV:

Divide the R, G, and B values by 255 to shift the range from 0… 255 to 0… 1.

$$\boldsymbol{R'} = \frac{\boldsymbol{R}}{\boldsymbol{255}} \boldsymbol{G'} = \frac{\boldsymbol{G}}{\boldsymbol{255}} \boldsymbol{B'} = \frac{\boldsymbol{B}}{\boldsymbol{255}}$$

$$C_{max} = \max(R', G', B')$$

$$C_{min} = \min(R', G', B')$$

$$\Delta = C_{max} - C_{min}$$

$$Hue\ Calculation: H = \begin{cases} 60° \times \left(\frac{R' - G'}{\Delta} + 4\right), C_{max} = B' \\ 60° \times \left(\frac{B' - R'}{\Delta} + 2\right), C_{max} = G' \\ 60° \times \left(\frac{G' - B'}{\Delta} mod6\right), C_{max} = R' \end{cases}$$

$$Saturation\ Calculation: S = \begin{cases} 0 & , \Delta = 0 \\ \frac{\Delta}{C_{max}} & , \Delta <> 0 \end{cases}$$

$$Value\ \ Calculation: V = C_{max} (1)$$

Because it is less susceptible to fluctuations in external illumination, HSV is closer to an image viewed by human vision, yet has a greater color spectrum than RGB color model. As a result, HSV color space outperforms RGB color space in the detection of traffic signs. As a result, the RGB color space of the image is converted to HSV during the pre-processing phase, that is more suitable for the next stage. Color spaces RGB and HSV are depicted in Figure 4.

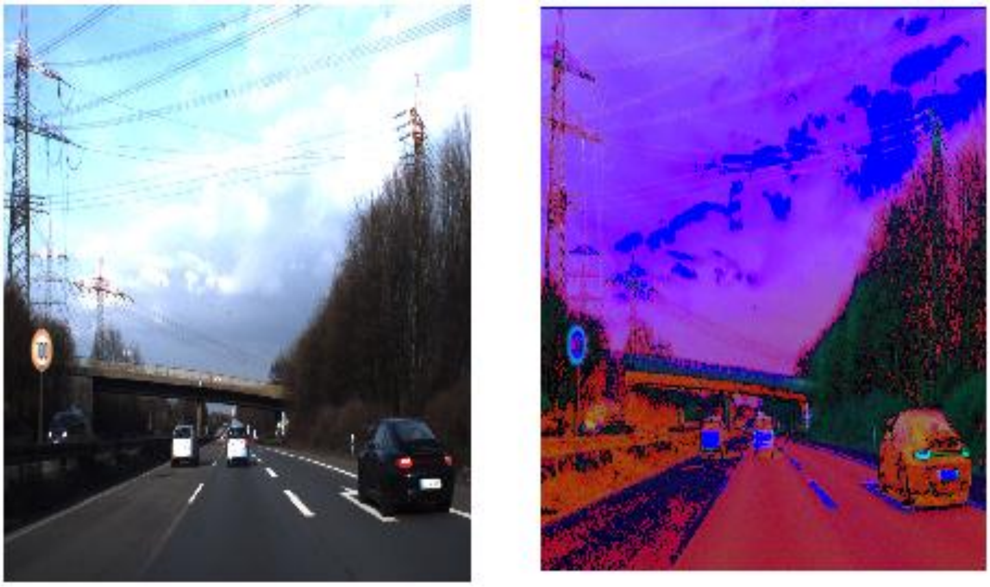

Figure 4. RGB and HSV Image.

3.2. Traffic Sign Detection

The proposed technique consists of two major components [21, 22]. The first is ROI segmentation using a color threshold. The image is then labeled and the candidate area is identified in the second stage. Detecting traffic signs with shape detection and region props analysis of each candidate region

3.2.1. Color Thresholding

Color thresholding is a method of establishing a color range and producing a black and white image. All colors between the start and stop colors (inclusively) become white, while the remaining image pixels become black.

Let I be the color image. Array splicing is used to extract and threshold the different color spaces because the image is represented as a [M*N*3] array. Table 1 illustrates the threshold values for color thresholding, to extract red, blue, green components. Equation 2 gives the formula for color thresholding.

Table 1. Threshold values for color thresholding.

ThR = 210	ThB = 70	ThG = 100

$$red(i,j) = true, \quad if\ r(i,j) \geq ThR$$
$$and\ g(i,j) \leq ThG$$
$$False, otherwise$$
$$blue(i,j) = true, \quad if\ b(i,j) \geq ThB$$
$$False, otherwise$$
$$Green(i,j) = true, \quad if\ g(i,j) \geq ThG$$
$$False, otherwise (2)$$

Color-based approaches make use of the fact that traffic signs are designed to be easily recognized from their surroundings and are frequently painted in highly visible contrasting color. Figure 5 is a Binary Image after color thresholding. These colors are retrieved from the input image and used as the detection foundation. Signs have distinct colors, but they also have distinct shapes that can be looked for.

Figure 5. Binary image after color thresholding.

3.2.2. Shape Detection

The road sign is made up of distinct colors and shapes such as round, octagonal, and rectangular. To detect the signboard based on shape, the smaller objects in the binary image must be deleted.

Smaller items are deleted based on threshold level, i.e. objects with less than the threshold number of pixels are removed (pixel values become 0), and holes and regions in the binary image are filled in the same way (pixel values become 1). The binary image's items are labeled, and their attributes such as Area and Perimeter are determined.

a) Using Region Props to Label Images and Classify Shapes

To begin, it must identify the relevant entities with in processed bi-level image to locate probable traffic sign areas. to locate probable traffic sign areas. The area of each identified region was estimated using the region props() function. Following the calculation of the area, each blob (ROI) is evaluated to determine which would be the traffic sign boards. However, there have been numerous items, as in the picture that could not be a traffic sign. Evaluating such objects was pointless and strenuous. Circularity, a parameter, is used to determine the shapes. Circularity is a measure of an object's roundness. It is typically given as in Equation 3.

$$circularity = \frac{4\pi * Area}{Perimeter^2} \quad (3)$$

As a result, after determining the area of each blob, regions that were too tiny or too large were deleted. Equation 4 was used to delete the superfluous object.Figure 6 is after deleting the superfluous objects, this is the logical image.

$$blob \begin{Bmatrix} true; for\ circles\ , circularity = 1 \\ for\ non\ circles, circularity > 1 \\ false; otherwise \end{Bmatrix} \quad (4)$$

Figure 6. After deleting the superfluous objects, this is the logical image.

b) Evaluating Each Candidate Region and Setting Bounding Boxes

When the picture frame has one or even more candidate regions, which implies blobs1 > 0, the program uses a "for" loop to determine whether such a road sign exists and also to display the bounding box just above the input image depending on the candidate region that is regarded as a road sig. Figure 7 illustrates the detected traffic sign.

Figure 7. Detected traffic sign.

3.3. Traffic Sign Recognition

There are two major phases at this stage of recognition [23-25].

3.3.1. Feature Extraction

HOG is one of the most efficient feature extraction techniques accessible today, out of the several available. Because it concentrates on the geometry or structure of the image, this technique is best suited for detecting algorithms. HOG is a feature-rich extractor for datasets involving characters, numbers, and people. The HOG descriptor is based on the idea that the image shape and the object's appearance may be expressed by spreading intensity gradients. The gradient orientation and magnitude are represented by this histogram. The gradient distribution indicates the features of each image. This property is gained by dividing the image into small areas known as cells. Each cell is structured as a gradient histogram. This histogram's combination is used as a description to represent an object. Figure 8 depicts the overall HOG algorithm.

According to Figure 8, the first phase of HOG is to calculate the gradient value of the input image using Equations 5 – 6. Gradients are minor changes in the x and y directions.

$$H_X = X_2 - X_1 \quad (5)$$

$$H_Y = Y_2 - Y_1 \quad (6)$$

Using the gradients generated in the previous step, magnitude and direction are calculated for each pixel using Equations 7 – 8.

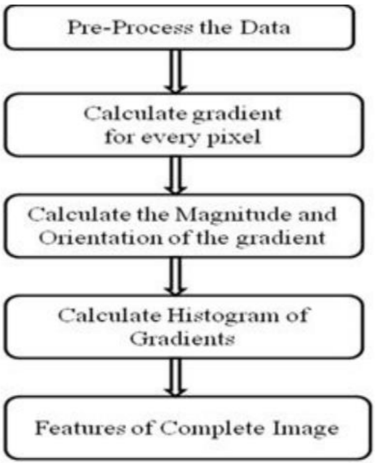

Figure 8. The overall HOG algorithm.

$$M = \sqrt{H_x^2 + H_y^2} \quad (7)$$

$$Angle(\Theta) = \tan^{-1}\left(\frac{H_x}{H_y}\right) \quad (8)$$

The calculated gradients' histograms are now generated. Histograms can be standardized to improve accuracy.

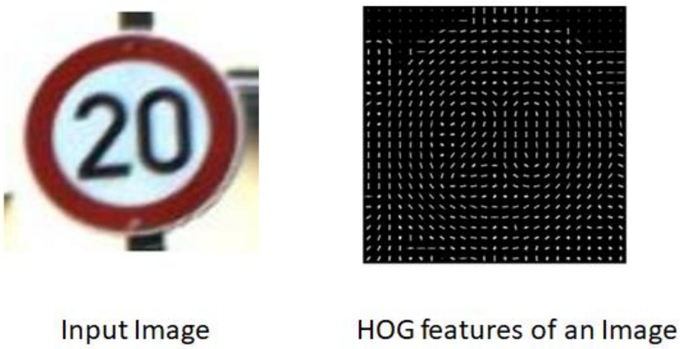

Figure 9. The input image and HOG features of the input image.

To compute the HOG features, we normalize the previously identified window to 200 × 200. The normalized window is divided into 8 × 8 overlapping blocks, with each block divided into 2 × 2 cells. Figure 9 is the input image and HOG features of the input image.

3.3.2. Classifier

Random Forests are gaining popularity because they can outperform single classifiers in terms of accuracy and robustness to noise. It is a collection of classification trees in which each tree casts a single vote for the most frequent class to be assigned to the input data. It adds a new level of randomization to bagging. Another feature of Random Forests is their simplicity, with only two parameters: the number of variables in the random subset at each node and the number of trees in the forest [23-26]. The values of the two parameters have little effect on Random Forests.

The following is how a random tree grows:

- With replacement, a subset I $\subset I_N$ of training samples is chosen at random. This subset is used to grow the tree, which is not trimmed.
- A subset F of features is chosen at random in each node. Using the feature f ϵ F and threshold t ϵ [min(f), max(f)]with the maximum information gain Δ, the current data subset is divided into I_l and I_r. Over the label frequencies in I, entropy E is determined in Equations 9 – 13.

$$\forall f \in F \; \forall t \in [\min(f), \max(f)] \quad (9)$$

$$I_l(t,f) = d \in I | f(d) < t \quad (10)$$

$$I_r(t,f) = \frac{I}{I_l(t)} \quad (11)$$

$$\Delta l = -\frac{|I_l(t,f)|}{|I|} E\left(I_l(t,f)\right)$$

$$= -\frac{|I_r(t,f)|}{|I|} E\left(I_r(t,f)\right) \quad (12)$$

$$f^{opt} = argmax_f \; \Delta(t,f) \quad (13)$$

The size of F is determined empirically. Too many features slow down training and increase the risk of overfitting. If F is small, randomization is stronger and training is faster, but the danger of underfitting increases.

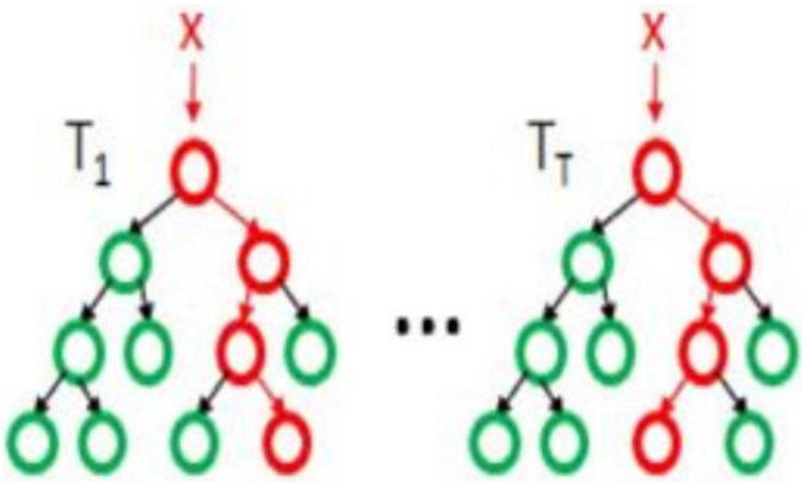

Figure 10. Classification of sample x in a random forest.

Completely randomized trees with |F| = 1 give greater classification accuracy for some data sets. Figure 10 depicts the classification of sample x in a Random Forest [27-31]. Each of the random trees $T_j \epsilon \{T_1, T_2, .., T_T$ is traversed in the Random Forest. $P_j(l|x)$ in the leaf acquired in Tj gives the posterior probability that x belongs to the class $l \in \{1,2, \ldots L\}$. The ensemble of trees' aggregated judgment is used to generate the class l^* of x as follows in the Equations 14 – 15.

$$P(l|x) = \frac{1}{T}\sum_{j=1}^{T} P_j\ (l|x) \quad (14)$$

$$l^* = \max_{L} P\ \ (l_i|x) (15)$$

In many multiclass classification applications, Random Forests outperform state-of-the-art performance over decision trees [2], [5], [7]. To identify the discovered signs, a machine learning classifier model is used. The model is based on the Random Forest method, which takes several decision tree outputs and uses a majority vote to determine the output. The extracted features are given as input with labels of the class of the images to the classifier. This trained model is used for the recognition of road signs.

4. EXPERIMENTAL RESULTS AND FINDINGS

The detection is correct if the ground truth bounding box corresponds to at least half of the traffic signs. The following are outcomes of traffic sign detection:

Figure 11. Traffic sign detection results.

Figure 11shows traffic signs. (i), (ii), (iii), (iv) and (v) are accurate since the bounding box area is exactly on the traffic signs.

The GTSDB and GTSRB datasets have been used to evaluate the proposed algorithm. The results demonstrate that detection and recognition accuracy is very good. The detection accuracy for the GTSDB dataset was 90.34 %, while the recognition accuracy for the GTSRB dataset was 95.59 %. The recognition stage was evaluated using the precision-recall curve, ROC curve, with the recall, precision, and F_1-score values computed as follows using Equations 16 – 18 [32]:

$$\text{Recall} = \frac{True\ positive}{True\ positive + False\ Negative} \quad (16)$$

$$\text{Precision} = \frac{True\ positive}{True\ positive + False\ positive} \quad (17)$$

$$F_1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (18)$$

When applied to the data set, the suggested approach's precision-recall curve and Receiver Operator Characteristic Curve are as follows the precision-recall curve depicts the trade-off between precision and recall for various threshold values. High scores for both indicate that the classifier is producing accurate results (high precision) and producing the majority of all positive results (high recall). As illustrated in Figure 12.

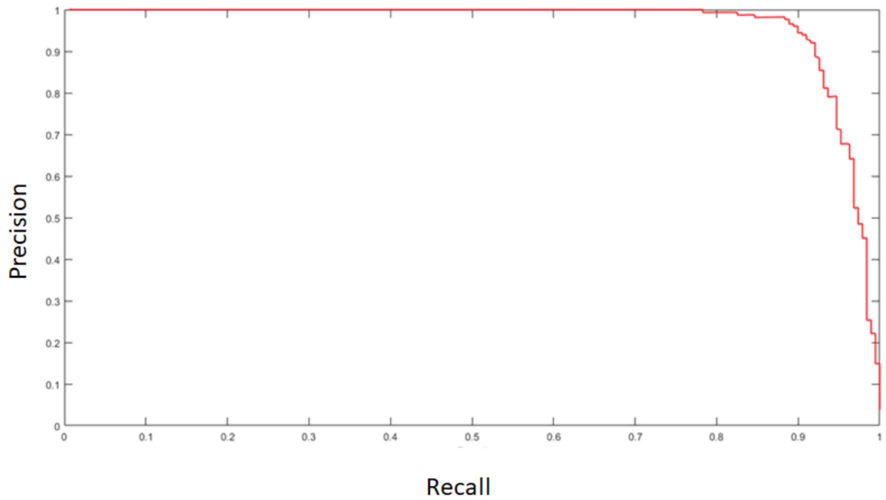

Figure 12. Precision-recall curve.

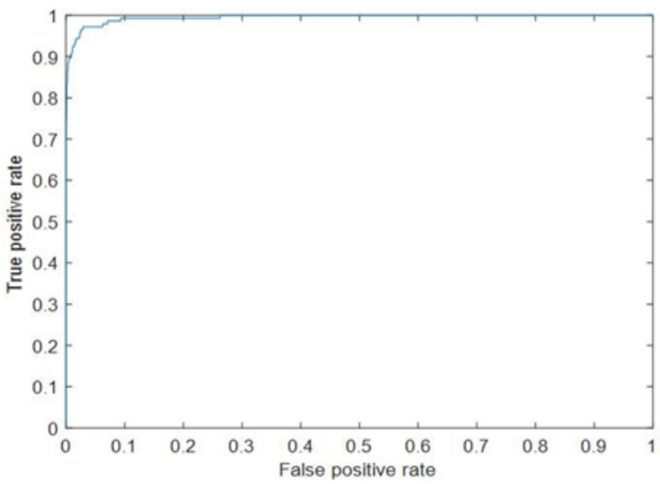

Figure 13. Receiver operator characteristic curve.

The ROC curve (Receiver Operator Characteristic Curve) is a probability curve, and AUC (Area Under Curve) is a measure of separability. The ROC curve demonstrates the trade-off between sensitivity (or TPR) and specificity (1 – FPR). As depicted in Figure13.

Figure14 (i), (ii), (iii) and (iv)depict the outcome of various recognized traffic sign boards.

Figure 14. Results of traffic sign recognition.

Table 2. Recall, precision, AUC, and F1- Score of TSR.

Method	Precision	Recall	AUC	F1-Score
Random Forest	97.55	95.37	99.61	0.9645

The Random Forest categorization produces more true positive values based on the test results on the dataset shown in Table 2. The classification approach employing RF has 99.61%; AUC, a precision of 97.55 % and a recall of 95. 37 %.

Comparison with existing methodologies:

Table 3shows area undercurve, precision and recall. It is observed that better Area undercurve, precision and recall are obtained for the proposed method.

Table 3. Comparison of Auc, Precision, Recall between proposed method and Cahya, et al. [6].

Method		AUC	Precision	Recall
Cahya, et al. [6]	Random Forest	99.4	96.4	90.0
Proposed method	Random Forest	99.61	97.55	95.37

Table 4. Comparison of accuracy between proposed method and Ivona, et al. [12].

Method		Dataset	Accuracy
Ivona, et al. [12]	Multi class SVM	GTSRB	`93.54
Proposed method	Random Forest	GTSRB	95.59

Table 4 shows accuracy for multiclass SVM and Random Forest Classifier. It is observed that better accuracy is obtained for Random Forest compared with multiclass SVM.

The proposed methodology was compared with other methods like Multiclass SVM and Random Forest Classifier. It was found that accuracy of the proposed method was more than Ivona, et al. [12] The AUC, precision and accuracy are greater for the proposed methodology.

5. CONCLUSION

The purpose of this research work was to create an efficient TSDR system based on a traffic sign dataset [26-30]. In the proposed method, images were captured by an onboard camera under various weather conditions, and image preprocessing was done using Median filtering and RGB to HSV color space conversion. A detection algorithm was proposed using color thresholding and shape detection. The recognition process was done using HOG and Machine Learning algorithms using Random Forest with a bagged kernel for traffic sign classification. For feature extraction, HOG was employed, and RF was used for classification. This algorithm was used on the GTSDB and GTSRB datasets. The proposed system produced promising results in terms of recognition accuracyof95.59%, detection accuracy of 90.34%, precision of 97.55%, recall of 95.37% and an F1-score of 96.45%. ROC curve analysis was used to assess recognition performance.

6. FUTURE SCOPE

The proposed approach will be expanded in the future to handle live video sequences that are used in advanced driver assistance systems. The system can be improved by employing low-cost solutions that assist the driver in notifying the distance between the road sign and the vehicle's current location.

Funding: This study received no specific financial support.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study.

REFERENCES

[1] M. Felix, F. Cristian, A. Manuel, and P. Daniel, "Detection and recognition of traffic signs using gabor filters," in *Proceedings of IEEE 34th International Conference on Telecommunications and Signal processing (TSP), Budapest*, 2011, pp. 554-558.

[2] B. Anass, B. Abdrrahim, B. Mohammed, and T. Ahmed, "An enhanced approach in detecting object applied to automotive traffic roads signs," in *Proceedings of IEEE 6th International Conference on Optimization and Applications (ICOA), Beni Mellal*, 2020.

[3] S. Ying, G. Pingshu, and L. Dequan, "Traffic sign detection and recognition based on convolutional neural network," in *Proceedings of IEEE 2019 Chinese Automation Congress (CAC), Hangzhou*, 2019.

[4] C. Ying-Chi, L. Huei-Yung, and T. Wen-Lung, "Implementation and evaluation of CNN based traffic sign detection with different resolutions," in *Proceedings of IEEE International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS), Taipei*, 2019.

[5] V. B. Hemadri and U. P. Kulkarni, *Recognition of traffic sign based on support vector machine and creation of the indian traffic sign recognition benchmark. In: Nagabhushan T., Aradhya V., Jagadeesh P., Shukla S., M.L. C. (Eds.), Cognitive Computing and Information Processing. CCIP 2017* vol. 801. Singapore: Communications in Computer and Information Science, Springer, 2018.

[6] R. Cahya, F. R. Isna, A. A. Rosa, and A. Supriatna, "Indonesian traffic sign detection and recognition using color and texture feature extraction and SVM classifier," in *Proceedings of IEEE International Conference on Information and Communications Technology (ICOIACT), Yogyakarta*, 2018, pp. 50-55.

[7] M. I. Tarequl, "Traffic sign detection and recognition based on convolutional neural networks," in *Proceedings of IEEE International Conference on Advances in Computing, Communication and Control (ICAC3), Mumbai*, 2019.

[8] P. Pranjali and K. Ramesh, "Traffic Sign Detection Using Template Matching Technique," in *Proceedings of IEEE Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune* 2018.

[9] S. Adonis, A. A. Patricia, O. Carlos, and R. Rosula, "Traffic sign detection and recognition for assistive driving," in *Proceedings of IEEE 2019 International Symposium on Multimedia and Communication Technology (ISMAC), Quezon City*, 2019.

[10] W. Immawan, K. Hendra, and A. S. Tri, "Traffic sign image recognition using gabor wavelet and principle component analysis," in *Proceedings of IEEE 2019 International Conference of Artificial Intelligence and Information Technology (ICAIIT), Yogyakarta*, 2019.

[11] C. Wang, "Research and application of traffic sign detection and recognition based on deep learning," in *Proceedings of IEEE International Conference on Robots & Intelligent System (ICRIS), Changsha*, 2018.

[12] M. Ivona, K. Zdravko, and R. Krešimir, "The speed limit road signs recognition using hough transformation and multi-class svm," in *Proceedings of International Conference on Systems, Signals and Image Processing, IWSSIP, Osijek, Croatia* 2019.

[13] W. Liu, R. Lu, and i. Liu, "Traffic sign detection and recognition via transfer learning," in *Proceedings of IEEE The 30th Chinese Control and Decision Conference (2018 CCDC), Shenyang*, 2018.

[14] T. George-Zamfir and P. Marian-Silviu, "Neural network based traffic sign recognition for autonomous driving," in *Proceedings of International Conference on Electrochemical and power Systems (SIELMEN), Craiova, Romania*, 2019.

[15] D. K. Amara, R. Karthika, and P. Latha, "Novel deep learning model for traffic sign detection using capsule networks," *arXiv preprint arXiv:1805.04424*, 2018.

[16] A. Jain, A. Mishra, A. Shukla, and R. Tiwari, "A novel genetically optimized convolutional neural network for traffic sign recognition: A new benchmark on Belgium and Chinese traffic sign datasets," *Neural Processing Letters*, vol. 50, pp. 3019-3043, 2019.Available at: https://doi.org/10.1007/s11063-019-09991-x.

[17] K. N. Sruthi and R. P. Aneesh, "Recognition of speed limit from traffic signs using naive bayes classifier," in *Proceedings of International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET), Kottayam, India* 2018.

[18] B. Ilya, T. Sergey, and Y. Dmitry, "Traffic sign recognition on video sequence using deep neural networks and matching algorithm," in *Proceedings of International Conference on Artificial Intelligence Applications and Innovations (IC-AIAI), Belgrade, Serbia*, 2019.

[19] H. T. Manjunatha, A. Danti, and K. L. ArunKumar, *A novel approach for detection and recognition of traffic signs for automatic driver assistance system under cluttered background. In: Santosh K., Hegadi R. (Eds.), Recent Trends in Image Processing and Pattern Recognition. RTIP2R 2018* vol. 1035. Communications in Computer and Information Science, Springer, Singapore, 2019.

[20] K. Bayoudh, F. Hamdaoui, and A. Mtibaa, "Transfer learning based hybrid 2D-3D CNN for traffic sign recognition and semantic road detection applied in advanced driver assistance systems," *Applied Intelligence*, vol. 51, pp. 124-142, 2021.Available at: https://doi.org/10.1007/s10489-020-01801-5.

[21] S. Santaji, S. Santaji, and S. Hallur, "Detection and classification of occluded traffic sign boards," in *2018 International Conference on Electrical, Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT). IEEE*, 2018, pp. 157-160.

[22] K. H. Moh, M. Shahjalal, Z. C. Mostafa, T. L. Nam, and M. J. Yeong, "Simultaneous traffic sign recognition and real-time communication using dual camera in ITS," in *Proceedings of International Conference on Artificial Intelligence in Information and Communication (ICAIIC), Okinawa, Japan*, 2019.

[23] T. Dogancan, C. Min-Hung, and A. Ghassan, "Traffic sign detection under challenging conditions: A deeper look into performance variations and spectral characteristics," in *Proceedings of IEEE Transactions on Intelligent Transportation Systems*, 2019, pp. 3663 - 3673.

[24] W. Jingyu, W. Weiran, and Z. Anliang, "The faster detection and recognition of traffic signs based on CNN," in *Proceedings of IEEE 14th International Conference on Intelligent Systems and Knowledge Engineering (ISKE), Dalian, China* 2019.

[25] N. D. Gabriel, A.-K. Abdullah, B. Jorge, G. F. Fernando, and F. L. Gerardo, "Traffic sign detection and 3D localization via deep convolutional neural networks and stereo vision," in *Proceedings of IEEE Intelligent Transportation Systems Conference (ITSC), Auckland, New Zealand*, 2019.

[26] L. Xi, Z. Jing, T. Qi, L. Jiafeng, and Z. Li, "A saliency guided shallow convolutional neural network for traffic signs retrieval," in *Proceedings of IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), Miami, FL, USA*, 2018.

[27] A. R. Edison, N. A. Joshua, R. P. V. Ryan, P. D. Elmer, and A. B. Argel, "Vision-based traffic sign compliance evaluation using convolutional neural network," in *Proceedings of IEEE International Conference on Applied System Invention (ICASI), Chiba, Japan*, 2018.

[28] S. Liu, "A traffic sign image recognition and classification approach based on convolutional neural network," in *Proceedings of 11th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), Qiqihar, China*, 2019.

[29] S. S. P. Sivagnana and V. S. Ganesh, "Automatic traffic sign identification system for real time operation," in *Proceedings of 2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India*, 2018.

[30] P. R. Shehan, S. Linu, R. Pradeep, and V. Sajith, "Fast and accurate traffic sign recognition for self driving cars using retinanet based detector," in *Proceedings of 2019 International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India*, 2019.

[31] A. J. Prakash and S. Ari, "A system for automatic cardiac arrhythmia recognition using electrocardiogram signal. In Bioelectronics and Medical Devices," ed: Woodhead Publishing, 2019, pp. 891-911.

[32] K. K. Patro, A. Jaya Prakash, M. Jayamanmadha Rao, and P. Rajesh Kumar, "An efficient optimized feature selection with machine learning approach for ECG biometric recognition," *IETE Journal of Research*, pp. 1-12, 2020.