International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An Ensemble Learning with Deep Feature Extraction Approach for Recognition of Traffic Signs in Advanced Driving Assistance Systems

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Submitted: 27/01/2024 **Revised:** 07/03/2024 **Accepted:** 13/03/2024

Abstract: — The research paper introduces an automatic traffic sign identification system tailored for the distinctive challenges posed by Indian traffic scenarios. This system leverages deep learning for feature extraction and ensemble learning for classification, effectively sorting traffic signs into their fundamental categories. The paper underscores the crucial significance of precise traffic sign recognition in fortifying autonomous driving assistance systems (ADAS) and ensuring the secure flow of vehicles on roads. Through extensive evaluation using Indian traffic sign databases, the proposed system exhibits superior performance when compared to existing technologies, significantly augmenting the overall efficiency of the recognition process. The reported performance analysis of 91.10% underscores the system's effectiveness in addressing the complex requirements of traffic sign recognition, thereby mitigating potential risks to public health, the environment, and infrastructure.

Keywords: *Advanced Driving Assistance Systems (ADAS), Convolutional Neural Network (CNN), Deep Learning, Ensemble Learning, Machine Learning, Traffic Sign Recognition.*

1. Introduction

In intelligent transportation systems like automatic driving and sophisticated driver assistance, vision-based traffic sign recognition is crucial. Automobiles have evolved into a necessary form of transportation for people's daily travel thanks to the current society's rapid economic and technological growth. Although cars have made people's lives much easier, they have also caused serious problems with traffic safety, such longer commute times and more accidents. The majority of subjective driver-related factors that affect traffic safety, including as distraction, poor driving technique, and disregard for the law, are now effectively eliminated by smart cars. The capacity to sense and understand one's environment under varying driving and environmental conditions is a key requirement for autonomous cars and most ADAS systems. The car is able to comprehend its environment through its sensors, and it collects all the necessary data to pinpoint any objects it finds, whether they are in the near or wider environs. Most sensors fall into one of four categories: cameras, radars, LIDARs, or ultrasonic devices. The use of all senses at once requires sensor/data fusion, yet it leads to better predictions and safer judgements. The use of a camera as a sensor to gather data from all angles surrounding the vehicle adds complexity and difficulty, but it yields the best results in terms of accuracy, texture, and resolution. Autonomous vehicle systems mostly need to function in real-time. That procedure may be made more challenging by a number of factors, such as sunlight reflection, bad weather, and a complex background. New companies are expected to focus on developing algorithms for object identification and classification, thanks to the explosive growth of the automobile sector [1][5][7].

Autonomous cars and advanced driver assistance systems rely heavily on the categorization of traffic signals. The intelligent application industry has recently seen a surge in interest in traffic sign recognition due to developments in areas like autonomous driving, mobile mapping, the ADAS system, and the availability of bigger datasets of traffic signs. Because they provide drivers with important information and force them to alter their driving habits to comply with the regulations of the road, traffic signs are an essential part of our road infrastructure. Traditionally, the creation of important characteristics in pictures for traffic sign identification and categorization has been labor- and time-intensively done manually. Techniques based on color or shape can also be used, although they have limitations with regard to things like changes in illumination, occlusions, scale, rotation, and translation. These problems could potentially be solved by advanced machine learning, although doing so would require a substantial amount of annotated data [8][10][12].

One solution is the use of road signs, which are displayed on public roadways to serve as warnings, instructions, or regulations for the conduct of drivers and other road users. Of paramount importance are the warning and regulatory signs that advise drivers of their responsibilities, limitations, and specific prohibitions while on the road. By contrast, many researchers have been developed in recent years to develop ADAS, whose primary function is to enhance vehicle safety by collaborating with the driver [15][18][21]. The main contributions of the paper are as follows:

- Prepared new Indian context-based traffic signs dataset for

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primary classes, mandatory, cautionary and information signs

• Designed hybrid approach for traffic sign classification and detection using hybrid approach with ensemble learning and deep learning.

• Used pre-trained 2D convolution network from deep learning for feature extraction with low level to high level features.

After this introduction, the article is structured as follows: Discussion of relevant research on the categorization of traffic signs follows in Section 2. The specifics of the suggested approach for classifying traffic signs are described in Section 3. In Section 4, we present the findings of an experimental examination. Part 5 concludes with the results and recommendations for the intended approach.

2. Literature Survey

Traffic sign recognition is typically accomplished using machine learning and deep learning techniques. The specific class that the traffic signs fall into is classified with great care by these algorithms. Below is a summary of the researcher's biography. In order to collaborate with the driver to improve vehicle safety, systems (ADAS) are now being developed.

The performance of minor traffic sign detection in driving scenarios that are designed for quick and accurate proposal production is to be improved using a deep learning-based technique [1]. The twin support vector machine (TWSVM), which has a higher computational efficiency than the CNN classifier, was combined with a CNN-TWSVM hybrid model and used to recognize traffic signs [2]. A new approach to traffic sign identification and classification is described, which is based on the Inception-v3 model and uses transfer learning. This method significantly reduces the quantity of training data required and the computing costs [3]. The problems with conventional traffic sign identification and the poor real-time performance of traffic sign recognition algorithms based on deep learning are addressed by presenting an improved method for autonomous cars [4]. Machine learning (ML) strategies for traffic sign recognition (TSR) have been presented, however no existing solution has ever managed to reach perfect classification skills or come to a consensus on a preferred ML algorithm [5]. Convolutional neural network (CNN) models are used to identify traffic signs and warn drivers in advance to ensure safe driving [6]. In order to effectively recognize traffic signs for decision-making when placed in driverless cars, a CNN based ML model is developed [7]. A deep learning method based on convolutional neural networks is suggested, and because of its small model size and quick inference time, it is amenable to embedded implementation [8]. The purpose of developing a full Convolutional Neural Network (CNN) classifier named "WAF-LeNet" is to aid autonomous driving technology in recognizing and identifying traffic signs [9].

We evaluate the performance of YOLOv5 based on our Traffic Sign Recognition (TSR) dataset, which shows how the deep learning model for visual object recognition works for TSR [10]. By improving the efficiency and effectiveness of machine learning classifiers throughout the process of identifying traffic signs, ADAS reliability and safety criteria may be met [11]. One new approach to TSR in IoT-based transport systems is a semi-supervised learning method that integrates global and local information [12].

The testing results utilizing the GTSRB dataset showed that the network architecture [13] based on LeNet5 employing Keras and the TensorFlow package could detect traffic signals with a 95% accuracy rate. We provide a neural network-based traffic sign recognition system that can function in real-time [14]. To classify convolutional neural networks, we used two separate designs and the Faster R-CNN (Region-Based Convolutional Neural Network) to identify traffic signals. We introduced a YOLO-based system that uses a CNN to improve its ability to identify traffic signs [15]. For a driver assistance system to work well on vehicles, the software component must be able to generate and simulate using real-time data [16]. Recognizing traffic signs has never been easier than with the use of deep learning, which employs image preprocessing to enhance the identification system's decision-making in diverse situations, whether it is with fluctuating illumination or weather conditions [17]. The goal of this improved NMS approach is to screen the prediction box, avoid erasing the prediction results of numerous targets, and improve the recall rate and detection precision of the targets [18]. To help drivers in Ecuador recognize and comply with traffic laws and warning signals, an algorithm was developed [19]. An algorithm was introduced [20] that can identify Ecuadorian-controlled traffic signs even in very bright daylight. A comprehensive review of traffic sign recognition, tracking, and classification was offered [21].

3. Methods

The goal of the traffic sign recognition system is to analyze, interpret, and identify different pictures of traffic signs. The training and testing phases are the two main components of the recognition system. A traffic sign identification system is schematically shown in Figure 1. Both the training and testing phases of traffic sign identification follow the same pattern of pre-processing, feature extraction, and feature selection.

3.1. **Indian Traffic Sign Dataset**

Define A benchmark database of different traffic sign images is created which has an extremely challenging set of over 2500+ original Indian Traffic Sign images captured and crowdsourced from over 50+ urban and rural areas of Amravati, Maharashtra District, where each image is manually captured, reviewed and verified by computer vision professionals. In this implementation, signs are employed as a super class under the headings Information Signs, Cautionary Signs and Mandatory/Regulatory Signs, and their sample images are shown in given figure 2. Also, traffic sign categories are shown in table 1.

Fig. 2. a) Some examples of mandatory/regulatory signs

Fig. 2. b) Some examples of cautionary signs

Fig. 2. c) Some examples of information signs

Table 1. Categories of traffic signs

Sr. No	Category	Traffic Signs
1	Mandatory/ Regulatory Signs (Category- I)	Speed Limit 10, 20, 25, 30, 40, 50, 60, 65, 80, Give Way, Go Slow, Heavy load vehicle prohibited, No Entry, No Horn, No Parking, No pedestrian crossing, One Way, Overtaking Prohibited, Railway Crossing, Railway Crossing Guarded, Stop
2	Cautionary Signs (Category- II)	Built up Area, Bumpy Road Ahead, Cross Road, Divider Gap in Median, High Voltage overhead Electric Cable, Hump, Left hand curve, Major Road Ahead, Narrow Bridge, Pedestrian crossing ahead, Reflective Merging Traffic ahead, Right hand curve, Risk of Collision. Sharp bend ahead First to Right dangerous turn, Side Road Left, Side Road Right, Staggered intersection, Start and End Dual Carriageway, Steep Ascent, Steep descent, T Junction Ahead Intersection, Traffic Signal Ahead, Y intersection
3	Information Signs (Category-III)	Bus stop, Compulsory Keep Left, Compulsory Sound Horn, Eating Place, Hospital, Parking, Petrol Pump, Police station nearby, School Ahead, Toll Booth, U turn

3.2 Pre-process and Features Extraction, Selection

Define A traffic sign's image is particularly vulnerable to environmental artifacts and noise because of its extreme sensitivity to these factors. Furthermore, the classification outcomes will be less than desirable when these contaminated images are used. For feature extraction, Inception V3 is employed using pre-trained 2D Conv Net models. There are four stages to this model: input, features, classification, and output. It is with this fusion layer that the input and feature layers are constructed. The input's spatial and spectral properties are defined by the features provided by the feature layer, which in turn offer a hierarchy of features from low to high level. Features at a higher level include objects and events, while those at a lower level include things like edges and blobs. For low-level feature extraction, methods from signal/image processing are employed. For high-level feature extraction, methods from machine learning are employed. For example, convolutional filters (for truly low-level material), SIFT, or HOG (for more abstract things like edges) can identify line or dot details, which are examples of low-level features. It is necessary to superimpose high-level characteristics a top low-level one to recognize objects and bigger shapes in the picture. Convolutional neural networks [22] build their capacity to identify common items and patterns in later layers, whereas the initial layers generate filters for locating lines, dots, curves, and other things. The fact that they are responsive to low-level visual processing features like corners and edges/gradients explains their low-level nature. The architecture of pre-trained CNN model of Inception V3 is as shown in figure 3.

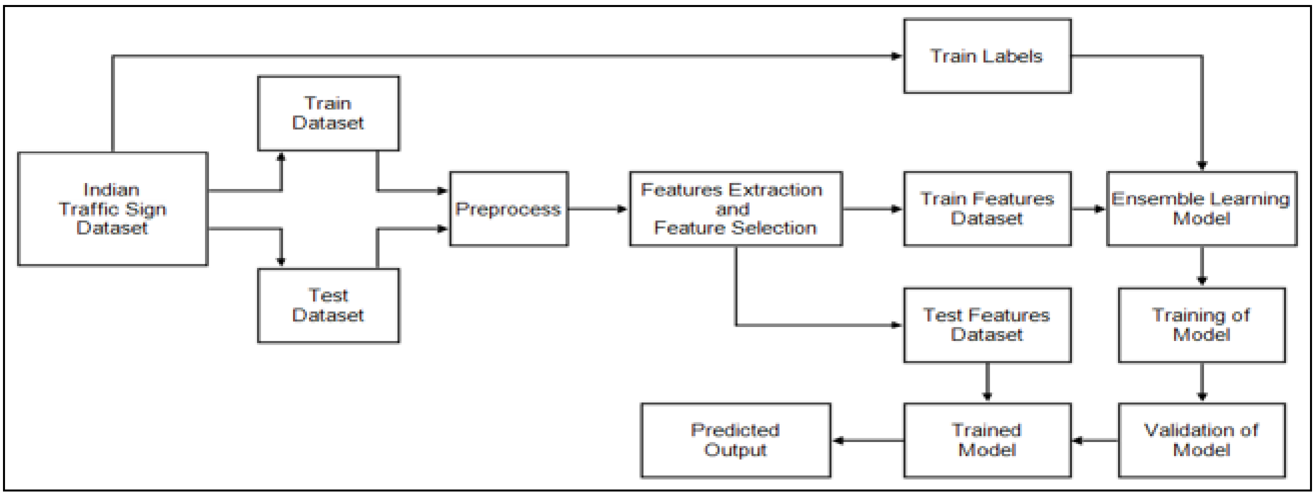


Fig. 1. Framework for a traffic sign recognition system

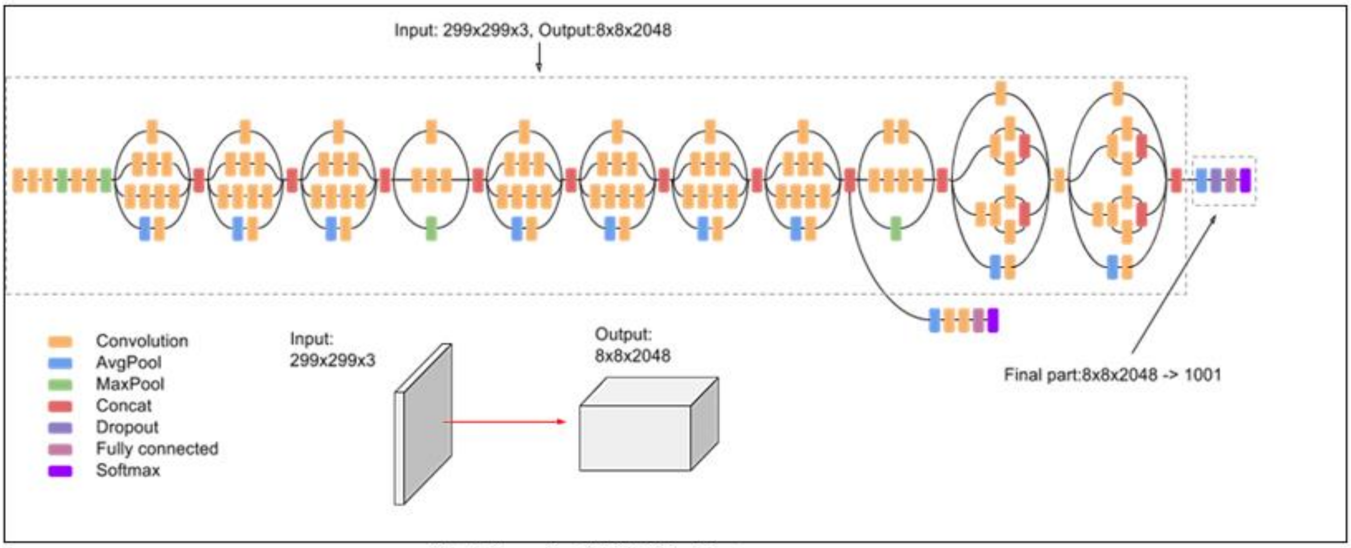


Fig. 3. Inception V3 CNN Architecture

3.3 Classification (train, validate and test)

The road sign classification process involved employing ensemble learning with train, validate, and test stages. The goal was to acquire the predicted output, which was the label of the traffic sign. The feature datasets used for training and testing were already prepared with the associated output labels. The work utilizes ensemble boosting and ensemble bagging, two powerful and dynamic ensemble learning methods. The defined output classes are shown in the table below. They include many different ones, such as stops, no entrances, parking, speed restrictions, bumps, and more. Using grid search optimization, classification can reach its peak accuracy with K-fold validation (K=10). The goal of grid search is to identify the optimal values for a model's hyperparameters. This is significant since the model's overall performance is affected by the hyperparameter settings. The trained model attempts to forecast the output label for the given dataset after a successful validation.

Consider an ensemble bagging and boosting technique where m stands for every attribute of the data. In order to construct the learning model, the following algorithms steps are used.

Algorithm 2: Ensemble Boosting

Step1: Set the dataset to its initial state and provide equal weight to all data points. Here is how to find the initial weighting:

$$\omega = 1/N \in [0,1] \tag{2}$$

where, N indicates the total number of data points and the number of records.

Step2: Find the data points that were wrongly classified by feeding this into the model. This real impact may be classified by utilizing

$$\alpha_t = \frac{1}{2}\ln\frac{(1-TotalError)}{TotalError} \tag{3}$$

where, Alpha indicates the weight that each stump had in the final judgement, the total error is the total number of misclassified data.

Step3: Points of data that were wrongly classified need to have greater weight than points of data that were rightly classified. After that, restore the initial values to each data point's weights. Using these formulas, sample weights are updated.

$$\omega_i = \omega_{i-1} * e^{\pm a} \tag{4}$$

To find the new sample weight, we multiply the old sample weight by Euler's number. A positive Alpha value indicates that the records have been correctly classified; a negative value indicates the opposite.

3.4 Experimental Flowchart

The model working flowchart is as shown in figure 4. It describes the working flow of process model, in which primary steps are

Algorithm 1: Ensemble Bagging

Step1: Construct a decision tree that is linked to the particular data points in the sample by randomly choosing k features from a set of m features, with the constraint that k << m, from the training data.

Step2: Determines the best way to partition the features using the specified k.

Step3: To make child nodes, split the parent node using the best-split algorithm.

Step4: Continue until you reach the leaf node.

Step5: Continue doing this until a forest of trees is formed. Once you have additional data points, find the predictions of each decision tree and put them in the most popular category. Classification trees allow us to use the majority vote to make predictions while B is bagging.

$$\acute{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(x') \tag{1}$$

feature engineering process i.e. pre-processing and feature extraction which can be applied to train and test image set. After that extracting the features from feature layer from pre-trained 3D CNN model, ensemble machine learning model is used as classification layer for prediction of traffic sign images.

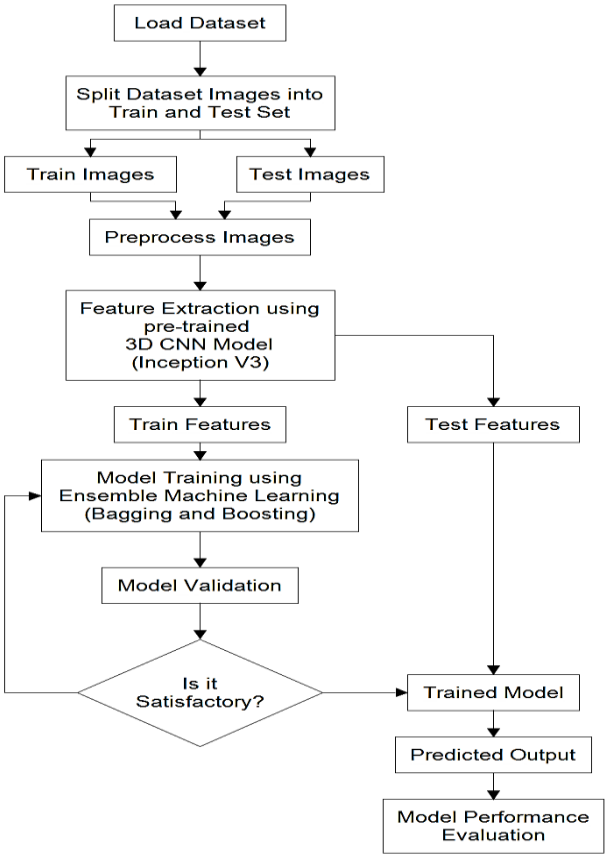


Fig. 4. Process flowchart

4. Experimental Evaluation and Discussion

The proposed experimentation proposes studies utilizing the standard benchmark Indian Traffic Sign Dataset [28] that use a collection of images based on an Indian context for categorization. Our Windows system, equipped with MATLAB R2018b, a core i5 CPU, and 8GB of RAM, was utilized for these experiments. Over six months, the collection's smartphone camera captured 4,700 images, which have been then classified into three semantic groups. As can be seen in the table below, the total number of scene images in each category. For both the training and testing phases, three parts of the dataset's images are utilized. Only 30% of the initial data matrix is in the independent test set; the remaining 70% is in the training set. Grid search hyperparameter optimization is used to optimize the parameters of the classifier model in the suggested experiment. By analysing the features of the confusion matrix, all performance metrics are evaluated.

The proposed work's quality has been evaluated using performance assessment standards that are based on a confusion matrix. A certain table layout, sometimes called an error matrix and used in supervised learning, allows one to observe how well an algorithm is doing. The rows of the matrix show the instances in each real class, whereas the columns show the instances in each anticipated class, or inversely. The precision with which a binary classification test includes or excludes a condition is reflected in its accuracy. The performance evaluation time required for classification of all three categories with both algorithm ensemble boosting and bagging algorithm is as shown in table 2. It is found that ensemble bagging algorithms required more time for training and testing the classification phase as described in figure 5.

Table 2: Performance Evaluation Time

Classification Phases	Training Time (sec)		Testing Time (sec)	
	Ensemble Boosting	**Ensemble Bagging**	**Ensemble Boosting**	**Ensemble Bagging**
Category I	81.54	90.16	35.90	42.46
Category II	64.89	78.48	29.27	32.85
Category III	89.41	93.71	39.50	45.37

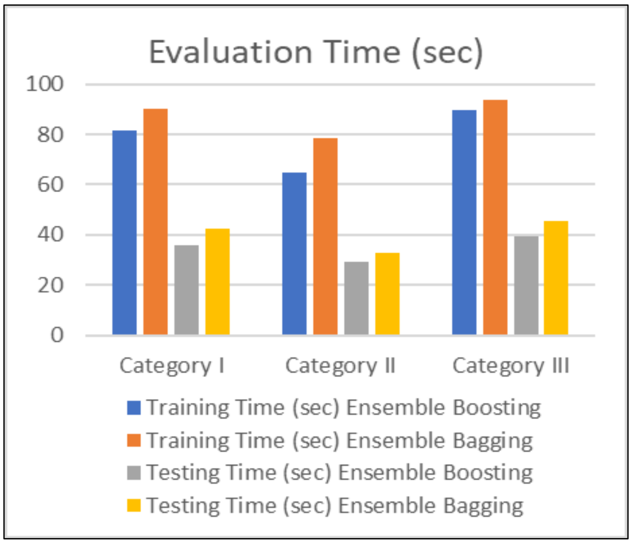
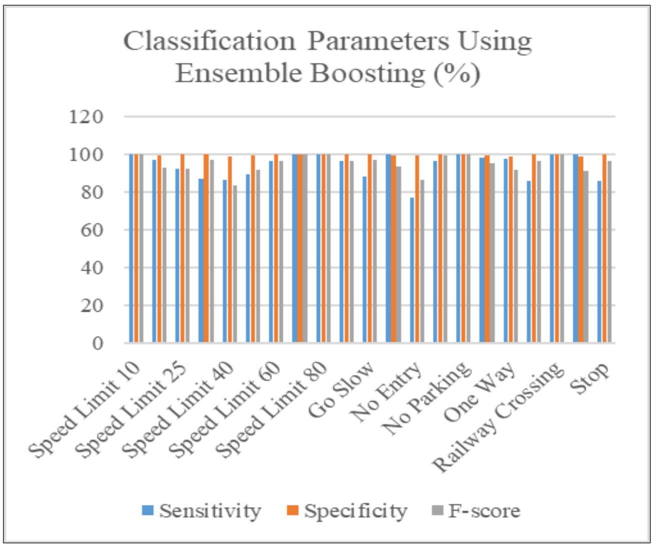


Fig. 5. Process evaluation time

The classification performance parameters, sensitivity, specificity and f-score are evaluated for three primary traffic sign category classification for both algorithms and mentioned in table 3, table 4 and table 5 respectively. Each category has various output labels or classes as per the traffic signs categories described in figures 6 and 7 for ensemble boosting and bagging algorithm for category I traffic sign classification respectively. It is observed that some traffic signs classes are classified with 100% performance for both algorithms.



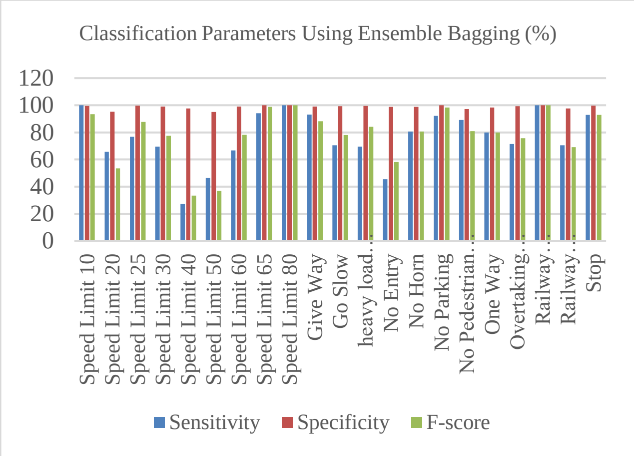


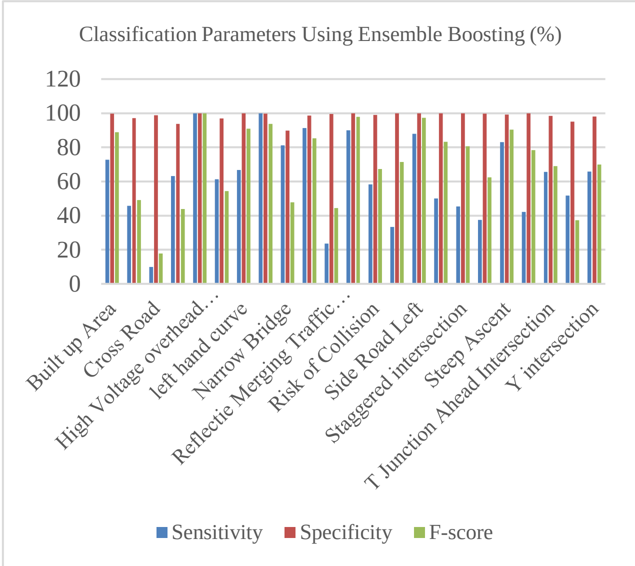
Table 3. Classification report performance for category I

Output Classes	Classification Algorithms					
	Ensemble Boosting			Ensemble Bagging		
	Sensitivity	Specificity	F-score	Sensitivity	Specificity	F-score
Speed Limit 10	100	100	100	100	99.58	93.49
Speed Limit 20	97.14	99.36	92.89	65.71	95.36	53.48
Speed Limit 25	92.30	99.79	92.30	76.92	99.79	87.71
Speed Limit 30	86.95	100	97.08	69.56	99.17	77.66
Speed Limit 40	86.36	99.18	83.33	27.27	97.74	33.33
Speed Limit 50	89.28	99.58	91.91	46.42	95.02	36.93
Speed Limit 60	96.29	99.79	96.29	66.66	99.17	78.26
Speed Limit 65	100	100	100	94.11	100	98.76
Speed Limit 80	100	100	100	100	100	100
Give Way	96.55	99.79	96.55	93.10	99.16	88.23
Go Slow	88.23	100	97.40	70.58	99.39	77.92
heavy load vehicle prohibited	100	99.58	93.49	69.56	99.58	84.21
No Entry	77.27	99.59	86.73	45.45	98.77	58.13
No Horn	96.77	100	99.33	80.64	98.74	80.64
No Parking	100	100	100	92.30	100	98.36
No Pedestrian crossing	98.18	99.34	95.40	89.09	97.14	80.85
One Way	97.5	99.14	91.98	80	98.29	80
Overtaking Prohibited	85.71	100	96.77	71.42	99.39	75.75
Railway Crossing	100	100	100	100	100	100
Railway Crossing Gaurded	100	99.15	91.39	70.58	97.68	68.96
Stop	85.71	100	96.77	92.85	99.79	92.85

Fig 6. Performance of category I using ensemble boosting

Fig. 7. Performance of category I using ensemble bagging

Similarly, for classification of category II, various output labels or classes as per the traffic signs categories described in figures 8 and 9 for ensemble boosting and bagging algorithm. It is observed that



some traffic signs classes are classified with 100% performance of specificity rate for both algorithms. The classification of categories III with various output labels are shown in figure 10 and 11 for both algorithms.

Table 4. Classification report performance for category II

Output Classes	Classification Algorithms					
	Ensemble Boosting			Ensemble Bagging		
	Sensitivity	Specificity	F-score	Sensitivity	Specificity	F-score
Bluilt up Area	72.72	99.82	88.88	77.27	99.31	80.18
Bumpy Road Ahead	45.71	97.18	49.07	54.28	95.07	42.60
Cross Road	10	98.79	17.85	5	98.79	9.61
Divider Gap in Median	63.15	93.80	43.79	52.63	93.62	38.16
High Voltage overhead Electric Cable	100	100	100	100	99.83	93.75
Hump	61.29	97.02	54.28	32.25	97.20	37.03
left hand curve	66.66	100	90.90	58.33	100	87.5
Major Road Ahead	100	99.83	93.75	91.66	99.66	85.93
Narrow Bridge	81.13	89.81	47.88	43.39	91.81	35.38
Right hand curve	90	100	97.82	86.66	99.30	86.66
Risk of Collision	58.33	98.96	67.30	20.83	97.58	25
sharp bend ahead First to Right dangerous turn	33.33	100	71.42	6.66	99.14	12.82
Side Road Left	88	100	97.34	76	98.78	73.64
Side Road Right	50	100	83.33	25	100	62.5
Staggered intersection	45.45	100	80.64	63.63	100	89.74
Start and End Dual Carriageway	37.5	99.83	62.5	25	100	62.5
Steep Ascent	83.05	99.26	90.40	96.61	96.50	78.51
Steep descent	42.10	100	78.43	47.36	99.14	60
T Junction Ahead Intersection	65.62	98.42	69.07	59.37	97.37	56.54
Traffic Signal Ahead	51.72	95.12	37.31	31.03	96.68	31.91
Y intersection	65.85	98.04	69.94	60.97	97.86	66.13

Fig. 8. Performance of category II using ensemble boosting

Fig. 9. Performance of category II using ensemble bagging

Table 5. Classification report performance for category III

Output Classes	Ensemble Boosting			Ensemble Bagging		
	Sensitivity	Specificity	F-score	Sensitivity	Specificity	F-score
Bus stop	82.05	96.75	78.81	79.48	94.58	69.50
Compulsory keep Left	80	98.28	80	92	96.56	73.24
Compulsory sound Horn	100	100	100	93.75	100	98.68
Eating Place	97.36	99.64	97.36	100	99.64	97.93
Hospital	53.33	100	85.10	60	100	88.23
Parking	78.94	100	94.93	63.15	99.66	84.50
Pass Either	96.77	96.49	78.53	70.96	96.84	70.96
Petrol Pump	90.90	99.65	94.33	77.27	100	94.44
police station near by	76.92	98.96	84.74	76.92	97.58	74.62
school Ahead	97.72	98.52	92.67	81.81	96.32	78.94
Toll Booth	100	100	100	94.73	99.66	94.73
U turn	86.36	98.63	83.33	72.72	98.29	75.47

(Header spanning all algorithm columns: Classification Algorithms)

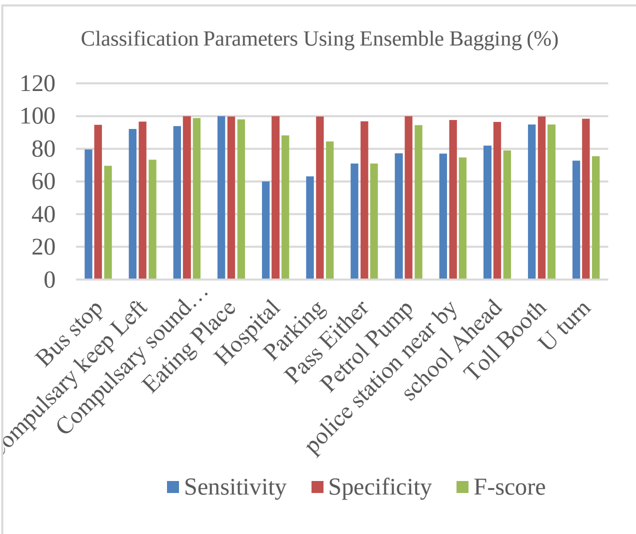
Fig. 10. Performance of category III using ensemble boosting

Fig. 11. Performance of category III using ensemble bagging

Table 6 shows the results of the accuracy evaluation of the overall performance characteristics, including the kappa score parameters for each of the three traffic sign categories. Figure 12 shows that when comparing two classification methods for category I traffic signs, the ensemble boosting approach achieves better accuracy.

Table 6. Overall performance classification report for all categories classification

Classification Phases	Accuracy (%)		Kappa Score (%)	
	Ensemble Boosting	Ensemble Bagging	Ensemble Boosting	Ensemble Bagging
Category I	94.70	75.49	81.63	72.99
Category II	88.33	77.37	85.29	80.48
Category III	90.29	84.32	83.36	78.17



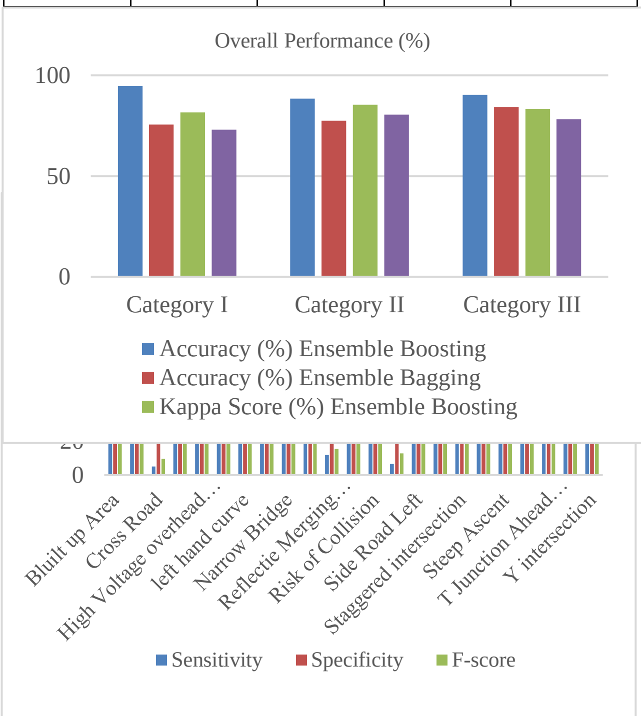
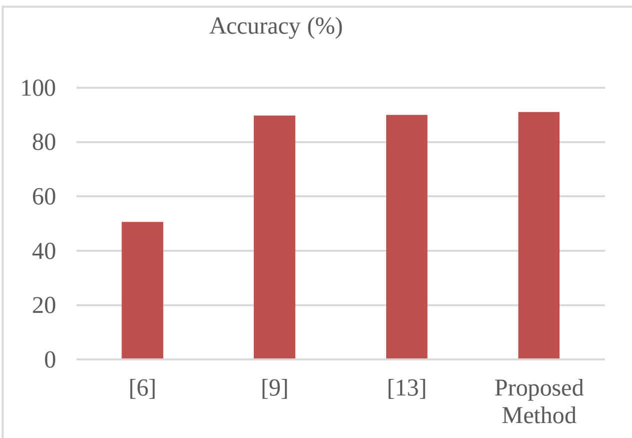


Fig. 12. Overall performance of all category

Table 7. Comparative analysis performance

References	Accuracy (%)
[6]	50.63
[9]	89.75
[13]	90
Proposed Method	91.10



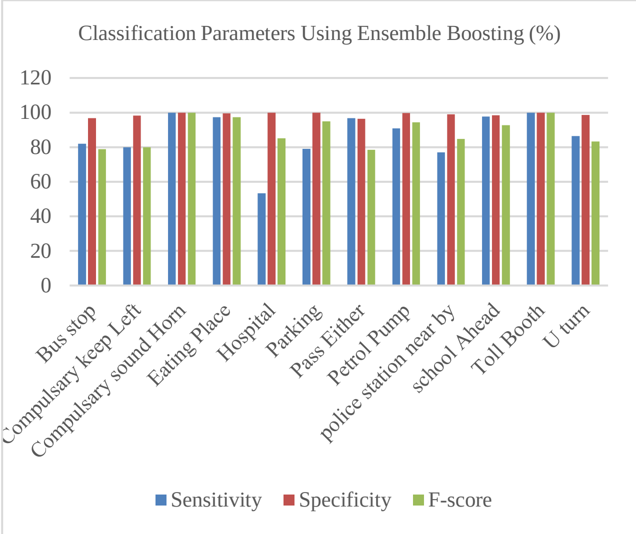


Fig 13. Comparative accuracy performance

5. Conclusion

As research into enhanced intelligence techniques continues to make advancements daily, the concept of self-driving autos is gaining popularity in ADAS. Images of Indian traffic signs were the subject of automated sign identification in this research. A pre-trained deep convolutional network is utilized initially in the feature engineering technique. Then, ensemble machine learning classifiers are used for classification to get the most out of the system. The results showed that the ensemble bagging method outperformed the ensemble boosting approach with an overall accuracy of 91.10% and that Indian traffic signs are the most accurately recognized. Both in terms of accuracy and training efficacy, the suggested method surpasses current techniques. Processing of tiny or low-quality pictures is within the future scope of the planned effort. Inadequate sign assessment and background segmentation might lead to unsatisfactory outcomes from the overall generation method. Then, large datasets and high-resolution photos can benefit from advanced deep learning with optimization techniques.

Author contributions

Akshay Utane: Conceptualization, Methodology, Software, Field study and writing. **Sharad Mohod:** Original draft preparation, Validation. And review process. **Ashay Rokade, Yogesh Thakare and Hemant Kasturiwale:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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