

A Machine Learning Framework for Traffic and Road Sign Classification

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Abstract- Accurate road sign detection and recognition play a vital role in the advancement of intelligent transportation and driver assistance systems. To overcome the limitations of conventional road sign detection methods, which are highly sensitive to environmental conditions, as well as the inadequate real-time performance of existing deep learning-based recognition techniques, this study proposes an enhanced road sign detection and recognition framework. The proposed approach integrates a Convolutional Neural Network (CNN) with a Pickle ensemble model to achieve reliable and efficient traffic sign classification. The system is evaluated using the German Traffic Sign Recognition Benchmark (GTSRB) dataset, which comprises 51,839 traffic sign images divided into training and testing subsets. Experimental evaluation demonstrates that the proposed model achieves an average recognition accuracy of approximately 99%, outperforming many existing road sign recognition approaches. The high recognition accuracy and robustness of the proposed method can significantly contribute to reducing road accidents, enhancing traffic safety, and supporting the continued development of intelligent driving assistance and autonomous vehicle technologies.

Key words: Informatory signs, Intelligent vehicle, Advanced Driver Assistance Systems, GSTRB, Traffic Sign recognition.

1. INTRODUCTION

The rapid advancement of automotive technology and the continuous increase in the number of vehicles have made road traffic safety a major global concern, particularly in developing and developed countries. Every year, millions of people are injured or lose their lives in road accidents, and the number of traffic-related fatalities continues to rise. As a result, Intelligent Transportation Systems (ITS) and Advanced Driver Assistance Systems (ADAS) have gained significant attention for enhancing driving safety and efficiency. ADAS incorporates various intelligent features, including adaptive cruise control, lane departure warning, collision avoidance, night vision, and traffic sign recognition (TSR), to assist drivers in making informed decisions and reducing the likelihood of accidents. Traffic information is typically conveyed through visual elements such as traffic signs, traffic lights, and road markings. However, a driver's ability to interpret these visual cues may be affected by factors such as fatigue, distraction, stress, or impaired driving. Therefore,

2. TRAFFIC SIGN IN INDIA

Traffic signs are the noiseless chatterers on the street. Is it the individual overdue the wheel or a unimaginative, having a detailed information about road safety is obligatory for whole previously thumping the streets. Traffic signs stretch information nearby the street

reliable traffic sign recognition systems play a crucial role in automatically identifying road signs and providing timely warnings to drivers, thereby improving situational awareness and overall road safety.

India possesses one of the largest and most extensive road networks in the world, supporting a rapidly growing number of vehicles and road users. Traffic signs serve as essential communication tools that guide drivers by providing information about road conditions, regulations, warnings, and directions. These signs help drivers make safe and informed driving decisions by indicating speed limits, prohibited actions, hazardous zones, and upcoming road conditions. Warning signs alert drivers to potential dangers, while regulatory signs enforce traffic rules and restrictions to ensure orderly traffic movement. Since understanding traffic signs is essential for safe driving, knowledge of these signs forms an important part of the driving license examination process. Consequently, the development of efficient and accurate automatic traffic sign detection and recognition systems is becoming increasingly important for improving driver assistance, minimizing human errors, and enhancing overall transportation safety.



Fig-1: Different traffic signs used during driving

Normally, all the traffic warbles use violent colors so that they can be effortlessly noticed by the drivers driving on the roads. All of them are retained very unassuming in expression so that even the driver driving at a very respectable speed can effortlessly read them. It's compulsory for all the drivers to realize and shadow all the traffic signs. The traffic signals are used to tell the guidelines and boundaries over that road with the help of unpretentious and easy graphical symbols.

environments gaining, proposition instructions to be pursued at the principal crossing or intersections, inform or controller drivers, and sanction proper operational of street traffic. Being unacquainted of street signs is corresponding to chucking attentiveness to the tempest. It can central to penalization of life and property. A person is imaginary to be habituated (get complete a adorned or oral test) with the

traffic signs and symbols before locating a driving license in India. Habitually, there are three unlike kinds of street symbols in India.

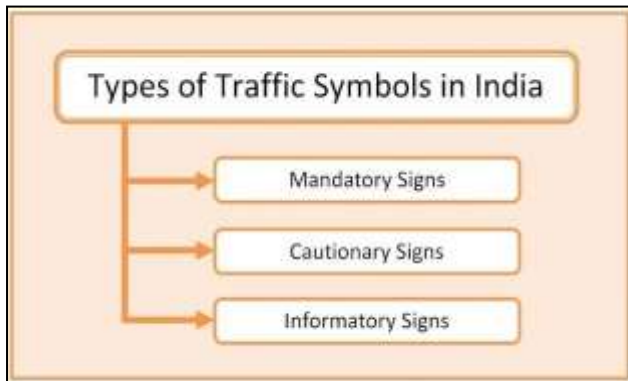


Fig- 2: Types of traffic symbols used in India

Traffic signs are essential components of the road transportation system, serving as silent communicators that provide important information to drivers and pedestrians. Whether a vehicle is operated manually or autonomously, understanding traffic signs is crucial for ensuring safe and efficient travel. These signs convey information about road conditions, traffic regulations, warnings, and navigation instructions, enabling drivers to make informed decisions while driving. Failure to recognize or obey traffic signs can result in traffic violations, accidents, and damage to life and property. In India, knowledge of traffic signs is a mandatory requirement for obtaining a driving license, and applicants are required to demonstrate their understanding through written or practical examinations. Traffic signs in India are generally classified into three major categories: Mandatory Signs, Cautionary Signs, and Informatory Signs.

Mandatory Signs:

Mandatory signs specify traffic rules and regulations that road users are legally required to follow. Non-compliance with these signs is considered a traffic offense and may result in penalties or fines. These signs regulate vehicle movement and ensure the safe and orderly flow of traffic. They communicate restrictions, prohibitions, and compulsory actions that drivers must observe while traveling. Common examples include Stop, Give Way, No Entry, No Parking, No Stopping, Speed Limit, Horn Prohibited, Pedestrian Prohibited, One Way, and Compulsory Turn signs. By enforcing traffic discipline, mandatory signs play a vital role in reducing accidents and maintaining road safety.

Cautionary Signs:

Cautionary signs are designed to warn drivers about potential hazards or unusual road conditions ahead, allowing them to take preventive measures and adjust their driving behavior accordingly. These warning signs improve driver awareness and help minimize the risk of accidents by providing advance notice of dangerous situations. Typical cautionary signs include Right-Hand Curve, Left-Hand Curve, Hairpin Bend, Steep Ascent, Steep Descent, Narrow Bridge, Slippery Road, Loose Gravel, Pedestrian Crossing, School Ahead, Men at Work, Cattle Crossing, Falling Rocks, and Ferry Crossing. By alerting drivers to possible risks, cautionary signs contribute significantly to safer road travel.

Informatory Signs:

Informatory signs provide guidance and useful information to assist road users during their journey. Unlike mandatory or cautionary signs, these signs do not impose restrictions but help drivers locate essential public services, facilities, and destinations. They improve travel convenience by indicating the availability of amenities and important locations along the route. Common examples include Petrol Pump, Hospital, First Aid Post, Public Telephone, Restaurant, Rest Area, Parking Area, Bus Stop, Railway Station, and Tourist Information signs. These signs enhance the overall driving experience by offering navigational assistance and facilitating access to essential services.

3. LITERATURE REVIEW

Jingwei Cao et al. (2019) improved traffic sign detection and recognition algorithm for intelligent vehicles is proposed to address problems such as how easily affected traditional traffic sign detection is by the environment, and poor real-time performance of deep learning-based methodologies for traffic sign recognition. Firstly, the HSV color space is used for spatial threshold segmentation, and traffic signs are effectively detected based on the shape features. Secondly, the model is considerably improved on the basis of the classical LeNet- 5 convolutional neural network model by using Gabor kernel as the initial convolutional kernel, adding the batch normalization processing after the pooling layer and selecting Adam method as the optimizer algorithm. Finally, the traffic sign classification and recognition experiments are conducted based on the German Traffic Sign Recognition Benchmark.[6]

Alexander Hanel et al. (2018) contributed the selected datasets are compared regarding the applicability for traffic sign detection. The comparison covers the process to produce the synthetic images and addresses the virtual worlds, needed to produce the synthetic images, and their environmental conditions. The comparison covers variations in the appearance of traffic signs and the labeling strategies used for the datasets, as well. A deep learning traffic sign detector is trained with multiple training datasets with different ratios between synthetic and real training samples to evaluate the synthetic SYNTHIA dataset. A test of the detector on real samples only has shown that an overall accuracy and ROC AUC of more than 95% can be achieved for both a small rate of synthetic samples and a large rate of synthetic samples in the training dataset.[7]

Q. Yao et al. (2016) motivated to efficiently survey traffic signs while mapping the road network and the roadsidescape. Inspired by the manual delineation of traffic sign, a drawing strategy is proposed to quickly approximate the boundary of traffic sign. The most common speed-limit sign circle and the statistic color model of traffic sign are studied in this paper. Anchorpoints of traffic sign edge are located with the local maxima of color and gradient difference. Starting with the anchor points, contour of traffic sign is drawn smartly along the most significant direction of color and intensity consistency. The temporally salient traffic sign is then detected statistically and automatically as the rare

event of having a traffic sign. The proposed algorithm is tested with a diverse set of images that are taken in Wuhan, China with the MMS of Wuhan University. Experimental results demonstrated that the proposed algorithm can detect traffic signs at the rate of over 80% in around 10 milliseconds. It is promising for the large-scale traffic sign survey and change detection using the mobile mapping system.[8]

Faming Shao et al. (2018) proposed a novel approach for real-time traffic sign detection and recognition in a real traffic situation was proposed. The experimental results based on Chinese and German traffic sign databases showed that the proposed method obtained a comparable performance with the state-of-the-art method, and furthermore, the processing efficiency of the whole process of detection and classification was improved and met the real-time processing demands.[9]

Xiaoguang HU et al. (2012) proposed a method using visual attention mechanism to detect traffic sign, which is reasonable. In our method, the whole scene will firstly be analyzed by visual attention model to acquire the area where traffic signs might be placed. And then, these candidate areas will be analyzed according to the shape characteristics of the traffic sign to detect traffic signs. In traffic sign detection experiments, the result showed the proposed method is effectively and robust than other existing saliency detection method.[10]

Victor J. D. Tsai et al (2016) aimed on developing techniques for detecting, extracting, and positioning of traffic signs from Google Street View (GSV) images along user-selected routes for low-cost, volumetric and quick establishment of the traffic sign infrastructural database that may be associated with Google Maps. The framework and techniques employed in the proposed system are described.[11]

Safat B.Wali et al.(2015) developed an efficient TSDR system which contains an enriched dataset of Malaysian traffic signs. The developed technique is invariant in variable lighting, rotation, translation, and viewing angle and has a low computational time with low false positive rate. The development of the system has three working stages: image preprocessing, detection, and recognition. The system demonstration using a RGB colour segmentation and shape matching followed by support vector machine (SVM) classifier led to promising results with respect to the accuracy of 95.71%, false positive rate (0.9%), and processing time (0.43 s). The area under the receiver operating characteristic (ROC) curves was introduced to statistically evaluate the recognition performance. The accuracy of the developed system is relatively high and the computational time is relatively low which will be helpful for classifying traffic signs especially on high ways around Malaysia. The low false positive rate will increase the system stability and reliability on real-time application.[12]

Yassmina Saadna and Ali Behloul(2017) introduced an overview of some recent and efficient methods in the traffic sign detection and classification. Indeed, the main goal of detection methods is localizing regions of interest containing traffic sign, and we divide detection methods

into three main categories: color-based (classified according to the color space), shape-based, and learning-based methods (including deep learning). In addition, we also divide classification methods into two categories: learning methods based on hand-crafted features (HOG, LBP, SIFT, SURF, BRISK) and deep learning methods. For easy reference, the different detection and classification methods are summarized in tables along with the different datasets. Furthermore, future research directions and recommendations are given in order to boost TSR's performance.[13]

Canan Tastimur et al. (2016) presented image processing techniques are used to detect traffic signs and Fuzzy Integral is used to recognize traffic signs. Both more accuracy rate results and low computational cost are obtained in terms of recognition stage by using positive aspects of algorithms taken as input parameters with Fuzzy Integral in the traffic sign recognition system. Experimental results showed that proposed method gives high accurate results in a reasonable time.[14]

Manjare and Hambarde (2014) presented two different methods for road sign detection and recognition which has based on color and shape. The first method is Gielis curve fitting. In this method algorithm is applied to different shapes like circular, triangular, octagonal. Fitting contour points into a Gielis curve takes a lot of time, which naturally cannot be acceptable in a real-time system. Hence, further investigation and improvement is required to decrease the processing time. It gives 85% accuracy for road sign recognition. The second method is based on neural network. The Neural network stages were performed to recognize the traffic sign patterns. The first step is to reduce the number of MLP inputs by preprocessing the traffic sign image, and the second step is to search for the best network architecture by selecting a suitable error criterion for training with LMA. Using neural network, road sign classification gives 90% accuracy for different type of signs (circular, triangular, octagonal).[15]

4. PROPOSED WORK

The proposed traffic sign detection and recognition system is designed to address the limitations of existing approaches, including sensitivity to environmental conditions, high computational complexity, and limited real-time performance. The framework employs a streamlined architecture that enhances recognition accuracy while reducing processing time.



Fig- 3: Architecture of traffic sign recognition system

The overall system consists of four major phases:.

- A. Image Acquisition
- B. Traffic Sign Detection
- C. Grayscale Conversion
- D. Traffic Sign Classification

A. Image Acquisition

The first stage involves capturing road scene images using a camera installed on the vehicle. The camera continuously records the surrounding environment and provides real-time digital images to the recognition system. These captured images serve as the input for subsequent processing stages, enabling the system to detect and classify traffic signs under real-world driving conditions.

B. Traffic Sign Detection

The acquired image generally contains multiple objects, including roads, vehicles, pedestrians, and traffic signs. Therefore, the next step is to isolate the traffic sign from the complete scene. This is achieved by detecting geometric features such as circular, triangular, rectangular, or octagonal shapes commonly associated with traffic signs. Various image processing techniques are employed to accurately locate and extract the region of interest (ROI), thereby reducing unnecessary information before classification.

C. Grayscale Conversion

After extracting the traffic sign, the image is converted from RGB to grayscale. Grayscale images require less storage space and lower computational resources than color images while preserving sufficient structural information for classification. Since the proposed Convolutional Neural Network (CNN) is trained using grayscale images, this conversion ensures consistency between the training and testing phases. The reduced image dimensionality significantly improves processing speed without compromising recognition accuracy.

D. Traffic Sign Classification

In the final stage, the grayscale image is provided as input to the trained CNN model for classification. The CNN extracts discriminative features and identifies the corresponding traffic sign category. To avoid repeated training and reduce computational overhead, the trained model is stored as a Pickle file. During prediction, the Pickle file is loaded directly, allowing the system to perform rapid and efficient real-time traffic sign recognition with high accuracy.

Data Flow Description

The overall operation of the proposed system is divided into two major phases:

Training Phase

Testing (Real-Time Prediction) Phase

Separating these phases eliminates the need to retrain the model whenever new images are processed. Once the CNN model has been trained, it is serialized and stored in a

Pickle file. This file contains the learned parameters of the trained model and can be loaded whenever predictions are required, significantly reducing computational cost and execution time.

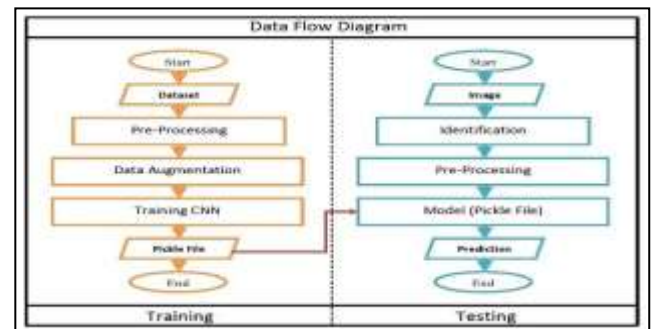


Fig- 4: Dataflow diagram of Proposed system

The proposed framework can process either previously captured images or live video streams obtained from an onboard vehicle camera. After detecting the traffic sign, the system classifies it and reports the predicted class along with the corresponding confidence score.

Training Phase

The training phase aims to develop a robust CNN model capable of accurately recognizing various traffic signs under different environmental conditions.

1. Dataset Collection

A comprehensive dataset containing images of different traffic signs is collected from publicly available sources such as the Kaggle repository. Images belonging to different traffic sign categories are organized into separate folders to facilitate supervised learning.

2. Image Pre-processing

The collected images vary in size, resolution, and color format. Therefore, preprocessing is performed to standardize the dataset by resizing all images to a fixed resolution (32 × 32 pixels), converting them to grayscale, and normalizing pixel values. These operations improve the efficiency and stability of the learning process.

3. Data Augmentation

To improve the robustness and generalization capability of the CNN model, data augmentation techniques are applied. Multiple variations of each training image are generated using transformations such as rotation, translation, scaling, brightness adjustment, and flipping. These augmented images enable the model to recognize traffic signs under varying illumination, viewing angles, and environmental conditions.

4. CNN Model Training

The augmented grayscale images are then used to train the Convolutional Neural Network. During training, the images serve as input features, while the corresponding traffic sign categories act as target labels. The CNN

automatically learns discriminative features that distinguish one traffic sign from another, resulting in an accurate classification model.

5. Model Serialization Using Pickle

After training is completed, the CNN model is serialized and stored in a Pickle file. Saving the trained model eliminates the need for repeated training and allows the classifier to be deployed efficiently in real-time applications.

Testing and Real-Time Prediction

The testing phase evaluates the performance of the trained CNN model using unseen traffic sign images or live camera input.

1. Image Acquisition

The system accepts either static images or continuous video captured from an onboard camera. These images are forwarded to the detection module for further processing.

2. Traffic Sign Detection

The traffic sign is extracted from the complete road scene using shape-based detection methods. The detected region of interest contains only the traffic sign, thereby minimizing background interference during classification.

3. Image Pre-processing

The detected traffic sign is resized to 32×32 pixels and converted to grayscale to match the format used during CNN training. This ensures consistency between training and inference.

4. Model Loading

The previously stored Pickle file is loaded into memory, and the trained CNN model is restored without retraining. The preprocessed image is then supplied to the model for classification.

5. Prediction

The CNN predicts the category of the detected traffic sign and produces a confidence score indicating the probability of the prediction. Performance is evaluated using a large number of test images, and recognition accuracy is measured to assess the effectiveness of the proposed system.

System Deployment

During deployment, the trained Pickle model is integrated into the vehicle's driver assistance system. Incoming images from the onboard camera are processed continuously, allowing the system to detect and recognize traffic signs in real time. The identified traffic sign, along with its prediction confidence, is displayed to the driver, thereby enhancing driving safety and assisting in timely decision-making.

Advantages of the Proposed System

The proposed traffic sign recognition framework offers several advantages over existing approaches:

Reduced Memory Requirement: The use of grayscale images significantly reduces storage requirements compared to RGB images.

Higher Processing Speed: Lower image dimensionality decreases computational complexity, enabling faster traffic sign recognition suitable for real-time applications.

Low Computational Cost: The trained CNN model is stored in a Pickle file and reused during prediction, eliminating the need for repeated model training.

Improved Robustness: The combination of grayscale preprocessing and data augmentation enables the system to recognize traffic signs effectively even under blurred images, illumination changes, and varying environmental conditions.

Simplified Architecture: The proposed framework employs a straightforward processing pipeline that improves implementation efficiency while maintaining high recognition accuracy.

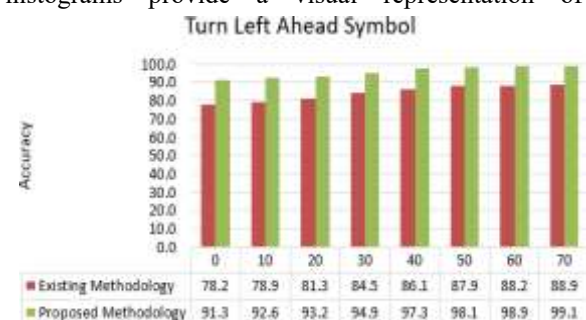
Real-Time Performance: The lightweight CNN architecture and serialized model enable rapid predictions, making the system well suited for Advanced Driver Assistance Systems (ADAS) and intelligent transportation applications.

High Recognition Accuracy: The proposed methodology provides reliable traffic sign classification with excellent prediction performance, thereby contributing to safer driving and reduced road accidents.

5. EXPERIMENTAL RESULTS

The performance of the proposed traffic sign recognition model is illustrated using accuracy histograms. The system is designed to identify traffic symbols from input images, and its performance was evaluated using a test dataset containing approximately 100–105 images for each of the 16 different traffic sign categories. During the testing phase, each image was provided as input to the model, and the predicted output was compared with the corresponding ground truth label to determine the recognition accuracy.

In the histograms, the x-axis represents the prediction accuracy (%) achieved by the model, while the y-axis indicates the number of test samples corresponding to each accuracy range. The height of each bar shows how many samples fall within a particular accuracy interval. Since the proposed model correctly identified all traffic symbols, the histograms provide a visual representation of the



distribution of prediction accuracies across the test samples for each traffic sign category.

Turn Right Ahead Traffic Sign Analysis

For the Turn Right Ahead traffic sign, a total of 102 test images were evaluated. Among these, 60 samples achieved a prediction accuracy of 99.2%, resulting in the highest bar in the corresponding histogram. This indicates that the majority of the test samples were recognized with an accuracy of 99.2% while maintaining correct traffic sign classification. The histogram therefore demonstrates the consistency and reliability of the proposed model in recognizing the Turn Right Ahead traffic sign with very high accuracy.

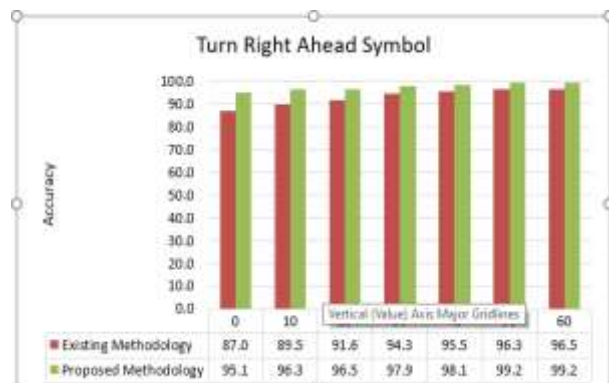


Fig. 5: Accuracy analysis of turn right ahead traffic symbol

Turn Left Ahead Traffic Sign Analysis

A total of 102 test images of the Turn Left Ahead traffic sign were used to evaluate the performance of the proposed recognition model. Among these, 78 samples achieved a prediction accuracy of 99.1%, resulting in the highest frequency within that accuracy range in the histogram. This demonstrates that most of the test samples were correctly classified as Turn Left Ahead with consistently high prediction accuracy, indicating the robustness of the proposed model.

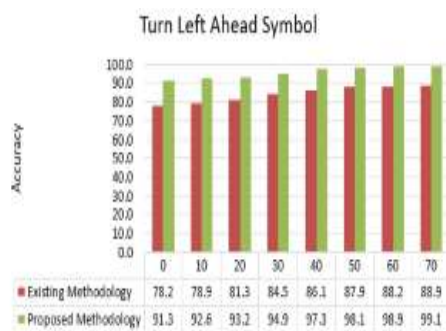


Fig. 6: Accuracy analysis of turn left ahead traffic symbol

Stop Traffic Sign Analysis

For the Stop traffic sign, 102 test images were evaluated. Out of these, 95 samples achieved a prediction accuracy of 99.7%, producing the tallest bar in the corresponding histogram. The results indicate that the proposed model accurately recognized the majority of the Stop traffic signs with a very high confidence level while maintaining correct class identification. This reflects the excellent performance and reliability of the recognition system for this traffic sign category.

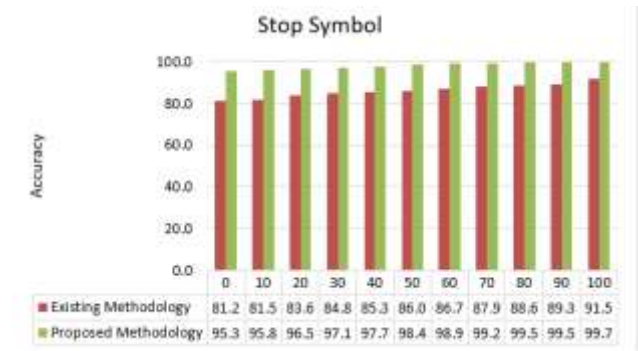


Fig. 7 Accuracy analysis of stop traffic symbol

Speed Limit (60 km/h) Traffic Sign Analysis

The performance of the proposed model for the Speed Limit (60 km/h) traffic sign was assessed using 102 test images. Among these, 100 samples achieved a prediction accuracy of 99.6%, representing the highest concentration of samples within that accuracy interval in the histogram. The results demonstrate that the model consistently recognized the Speed Limit (60 km/h) sign with exceptional accuracy and correctly classified almost all test images, highlighting the effectiveness of the proposed traffic sign recognition approach.

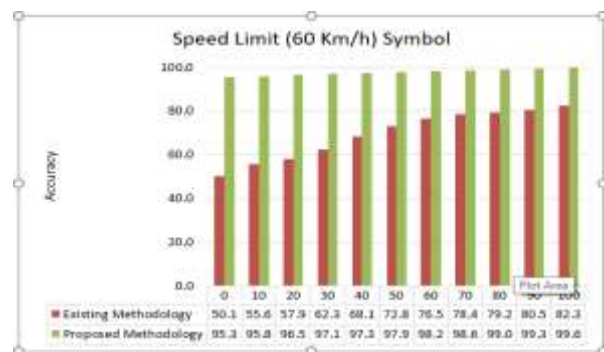


Fig. 8: Accuracy analysis of speed limit (60km/hr) traffic symbol

6. CONCLUSION

This paper presents a novel traffic sign detection and recognition framework for Indian road signs based on a Convolutional Neural Network (CNN) architecture. The proposed approach processes grayscale images and employs a robust CNN classifier for accurate traffic sign recognition. Grayscale images are used because they reduce the dimensionality of the input data without significantly affecting the discriminative features required for classification. Consequently, the computational complexity and processing time are reduced, enabling faster image analysis while maintaining high recognition performance. This makes the proposed approach well suited for intelligent traffic sign recognition systems.

To improve efficiency, the trained CNN model is stored using a pickle file. Saving the trained model eliminates the need for repeated training, thereby reducing computational overhead and allowing the model to be directly loaded for future prediction tasks. Experimental results demonstrate that the segmentation and recognition processes remain robust under varying illumination conditions, leading to reliable traffic sign detection and classification.

The experimental evaluation shows that the proposed CNN-based framework achieves an overall classification accuracy of approximately 99%, demonstrating its effectiveness in recognizing Indian traffic signs. Comparative analysis with existing state-of-the-art methods further indicates that the proposed CNN model consistently outperforms conventional classifiers in terms of recognition accuracy and robustness. These results confirm the suitability of the proposed approach for enhancing the safety and efficiency of intelligent transportation systems.

Although the proposed system provides highly accurate traffic sign detection and recognition, it is currently limited to a subset of traffic sign categories. Future research will focus on extending the capabilities of the system by addressing the following objectives:

- A. Recognize a comprehensive range of road traffic signs.
- B. Detect and classify multiple traffic signs present within a single scene.
- C. Improve recognition performance for images captured under low-light and nighttime conditions.
- D. Expand and diversify the training dataset to enhance model generalization.
- E. Develop a real-time traffic sign detection and recognition system suitable for deployment in Advanced Driver Assistance Systems (ADAS) and autonomous vehicles.

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