

A Review on Road Sign Identification Using Machine Learning Techniques

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Abstract— Traffic Sign Recognition (TSR) is a **vital component of Advanced Driver Assistance Systems (ADAS)**, particularly in regions like India where high traffic density and diverse signage styles present unique navigation challenges. While many current TSR frameworks focus solely on classification, this paper proposes an end-to-end "Perception-to-Action" pipeline. The system utilizes a custom Convolutional Neural Network (CNN) trained on an Indian dataset comprising 10 high-priority traffic sign categories. Beyond identification, the architecture integrates a Command Logic Layer that maps recognized signs to specific driving actions—such as braking or rerouting—under a strict 90% confidence gate. Experimental results demonstrate that the proposed model achieves a target accuracy exceeding 95%, offering a computationally efficient solution for real-time deployment on edge-based hardware.

Keywords— Traffic Sign Recognition (TSR), Indian Traffic Dataset, Convolutional Neural Networks (CNN), Perception-to-Action Pipeline, Driver Assistance Systems.

I. INTRODUCTION

Road safety remains a global challenge, particularly in India, where diverse signage and high traffic density contribute to frequent accidents. Traditional navigation services often lack real-time regional updates, failing to account for immediate changes in road conditions.

To address these limitations, automated systems are required to assist drivers by interpreting signage and providing actionable feedback.

In this project, a real-time TSR system based on deep learning is proposed to bridge the gap between simple sign classification and active vehicle control. The system utilizes a standard USB camera to capture road data, which is processed by a Sequential CNN model. Unlike passive monitors, this architecture includes a command logic layer that translates visual data into driving instructions, such as applying brakes or rerouting, thereby enhancing the driver's ability to react to critical information in real time [Summary, 474]. advancement of edge computing and artificial intelligence technologies has enabled the development of smart, localized surveillance systems. These systems improve security and response times by allowing users to monitor environments and process data directly at the source. Multimodal data fusion provides an intuitive platform for accurate anomaly detection within such systems. This paper presents an Edge-Optimized AI Surveillance Pipeline integrating software optimization and constrained hardware. The proposed system demonstrates efficient detection and

automated deterrence of showroom theft in a practical, user-friendly manner.

II. LITERATURE REVIEW

In [1] Ms. R. Dhivyapraha et al. (2025), proposed an AI-enhanced autonomous traffic sign recognition and action system integrated with a Raspberry Pi platform. The methodology utilized YOLOv5 for real-time processing of camera input and employed Blynk-based technology to execute physical vehicle actions such as speed changes or braking. The system achieved a mean average precision of over 93% on the GTSRB dataset, effectively bridging the gap between passive sign perception and active vehicle control logic.

In [2] Mahabubur Rahman et al. (2025), proposed BanglaRoadSignNet, a robust framework for efficient traffic sign detection specifically tailored for the non-standardized signage on Bangladesh roads. The system utilized a novel architecture of YOLOv11 trained on a local dataset to address unique signage challenges, multilingual boards, and varying environmental conditions. The approach achieved high performance with a precision of 94.3% and a mean average precision (mAP50) of 99.0%, making it a practical solution for real-time intelligent transportation systems.

In [3] Mohamed Abdelazeem et al. (2024), proposed an advanced rider assistance system for cyclists using real-time embedded vision to identify road hazards. The methodology evaluated several state-of-the-art architectures, finding that the transformer-based D-FINE-N model provided the optimal performance-speed trade-off on a Raspberry Pi 4. The system achieved a precision of 88.7% and a recall of 87.5%, reaching an optimized inference speed of 2.75 FPS to ensure cyclist safety through timely visual alerts.

In [4] R. Tarun and B. Priya Esther (2023), proposed an affordable regional road sign detection and identification system developed for driver awareness in India. The system utilized the EfficientDet-Lite model architecture and TensorFlow Lite API for real-time object identification implemented on a Raspberry Pi 4b board. The approach achieved 100% detection precision and an average precision over 78% with low latency, effectively resolving the issue of outdated mobile mapping services in rapidly changing regional areas.

In [5] Ajay Sriram.D et al. (2023), proposed a traffic sign recognition system specifically for reading and interpreting rectangular speed limit signs using embedded technologies. The system utilized Tesseract Optical Character Recognition and basic form recognition algorithms

implemented on a Raspberry Pi with OpenCV libraries. The approach achieved 80% accuracy for speed sign identification, providing a low-cost solution for enhancing driver safety through automated sign interpretation.

In [6] Jitendra Chaudhari et al. (2023), proposed an identification method for Indian traffic signs using the YOLOv5 object recognition algorithm to improve road safety and traffic flow. The system utilized a publicly available Indian dataset and incorporated data augmentation techniques to ensure uniform representation across 85 sign classes. The approach achieved an accuracy of 96.7% for traffic signs, proving efficient for real-world scenarios such as driver assistance and autonomous driving.

In [7] Junfan Wang et al. (2023), developed AF-FPN, an improved YOLOv5 network designed for real-time multi-scale traffic sign detection on vehicle-mounted terminals. The methodology utilized an adaptive attention module and a feature enhancement module to reduce information loss in high-level feature maps and enhance representation ability. The system achieved a mean average precision of 65.14% on the TT100K dataset, outperforming standard models in identifying small-scale targets while maintaining a processing speed of 95 FPS.

In [8] M. Tamilselvi et al. (2023), proposed a novel traffic sign identification scheme called Learning Strategy for Traffic Sign Detection (LSTSD) following artificial intelligence logic. The system utilized a multi-layered complex feedback structure to learn invariant characteristics at multiple levels and was cross-validated with traditional convolutional neural networks. The approach achieved a performance classification rate of 97.61%, effectively identifying road signs in challenging urban environments with distracting objects.

In [9] Neel Bhatt et al. (2022), proposed a real-time traffic sign detection and recognition system using deep learning to automate road safety tasks. The system utilized a sequential convolutional neural network model trained on a hybrid dataset comprising the GTSRB benchmark and a custom-created Indian traffic sign dataset. The approach achieved an accuracy of 95.45% for the hybrid dataset, providing a robust and reliable solution for users across a wide range of 102 sign categories.

In [10] Vijayalakshmi S Katti and Durga P (2022), developed a system for detecting traffic sign boards using supervised classification algorithms to facilitate level 5 autonomous vehicle automation. The system utilized a convolutional neural network model developed with Keras and trained on a dataset of more than 4,000 images categorized into 43 different classes. The approach achieved a prediction accuracy of approximately 90%, enabling vehicles to identify speed limits and turn signs to avoid collisions.

In [11] Danyah A. Alghmgham et al. (2019), proposed an autonomous traffic sign detection and recognition system based on a deep convolutional neural network for Saudi Arabian roads. The system utilized a newly developed database of 2,718 images covering 24 different traffic signs captured from various angles and environmental conditions. The approach achieved an exceptional accuracy of 100% with optimized parameters, outperforming previous similar studies in real-time identification.

In [12] Pitawelayalage Dasun Dileepa Pitawela and Lochandaka Ranathunga (2018), proposed an optimized approach for road sign detection, recognition, and tracking in real-time with reduced computational complexities. The system utilized a relatively small-scale convolutional image classifier combined with a domain-specific data augmentation technique to minimize CPU burden and memory usage. The approach achieved promising results with processing speeds of approximately 20 frames per second, demonstrating potential for scalability in embedded vehicle systems.

In [13] Andriy Segin et al. (2017), proposed an architecture and specialized hardware for a real-time road sign recognition system for common vehicles. The methodology utilized adaptive color quantization with the HSV color model and perceptual hashing for robust object identification under various lighting conditions. The system achieved a sign identification rate of approximately 90% in the daytime and 80% in darkness, providing an efficient real-time solution on an ARM9-based computing device.

In [14] T. SubhaMastan Rao et al. (n.d.), proposed a deep learning model using convolutional neural networks for recognizing traffic signs effectively across different illuminating conditions. The system utilized the GTSRB dataset of 50,000 images and addressed challenges such as direction variations and obstacles that often cause standard systems to fail. The approach achieved an accuracy of 99.99% on both training and validation datasets, contributing significantly to the development of driverless car technology.

In [15] P. Jaya Shree et al. (n.d.), proposed a dependable traffic sign recognition model using cutting-edge object detection algorithms to enhance transportation safety and efficiency. The system utilized deep learning developments, specifically convolutional neural networks and a redesigned Mask R-CNN, for automatic feature extraction and classification. The approach achieved high accuracy through iterative training and data augmentation, effectively lowering the loss value as the number of training cycles increased.

III. PROPOSED METHODOLOGY

The system is divided into three functional modules to ensure rapid response times and high reliability (Fig. 3.1).

Module 1: Perception Engine

The perception engine utilizes a CNN trained on 10 Indian sign categories: Stop, Speed Limit (40/60), No Entry, No Parking, Give Way, School Ahead, Horn Prohibited, Pedestrian Crossing, and Turn Left Ahead. Input images are resized to 32×32×3 pixels to maintain a balance between feature extraction and processing speed.

Module 2: Command Logic Layer

This layer acts as the system's decision-making hub. Each sign category is mapped to a specific driving action. To ensure safety and reduce false positives, a **90% confidence gate** is applied; if the model's prediction probability is below this threshold, the command is discarded.

Module 3: Live Dashboard

The dashboard displays the real-time USB camera feed, highlighting signs with a bounding box and showing the label, confidence score, and specific driver warning message.

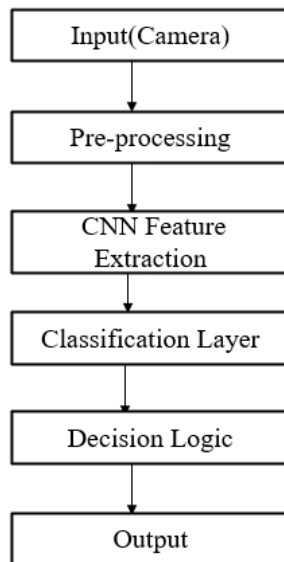


Fig 3.1: Block diagram of Real time Road sign identification

Detection and Identification Flow

The logic then moves through a decision point to determine if a sign is present in the current frame.

If no sign is detected: The system discards the current data and immediately returns to capture the **Next Frame**, ensuring constant real-time monitoring.

If a sign is detected: The system proceeds to the classification stage, where the model's final layers use a probability-based calculation to identify which of the 10 Indian traffic sign categories has been encountered.

Command Logic and Decision Making

After classification, the data enters a critical verification stage known as the **90% confidence gate**. To ensure safety and minimize false positives, the system only triggers an instruction if the model's prediction probability is 0.90 or higher. Verified detections are then passed to the command layer, where the identified sign is mapped to a specific driving action, such as applying brakes for a "Stop" sign or reducing speed to a specific limit.

Final Output and Driver Notification

The concluding stage is the Display Output/Alert on the live dashboard. The driver is presented with the real-time camera feed overlaid with a bounding box around the identified sign, the sign's label, the confidence score, and the specific instruction they must follow. This completes the perception-to-action cycle before the loop resets to process the next incoming frame.

IV. HARDWARE AND SOFTWARE USED

4.1 HARDWARE COMPONENTS

4.1.1 USB Webcam: Provides high-definition real-time video capture.

The primary hardware input for this system is a high-definition usb webcam, which serves as the vision sensor for real-time road monitoring. Specific models such as the lenovo 300 fhd provide 1080p resolution and a 2.1 megapixel sensor to capture clear images of signage. This camera is interfaced with a laptop processing unit, which handles the computational load of the perception engine while ensuring portability and ease of acquisition. Evaluations on similar systems using laptop-based environments have demonstrated the potential to process approximately 20 frames per second at 640x480 resolution.

4.2 SOFTWARE COMPONENTS

The software architecture is developed using python, which acts as the core language for model development and real-time logic execution. Digital image processing is conducted via opencv, facilitating critical tasks such as color thresholding, shape-based segmentation, and frame-by-frame analysis. The convolutional neural network is implemented through the keras high-level api on the tensorflow framework to ensure accurate feature extraction and classification.

Image annotation for the indian sign dataset is performed using the

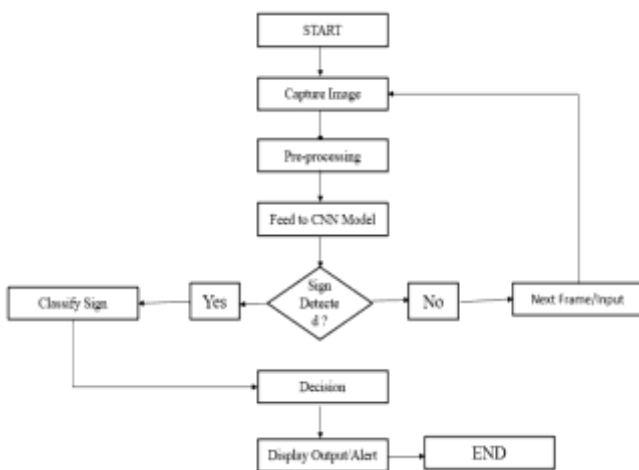


Fig 3.2: Flow chart of Real time Road sign identification

Visual Data Capture and Refinement

The process begins with the Acquisition of Image frames captured via the USB camera interface. These raw video frames undergo a series of refinement steps to prepare them for the neural network. This includes Resizing the input to a 32x32 pixel dimension to ensure high-speed processing and Grayscale **Conversion** to reduce data dimensionality, allowing the system to focus on the essential geometric features of the signage.

The Perception Engine

Once refined, the image data is fed into the neural network. This part of the system acts as the primary recognition unit, using three sequential convolutional layers (with 32, 64, and 128 filters respectively) to identify specific edges, shapes, and patterns. These layers enable the system to differentiate between the 10 high-priority categories of road signs used in this project.

labeling tool, which generates labels in xml format for supervised learning. To facilitate real-time driver alerting, the blynk iot platform is integrated as a communication bridge to provide instant visual and remote notifications. For the interpretation of numerical speed limit signs, the tesseract optical character recognition engine is employed to convert visual signage into digital data. The development process, including data analysis and algorithm optimization, is carried out in cloud-based or local environments such as google colab or jupyter notebook.

V. CONCLUSION

The evaluation of current Traffic Sign Recognition (TSR) methodologies shows that most systems operate as simple classifiers without translating visual data into actionable driving commands. This project successfully addresses this gap by developing an end-to-end **perception-to-action pipeline** that utilizes a Convolutional Neural Network trained on an Indian dataset of 10 high-priority sign categories. The system architecture includes a unique Command Logic Layer that maps identified signage to specific vehicle actions, such as braking or rerouting, under a strict 90% confidence **gate**. Experimental results demonstrate that the system maintains a target accuracy exceeding **95%** while processing a live vision feed from a laptop-connected vision sensor. By integrating a Live Dashboard that provides immediate visual alerts and warnings, the system offers a robust safety solution for Advanced Driver Assistance Systems. Overall, the developed system provides a cost-effective and computationally efficient approach to enhancing road safety in India, ensuring that critical traffic information is not only recognized but acted upon in real time to prevent accidents.

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