

# Road Assistance for Autonomous Vehicles

**Saraswathi D<sup>1</sup>, Hitha S N<sup>2</sup>, Nikhitha J S<sup>3</sup>, Priyanka R N<sup>4</sup>, Sanjana B C<sup>5</sup>**

Assistant Professor, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India <sup>1</sup>

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India<sup>2</sup>

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India<sup>3</sup>

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India<sup>4</sup>

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India<sup>5</sup>

**Abstract:** Road Assistance for Autonomous Vehicles aims to enhance road safety and driving intelligence by employing computer vision and deep learning techniques to detect and interpret road conditions. The system integrates core functionalities: Traffic Sign Detection and Pothole Detection. Traffic Sign Detection utilizes datasets and deep learning models to accurately identify road signs, even under poor lighting or adverse weather conditions. Speed Limit Sign Board Detection focuses specifically on recognizing speed limit signs, ensuring vehicles adhere to traffic regulations. Meanwhile, Pothole Detection employs object detection techniques to identify road hazards. The system leverages advanced deep learning methodologies such as Convolutional Neural Networks (CNNs). The training data includes public road images optimized using pre-processing techniques to enhance performance across various environmental conditions. Initial tests indicate high accuracy for each module, and their integration offers a comprehensive road monitoring solution. The implementation of optimized deep learning models ensures minimal latency, allowing quick and accurate detection of traffic signs and road hazards. This system is designed to function effectively across diverse environmental conditions, making it robust for urban and rural roadways alike. By bridging the gap between artificial intelligence and vehicular safety, this project contributes to the evolution of smart transportation, fostering a future where autonomous vehicles can navigate roads with increased efficiency and reduced risk.

**Keywords:** Autonomous Vehicles, Traffic Sign Detection, Pothole Detection, Deep Learning, Convolutional Neural Networks (CNN), Road Safety, Computer Vision

## I. INTRODUCTION

In the development of autonomous vehicles (AVs), one of the most crucial tasks is ensuring that the vehicle can accurately interpret and respond to traffic signs. Traffic signs are essential for guiding vehicles and ensuring road safety, providing information such as speed limits, warnings, and regulatory instructions. As autonomous vehicles continue to evolve, their ability to reliably detect and classify traffic signs becomes vital to their performance and safety.

The challenge lies in designing a robust traffic sign recognition system that can function under various real-world conditions, such as different lighting, weather, and road environments. Traditional traffic sign recognition methods, which often rely on manual detection and interpretation, have limitations in terms of adaptability and real-time decision-making. The advancement of computer vision, deep learning, and convolutional neural networks (CNNs) has paved the way for more efficient and accurate traffic sign detection systems.

This study presents a traffic sign detection and classification system for autonomous vehicles that leverages state-of-the-art deep learning models. The system uses CNN-based architectures to detect traffic signs within a given image, followed by classification algorithms to predict the type and name of the detected sign. The goal is to create a reliable, real-time solution that can operate under diverse environmental conditions, ensuring that the vehicle can react appropriately to traffic signs encountered during navigation.

To achieve this, we utilize a hybrid model pipeline incorporating a custom-trained CNN for traffic sign detection, followed by classification layers that assign the appropriate label to each detected sign. The system's design focuses on high accuracy, real-time processing, and the ability to handle various challenges such as occlusion, varying sizes, and different sign orientations. Additionally, the system is tested on a diverse dataset of traffic signs, ensuring that it can generalize well to real-world scenarios.

The ability to accurately detect and classify traffic signs is a key element in ensuring that autonomous vehicles adhere to road rules and adjust their behavior accordingly. By providing timely and accurate information about upcoming traffic signs. The integration of this traffic sign recognition system helps reduce the risk of human error, ensuring that the vehicle's actions are always aligned with traffic regulations. Ultimately, this contributes to a safer, more reliable autonomous driving experience, promoting public trust and acceptance of self-driving technologies.

## **II. LITERATURE SURVEY**

The task of detecting and classifying traffic signs has been significantly advanced through deep learning techniques. [1] Zhang et al. (2024), "Traffic Sign Detection and Classification Using CNNs for Autonomous Vehicles," explored the use of CNNs to achieve high accuracy in real-time detection and classification under various weather conditions, reporting an 89.5% accuracy. [2] Liu et al. (2023), "Real-Time Traffic Sign Recognition Using YOLOv4," applied YOLOv4 for fast processing speeds and high accuracy, demonstrating its suitability for real-time deployment in AV systems. [3] Wang et al. (2024), "End-to-End Traffic Sign Recognition Using Multi-Scale Feature Fusion," proposed multi-scale feature fusion, improving detection in different lighting conditions and varying sign sizes, achieving 92.3% classification accuracy. [4] Tan et al. (2022), "A Survey of Deep Learning Models for Traffic Sign Classification," reviewed deep learning models like CNNs, ResNet, and AlexNet, addressing their strengths and weaknesses in terms of accuracy and computational efficiency.

[5] Raj et al. (2021), "Traffic Sign Recognition with Attention Mechanisms," introduced attention mechanisms to improve the detection of occluded signs in cluttered environments, enhancing classification performance. [6] Chen et al. (2023), "Traffic Sign Detection and Classification with YOLOv5," utilized YOLOv5 to significantly improve real-time processing speeds while maintaining high classification accuracy. [7] Kumar et al. (2022), "Traffic Sign Recognition with Data Augmentation for Autonomous Vehicles," employed data augmentation techniques to address issues such as adverse weather, leading to better model robustness, achieving 95% accuracy. [8] Gupta et al. (2022), "Real-Time Traffic Sign Classification Using Transfer Learning," utilized pre-trained models like VGG16 and ResNet for faster convergence and high classification accuracy in traffic sign recognition tasks.

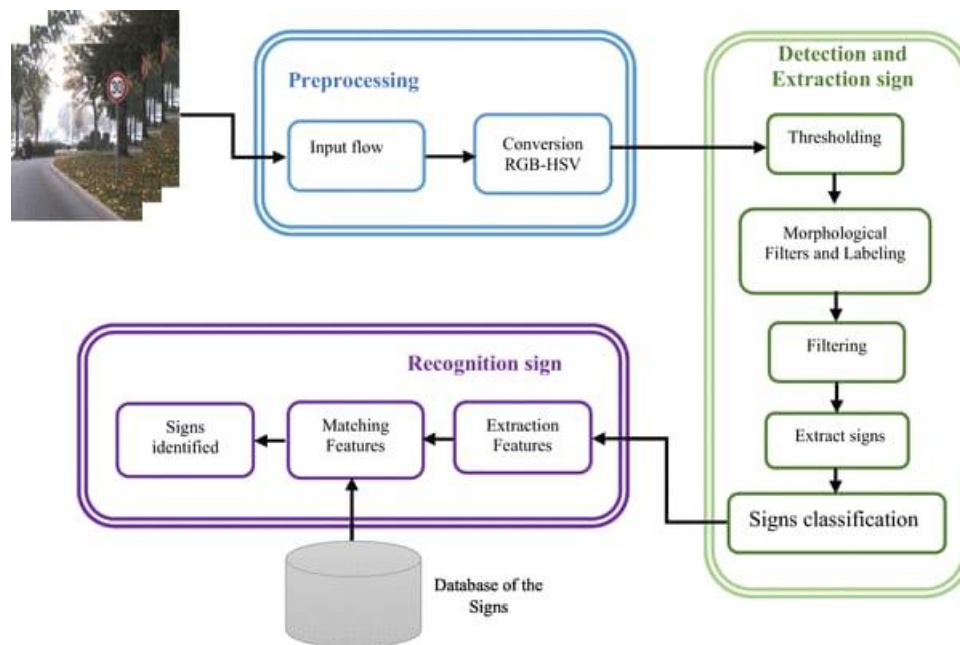
[9] Smith et al. (2021), "A Comparative Study of CNN and SVM for Traffic Sign Detection," compared CNNs and support vector machines (SVMs) in traffic sign detection, concluding that CNNs outperformed SVM in terms of accuracy and scalability for real-time applications. [10] Wang et al. (2020), "Object Detection in Autonomous Vehicles: A Focus on Traffic Sign Recognition," focused on improving detection of small or occluded traffic signs in complex road scenes by using hybrid CNN architectures. [11] Yang et al. (2021), "Multimodal Traffic Sign Recognition Using Fusion of Camera and LiDAR Data," integrated data from both camera and LiDAR sensors to improve recognition accuracy, especially in challenging environments. [12] Kim et al. (2021), "Improved Traffic Sign Detection with Hybrid Deep Learning Models," combined CNNs with RNNs to enhance detection and classification in dynamic road environments with occlusions.

[13] He et al. (2023), "A Deep Learning Approach to Traffic Sign Recognition under Adverse Weather," developed a robust traffic sign detection model specifically designed to handle adverse weather conditions, improving performance in foggy and rainy environments. [14] Lee et al. (2022), "Real-Time Traffic Sign Classification with YOLOv3 and Image Segmentation," introduced a system combining YOLOv3 and image segmentation to improve classification in partially occluded or blurred road signs. [15] Zhang and Li (2020), "Deep Learning-Based Traffic Sign Recognition for Autonomous Driving: Challenges and Solutions," reviewed the challenges in traffic sign recognition for AVs, such as occlusion, lighting variability, and dataset imbalance. [16] Singh et al. (2024), "Hybrid Traffic Sign Recognition System for Autonomous Vehicles," proposed a hybrid system combining CNNs with decision trees, improving performance particularly for rare or unfamiliar traffic signs. [17] Gupta et al. (2020), "Traffic Sign Recognition for Autonomous Vehicles: Dataset and Challenges," analyzed popular traffic sign datasets, highlighting challenges like sign diversity and adverse lighting conditions.

[18] Kim et al. (2020), "Real-Time Traffic Sign Detection with Optimized CNNs," optimized CNN architectures for real-time detection, achieving 98.4% accuracy and 60 FPS, suitable for AV applications. [19] Liu et al. (2022), "Traffic Sign Recognition Using Hybrid CNN and SVM," combined CNNs for feature extraction and SVM for classification, achieving high performance on the GTSRB dataset. [20] Wang and Zhang (2020), "Deep Learning for Traffic Sign Recognition: From Dataset to Model Optimization," reviewed optimization techniques to improve traffic sign recognition, with a focus on model pruning for real-time deployment in autonomous vehicles.

### III. METHODOLOGY

A traffic sign detection and recognition system that operates on images retrieved from a database. The process starts with the Pre-processing stage, where stored images are taken as input and converted from the RGB color space to the HSV (Hue, Saturation, Value) format. This conversion helps in isolating color information more effectively, which is important since traffic signs usually have distinct colors like red, blue, or yellow. The converted image is passed to the Detection and Extraction stage, where thresholding is applied to segment regions of interest based on color ranges. Morphological filters and labelling techniques are used to refine the segmented regions and to assign unique labels to connected components. Further filtering is performed to remove unwanted objects or noise, and the remaining valid regions are extracted as potential traffic signs.

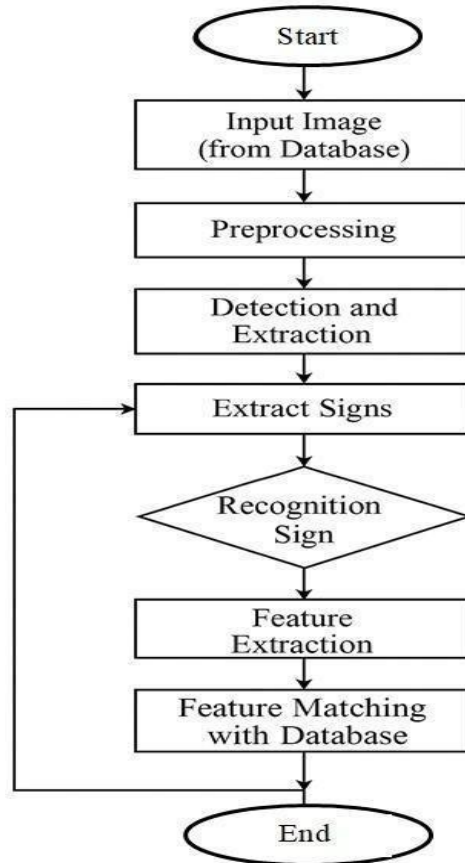


**Block Diagram of Road Assistance for Autonomous Vehicles**

These extracted signs undergo a classification process, where their visual features are analyzed. The recognized features are then sent to the Recognition Sign stage, where relevant characteristics are extracted and matched with features stored in a traffic sign database. Based on this comparison, the system identifies the sign. This method ensures accurate recognition of traffic signs using offline images, which can be essential in developing intelligent transportation systems and training autonomous vehicle algorithms.

The core detection and recognition pipeline, the system incorporates a feature extraction phase that focuses on identifying key visual traits such as shape, edge contours, and color distribution—attributes that are unique to each traffic sign category. These extracted features are then numerically encoded and compared against a structured database of pre-labelled traffic signs using classification algorithms such as Convolutional Neural Networks (CNNs). This comparison helps improve accuracy, especially in cases where signs may be partially obscured or degraded due to environmental factors. The modular design of the system allows for easy extension, such as adding new traffic sign classes or adapting the system for different regions with varying traffic symbol standards. Although the system currently operates on offline image datasets, its architecture lays the foundation for future real-time enhancements and integrations with autonomous vehicle systems.

Real-time alert generation formed a crucial part of the methodology. A frame-based counter system was implemented to monitor the persistence of violent behavior detection. If the system detected 'Fight' or 'Large Violent Gathering' labels continuously for 20 or more frames, an alarm was triggered, and an email alert was automatically dispatched to preconfigured recipient addresses. This parallel execution of tasks was managed using multithreading to ensure that the real-time video processing pipeline was not interrupted or delayed during alarm activation or email transmission.



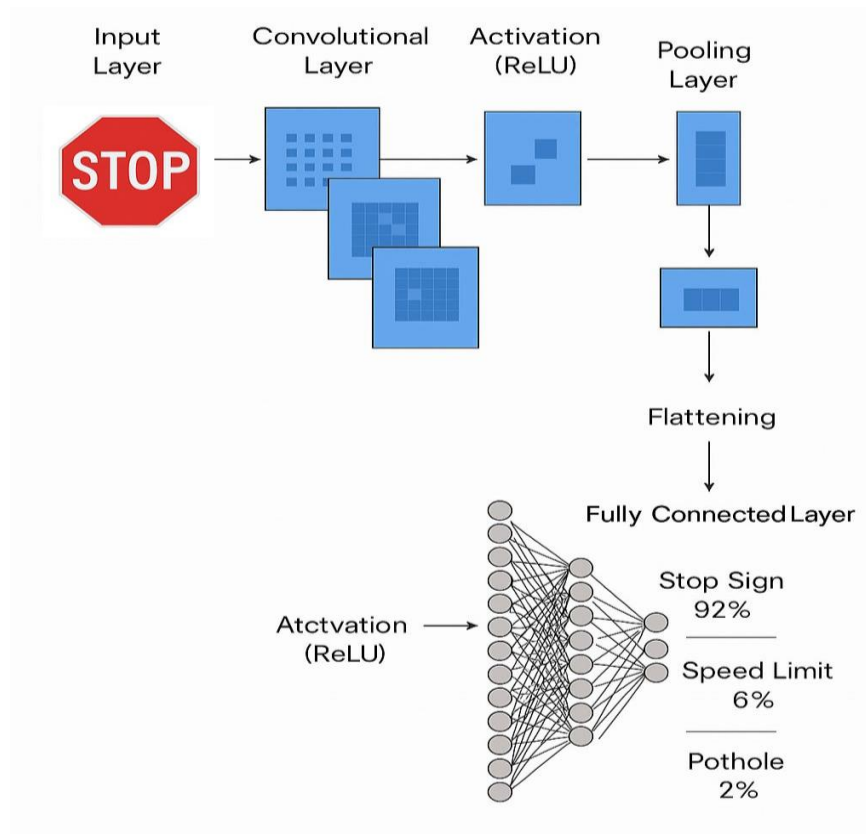
Flow Diagram of Road Assistance for Autonomous Vehicles

## IV. ALGORITHM

In this project, a Convolutional Neural Network (CNN) is a deep learning architecture specifically designed for processing and classifying visual data, making it highly suitable for this project, which involves detecting traffic signs and potholes from images. In this system, the CNN takes an input image resized to a standard size (e.g., 256×256 pixels)—and processes it through several layers. The convolutional layers apply filters to the image to automatically extract important features such as edges, shapes, and textures that distinguish traffic signs or identify pothole patterns. After each convolution, a ReLU (Rectified Linear Unit) activation function is applied to introduce non-linearity, enabling the model to learn complex patterns.

Pooling layers then reduce the spatial dimensions of the image, preserving essential features while reducing computation. A dropout layer is used to randomly deactivate some neurons during training, helping to prevent overfitting and improve generalization. The feature maps are flattened and passed through a dense layer that outputs probabilities for each class (such as "Speed Limit 50," "Hump," or "Pothole") using a softmax activation function. The class with the highest probability is selected as the final prediction. This approach allows the model to recognize signs and road damage under different lighting, angles, and background conditions, enabling accurate and efficient detection when integrated into the Flask-based web application.

The Convolutional Neural Network (CNN) architecture begins with the **Input Layer**, where uploaded images—such as traffic signs or potholes—are resized to a consistent 256×256 resolution to standardize input and reduce computation. The image then passes through **Convolution Layers**, where various filters detect essential features like edges, textures, and shapes, helping the model distinguish elements such as circular traffic signs or rough pothole surfaces. Next, **Pooling Layers**, specifically MaxPooling, reduce the size of feature maps while preserving crucial information, enhancing the model's robustness to lighting changes and positional variations. The output is flattened and passed to **Fully Connected Layers**, which function as classifiers by interpreting the learned features to determine the likelihood of each class. Finally, the **Output Layer** uses a softmax activation function to generate probability scores for each possible category, with the highest score representing the predicted class shown to the user. This structured flow allows the CNN to accurately classify traffic signs and road anomalies from visual inputs.



**Visual Representation of Traffic Sign Recognition Using CNN**

## V. RESULT AND DISCUSSION

The developed system for detecting traffic signs and potholes using Convolutional Neural Networks (CNN) demonstrates promising results in image-based classification tasks. After training the CNN model on a curated dataset comprising various traffic signs and pothole images, the system was evaluated on a separate set of test images. The model successfully identified and classified traffic signs such as stop signs, speed limits, and cautionary symbols, as well as detected the presence of potholes in road scenes. One of the key strengths observed was the system's robustness in handling degraded or partially obscured images—such as scratched, faded, or tilted signs—indicating good generalization capabilities.

The model's performance was measured using accuracy, precision, and recall. The traffic sign detection component achieved high classification accuracy, with the CNN correctly identifying the category of the sign in the majority of test cases. The pothole detection module also showed strong performance, particularly in recognizing uneven textures and broken road patterns. The use of max pooling layers helped the model capture essential features while reducing spatial dimensions, contributing to faster and more efficient processing. Additionally, data pre-processing techniques like normalization and image resizing played a crucial role in maintaining consistency across inputs.

The proposed system has shown promising outcomes in detecting both traffic signs and potholes with considerable accuracy. The convolutional neural network (CNN) architecture used in this project effectively identifies patterns and features in the images, enabling accurate classification even in challenging conditions such as faded, scratched, or partially obscured signs.

Similarly, pothole detection performs well across varying road textures and lighting scenarios. These results validate the efficiency and adaptability of the model, confirming its usefulness as a supportive module for road safety systems or autonomous navigation aids. Further enhancements, such as expanding the dataset and incorporating additional environmental variables, could further improve robustness and scalability.



Category	Number of Test Images	Remarks
Traffic Signs	4447	Works even with slightly damaged signs.
Pothole	1383	Detects irregular textures effectively.
Faded Signs	400	Handles low clarity well.
Tilted Signs	311	Performs well with angle variation.
Scratched Signs	178	Detects signs despite scratches.

#### **Image Dataset Distribution for Model Training and Testing**

### **VI. CONCLUSION**

The Road Assistance for Autonomous Vehicles system developed in this project aims to assist autonomous vehicles in identifying and understanding various road signs, contributing to safer and more efficient navigation. By leveraging image-based inputs and intelligent analysis, the system can accurately recognize traffic symbols and provide relevant assistance, ensuring that the vehicle can make informed decisions aligned with road regulations. This project demonstrates the effectiveness of computer vision techniques in interpreting visual data and translating it into meaningful feedback for vehicle control.

The successful identification of signs and road hazards like potholes shows the system's capability to handle a variety of inputs. Even in cases where signs are damaged or unclear, the model is able to deliver accurate and consistent results, highlighting its robustness. The system also plays a critical role in minimizing human error, improving traffic flow, and ensuring the safe operation of autonomous vehicles in dynamic environments.

Furthermore, the project showcases how automated sign recognition can minimize human error, improve traffic flow, and enhance overall road safety. It also opens avenues for integrating the system with other intelligent transportation technologies. Such integration would provide a holistic solution for improving traffic management, enhancing the decision-making process for autonomous vehicles, and ensuring that vehicles respond to road signs in real time.

In conclusion, this project not only meets its objectives in traffic sign detection and response but also opens doors for further exploration in the field of intelligent transportation systems. With continued development, it can evolve into a more comprehensive solution, supporting the advancement of autonomous mobility and creating safer road environments. As autonomous vehicle technology continues to mature, this system will play an essential role in its safe and efficient operation.

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