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AI-Based Traffic Sign Recognition for Smart Vehicles

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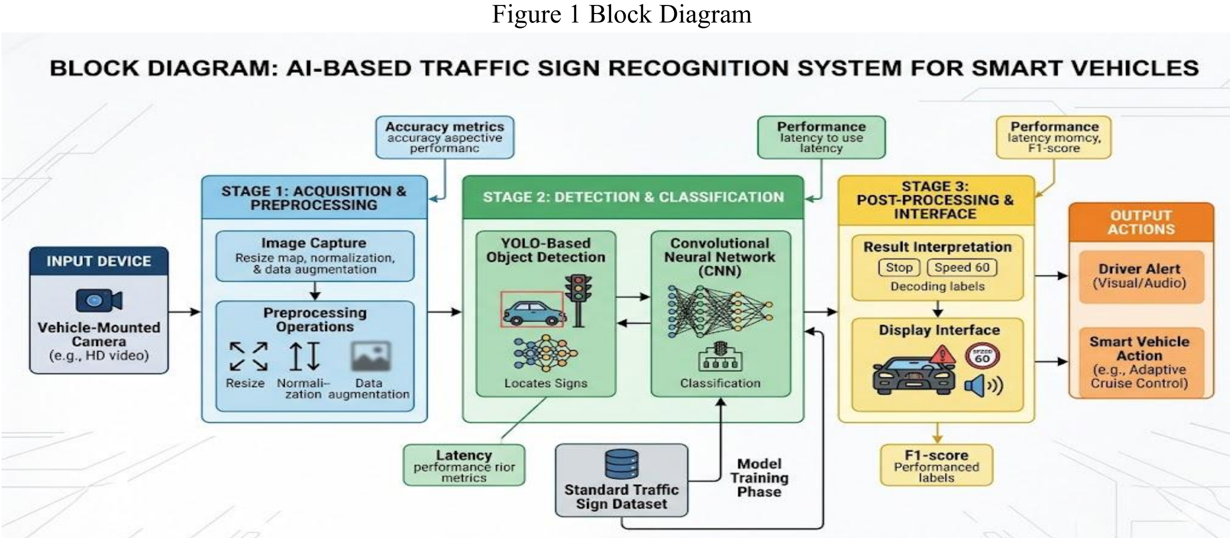
***Abstract*—Traffic signs play a crucial role in maintaining road safety and guiding drivers by providing important information regarding speed limits, warnings, and traffic regulations. However, drivers may fail to notice or correctly interpret traffic signs due to fatigue, distractions, poor weather conditions, or low visibility, which can lead to serious road accidents. To address this issue, this project presents an AI-Based Traffic Sign Recognition System for Smart Vehicles that automatically detects and classifies traffic signs in real time using deep learning and computer vision techniques.**

The proposed system utilizes a vehicle-mounted camera to capture road images continuously. The captured images undergo preprocessing operations such as resizing, normalization, and data augmentation to improve image quality and enhance model robustness. A Convolutional Neural Network (CNN) and YOLO-based object detection approach are employed to identify and classify different categories of traffic signs accurately. The model is trained using a standard traffic sign dataset containing multiple classes of road signs. The system is designed to provide fast and reliable recognition suitable for real-time smart vehicle applications. Performance evaluation is carried out using metrics such as accuracy, precision, recall, F1-score, and processing speed. Experimental results demonstrate that the proposed system achieves high recognition accuracy with low latency, making it effective for practical intelligent transportation systems and Advanced Driver Assistance Systems (ADAS). The optimized architecture balances computational efficiency and detection performance, enabling deployment in embedded smart vehicle environments.

The developed system contributes to improving road safety, reducing driver errors, and supporting autonomous driving technologies. Future enhancements may include multilingual sign recognition, weather-adaptive models, and integration with fully autonomous vehicle control systems for enhanced intelligent transportation capabilities.

***Index Terms*—Artificial Intelligence (AI), Traffic Sign Recognition, Deep Learning, Convolutional Neural Network (CNN), YOLO, Computer Vision, Smart Vehicles.**

Figure 1 Block Diagram



The AI-Based Traffic Sign Recognition (TSR) system for smart vehicles utilizes a vehicle-mounted camera to capture real-time road images. The architecture is divided into three primary stages: Acquisition and Preprocessing, Detection and Classification, and Post-processing. During preprocessing, images undergo resizing, normalization, and data augmentation to enhance robustness against poor weather or low visibility.
The core processing utilizes YOLO-based detection to locate signs and a Convolutional Neural Network (CNN) for accurate classification. Once interpreted, the system triggers output actions such as driver alerts or autonomous speed adjustments. This optimized framework ensures high accuracy and low latency for advanced driver assistance.

I. INTRODUCTION

The rapid growth of automobiles and urban transportation has significantly increased the complexity of road traffic systems across the world. Traffic signs are essential components of transportation infrastructure, as they provide important information related to speed limits, warnings, directions, and road regulations. Proper understanding and interpretation of these traffic signs are crucial for ensuring road safety and smooth vehicle movement. However, in real-world driving conditions, drivers may fail to notice traffic signs due to fatigue, distraction, poor visibility, adverse weather conditions, or high-speed driving. Such failures can lead to traffic violations, accidents, and loss of human life. Therefore, intelligent systems capable of automatically recognizing and interpreting traffic signs have become an important research area in modern transportation technologies.
Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have enabled the development of smart vehicle systems capable of understanding road environments in real time. Traffic Sign Recognition (TSR) systems are widely used in Advanced Driver Assistance Systems (ADAS) and autonomous vehicles to improve driving safety and reduce human error. These systems use cameras and deep learning algorithms to detect, classify, and interpret traffic signs from road images. Among various AI techniques, Convolutional Neural Networks (CNNs) and YOLO (You Only Look Once) object detection models have shown remarkable performance in image classification and real-time object detection tasks. Their ability to automatically extract meaningful features from images makes them highly effective for traffic sign recognition applications.
The motivation behind this project is to design an efficient and accurate AI-based traffic sign recognition system that can support smart vehicles in identifying traffic signs automatically and reliably. Existing systems often face challenges such as reduced accuracy under poor lighting conditions, occlusion, weather variations, motion blur, and complex road environments. In addition, many high-accuracy deep learning models require powerful computational hardware, making them difficult to implement in embedded vehicle systems where computational resources are limited. Lightweight models improve processing speed but may compromise recognition accuracy and robustness. These limitations create a need for an optimized solution that balances accuracy, speed, and computational efficiency.
This project proposes a real-time traffic sign recognition system using deep learning techniques integrated with computer vision methods. The system captures road images using a vehicle-mounted camera and applies preprocessing operations such as resizing, normalization, and data augmentation to improve image quality and model performance. A CNN and YOLO-based framework is employed to detect and classify traffic signs accurately in real time. The model is trained using a standard traffic sign dataset containing multiple categories of signs. Performance evaluation is carried out using metrics such as accuracy, precision, recall, F1-score, and processing speed to validate the effectiveness of the proposed system.
The research gap identified from previous studies indicates that many existing methods focus mainly on achieving high accuracy in controlled datasets but fail to provide reliable performance in practical driving environments. Some methods emphasize speed while sacrificing accuracy, whereas others require expensive hardware resources. Hence, this project aims to develop a balanced and optimized AI-based traffic sign recognition system that ensures high accuracy, low latency, and real-time adaptability for smart vehicle applications. The proposed work contributes to improving road safety, enhancing driver assistance

technologies, and supporting the future development of intelligent and autonomous transportation systems.

II. LITERATURE REVIEW

1. Mulyono and Yohannes (2024)Mulyono and Yohannes (2024) proposed a detector-based deep learning approach for traffic sign recognition using the Single Shot MultiBox Detector (SSD) algorithm. Their research focused on improving real-time traffic sign detection for intelligent transportation systems and smart vehicle applications. The authors utilized a dataset containing multiple traffic sign categories and trained the SSD model to identify and classify signs accurately. Preprocessing methods such as image resizing, normalization, and augmentation were implemented to improve detection performance and reduce noise in the captured images. Experimental results demonstrated that the proposed system achieved good localization accuracy and fast processing speed, making it suitable for Advanced Driver Assistance Systems (ADAS). The study highlighted the capability of deep learning object detection models in handling real-time road scenarios efficiently. However, the model showed reduced performance under poor lighting conditions and highly cluttered road environments. The authors concluded that additional optimization and robust preprocessing methods are necessary for improving performance in challenging real-world situations.

2.Smita, Pranika, and Meghana (2023)
Smita, Pranika, and Meghana (2023) developed a deep learning-based traffic sign recognition system for autonomous driverless vehicles using Convolutional Neural Networks (CNNs). Their work focused on enhancing traffic sign classification accuracy under varying environmental conditions such as rain, fog, shadows, and illumination changes. The researchers applied preprocessing techniques including contrast enhancement, image normalization, and noise reduction to improve image quality before feeding the data into the CNN model. The trained CNN architecture successfully classified multiple categories of traffic signs with high accuracy. Experimental analysis showed that the system performed effectively under moderate environmental variations and supported real-time decision-making for autonomous vehicles. The study demonstrated that CNN models are highly effective in extracting image features and improving recognition accuracy. However, the model required a large amount of labelled training data and high computational power for training and deployment. The authors identified the need for lightweight and computationally efficient architectures for embedded smart vehicle systems.

3.Alawaji, Hedjar, and Zuair (2024)
Alawaji, Hedjar, and Zuair (2024) proposed a multi-task deep learning framework for traffic sign recognition in self-driving vehicles. Their research combined Convolutional Neural Networks (CNNs) with YOLOv7 object detection techniques to improve both traffic sign detection and classification performance simultaneously. The proposed system extracted regions of interest from road images and classified traffic signs using shared feature extraction layers. The authors used large-scale traffic sign datasets and implemented data augmentation methods to increase dataset diversity and reduce overfitting. Experimental results indicated that the proposed framework achieved very high accuracy and fast detection speed suitable for real-time autonomous driving systems. The study showed that multi-task learning improved feature sharing and enhanced overall recognition efficiency compared to traditional single-task approaches. However, the architecture required high computational resources and longer training time because of its complex model structure. The authors suggested that future research should focus on reducing computational complexity while maintaining high recognition performance.

4.Gezgin and Alkan (2024)
Gezgin and Alkan (2024) developed a traffic sign detection and recognition system using the ResNet-50 deep learning model with data collected from mobile mapping systems. Their study focused on improving traffic sign recognition accuracy in real-time road scenarios. The authors used high-resolution road images captured using mobile mapping technology and applied preprocessing operations such as image enhancement and normalization. The ResNet-50 architecture was trained to classify different categories of traffic signs efficiently. Experimental results showed that the proposed model achieved high classification accuracy and reliable detection performance in real-world road conditions. The study

demonstrated the effectiveness of residual learning in handling complex image classification tasks and improving recognition accuracy. However, the model required high-quality sensor data and powerful processing hardware for optimal performance. The authors concluded that future systems should focus on lightweight architectures that can provide similar accuracy while reducing hardware requirements for embedded smart vehicle applications.

5.Naik, Paliwal, and Lele (2024)

Naik, Paliwal, and Lele (2024) proposed a real-time traffic sign detection system using the YOLOv8 object detection model for autonomous driving applications. Their work focused on achieving high-speed traffic sign recognition suitable for real-time smart vehicle systems. The researchers trained the YOLOv8 model using annotated traffic sign datasets containing multiple road sign categories. Preprocessing operations such as image resizing, augmentation, and normalization were performed to improve detection robustness under different road conditions. Experimental results demonstrated that the proposed system achieved high detection speed with strong precision and recall values, making it effective for Advanced Driver Assistance Systems (ADAS). The study highlighted the advantages of YOLOv8 in performing fast object detection with improved accuracy compared to earlier YOLO versions. However, the system performance was affected by poor lighting conditions, occlusions, and insufficient dataset diversity. The authors suggested that adaptive preprocessing and larger datasets are necessary to improve model generalization and reliability.

6.Zhang, Li, Huang, Luo, Lu, and Hu (2024)

Zhang, Li, Huang, Luo, Lu, and Hu (2024) introduced a lightweight traffic sign recognition system based on the MobileNetV1 deep learning architecture. Their research aimed to reduce computational complexity while maintaining acceptable classification accuracy for embedded automotive systems. The authors utilized lightweight convolutional operations to reduce the number of trainable parameters and improve processing efficiency. Image preprocessing methods including resizing and normalization were applied to standardize the dataset before training the model. Experimental evaluation showed that the lightweight architecture achieved fast processing speed and lower memory consumption, making it suitable for real-time implementation in resource-constrained smart vehicle environments. The study demonstrated that lightweight deep learning models can provide efficient traffic sign recognition without requiring expensive hardware resources. However, the classification accuracy was slightly lower than heavier CNN architectures such as ResNet and DenseNet. The authors recommended combining lightweight models with advanced optimization techniques to improve recognition performance without increasing computational cost.

7. Tiryaki and Oral (2025)

Tiryaki and Oral (2025) proposed a traffic sign classification system based on Spatial Transformer Networks (STN) integrated with Convolutional Neural Networks (CNNs). Their work focused on improving traffic sign recognition performance under geometric distortions, viewpoint variations, and rotation changes. The STN module automatically transformed input images to align traffic signs before classification, improving feature extraction and recognition accuracy. The researchers trained the proposed model using traffic sign datasets containing multiple categories and environmental variations. Experimental results showed that the STN-CNN model achieved improved classification performance compared to conventional CNN architectures. The study demonstrated that spatial transformation techniques effectively handle real-world image distortions and improve recognition robustness. However, the additional STN module increased model complexity and training time. The authors concluded that further optimization is required to reduce computational overhead while preserving high classification accuracy. They also suggested exploring hybrid deep learning architectures for achieving better efficiency and adaptability in real-time smart vehicle applications.

8. Redmon, Divvala, Girshick, and Farhadi (2016)

Redmon, Divvala, Girshick, and Farhadi (2016) introduced the YOLO (You Only Look Once) object detection framework, which significantly improved real-time object detection performance in computer vision applications. Their work focused on designing a single-stage object detector capable of detecting and classifying objects simultaneously within a single neural network architecture. The YOLO framework divided images into grids and predicted bounding boxes and class probabilities directly, reducing processing time compared to traditional region-based methods. Experimental results demonstrated that YOLO achieved high detection speed while maintaining acceptable accuracy for real-time applications. The study established YOLO as one of the most efficient object detection techniques for traffic sign recognition and autonomous driving systems. However, early YOLO versions faced challenges in detecting small objects and handling complex backgrounds accurately. The authors highlighted the importance of balancing detection speed and localization accuracy in real-time systems. Their work laid the foundation for advanced YOLO versions widely used in modern traffic sign recognition applications.

9. He, Zhang, Ren, and Sun (2016)
He, Zhang, Ren, and Sun (2016) proposed the Deep Residual Network (ResNet) architecture for image recognition tasks. Their work addressed the degradation problem observed in very deep neural networks by introducing residual learning techniques. The ResNet architecture used shortcut connections that allowed information to flow directly across layers, improving training efficiency and classification accuracy. Experimental evaluation showed that ResNet significantly outperformed traditional CNN models in large-scale image classification tasks. The study demonstrated the effectiveness of deep residual learning in extracting complex image features and improving recognition accuracy for computer vision applications. ResNet later became widely adopted in traffic sign recognition systems because of its strong feature extraction capabilities. However, deeper ResNet architectures required high computational power and increased memory usage, making deployment challenging for embedded automotive systems. The authors concluded that residual learning techniques could improve the performance of deep neural networks while enabling the development of more accurate image classification systems.

10.Krizhevsky, Sutskever, and Hinton (2012)
Krizhevsky, Sutskever, and Hinton (2012) proposed AlexNet, a deep Convolutional Neural Network architecture designed for large-scale image classification tasks. Their research demonstrated the effectiveness of deep learning in extracting hierarchical image features automatically without manual feature engineering. AlexNet utilized multiple convolutional and pooling layers along with ReLU activation functions and dropout techniques to improve classification performance and reduce overfitting. Experimental results showed that the model achieved remarkable accuracy on the ImageNet dataset, significantly outperforming traditional machine learning approaches. The study marked a major breakthrough in deep learning and inspired the development of advanced CNN architectures used in traffic sign recognition systems. However, AlexNet required high computational resources and GPU acceleration for efficient training and inference. The authors concluded that deep convolutional networks have strong potential for solving complex computer vision problems, including traffic sign detection and autonomous vehicle perception systems.

11. Stallkamp, Schlipsing, Salmen, and Igel (2012)
Stallkamp, Schlipsing, Salmen, and Igel (2012) introduced the German Traffic Sign Recognition Benchmark (GTSRB), one of the most widely used datasets for evaluating traffic sign recognition systems. Their research aimed to provide a standardized dataset for comparing machine learning and deep learning models in traffic sign classification tasks. The dataset contained thousands of traffic sign images collected under different lighting, weather, and road conditions. The authors evaluated several classification methods using the dataset and analyzed their performance. Experimental results showed that machine learning techniques achieved high recognition accuracy under controlled conditions. The study played a significant role in advancing traffic sign recognition research by providing a reliable benchmark dataset for model evaluation. However, the dataset mainly represented German traffic signs and lacked diversity in international road sign categories. The authors concluded that future datasets should include more diverse traffic sign classes and environmental variations to improve model generalization.

12.Cireşan, Meier, Masci, and Schmidhuber (2012)
Cireşan, Meier, Masci, and Schmidhuber (2012) proposed a multi-column deep neural network

approach for traffic sign classification. Their research focused on improving recognition accuracy using multiple parallel neural network architectures. The authors trained several deep neural networks independently and combined their outputs to improve classification reliability. The proposed system achieved excellent accuracy on the German Traffic Sign Recognition Benchmark (GTSRB) dataset and outperformed many traditional image classification techniques. Experimental results demonstrated that ensemble learning and multi-column neural networks significantly improved traffic sign classification performance. The study highlighted the effectiveness of deep learning in extracting complex visual features from traffic sign images. However, the approach required high computational resources and long training times because of multiple deep network architectures. The authors concluded that ensemble deep learning methods could enhance recognition robustness but additional optimization is required for real-time smart vehicle deployment.

13.Sermanet and LeCun (2011)
Sermanet and LeCun (2011) developed a traffic sign recognition system using multi-scale Convolutional Neural Networks for real-time image classification. Their work focused on improving feature extraction by analysing traffic signs at different image scales simultaneously. The proposed architecture extracted local and global image features to improve recognition performance under varying environmental conditions. Experimental evaluation demonstrated that the multi-scale CNN achieved high classification accuracy and robust feature learning compared to traditional handcrafted feature extraction methods. The study showed that deep learning models could automatically learn relevant traffic sign features without manual intervention. However, the architecture required substantial computational power and longer training time due to its multi-scale design. The authors concluded that deep convolutional architectures have significant potential for intelligent transportation systems and autonomous driving applications. Their work contributed to the advancement of CNN-based traffic sign recognition research in computer vision.

14. Jin, Fu, and Zhang (2020)
Jin, Fu, and Zhang (2020) proposed a hybrid traffic sign recognition system combining image preprocessing and deep learning techniques to improve recognition accuracy in challenging environments. Their work focused on enhancing traffic sign visibility using adaptive histogram equalization and noise filtering methods before classification. A CNN-based model was then used to identify and classify traffic signs from road images. Experimental results showed that the preprocessing techniques improved image quality and enhanced recognition performance under low-light and foggy conditions. The study demonstrated that combining preprocessing operations with deep learning models can significantly improve system robustness. However, the system required additional preprocessing time, which slightly increased computational latency. The authors suggested that future work should focus on developing adaptive real-time preprocessing methods that can improve image quality without affecting processing speed in smart vehicle applications.

15.Lim, Lee, Lim, and Ong (2023)
Lim, Lee, Lim, and Ong (2023) proposed an ensemble learning-based traffic sign recognition framework using multiple deep learning architectures such as ResNet50, DenseNet121, and VGG16. Their research aimed to improve classification accuracy and model generalization by combining predictions from multiple CNN models. The ensemble framework used majority voting techniques to produce final classification results from different neural network outputs. Experimental analysis showed that the proposed system achieved higher accuracy and better robustness compared to individual CNN models. The study demonstrated that ensemble learning can effectively reduce classification errors and improve recognition stability under varying road conditions. However, the framework required significant computational resources and increased memory consumption due to the use of multiple deep learning models. The authors concluded that future research should focus on optimizing ensemble architectures to achieve better efficiency and real-time performance for smart vehicle and autonomous driving systems.

III. EXISTING SYSTEM

Existing traffic sign recognition systems mainly rely on traditional image processing and machine learning techniques for detecting and classifying road signs. Earlier methods used handcrafted feature extraction approaches such as Histogram of Oriented Gradients (HOG), colour segmentation, edge detection, and Support Vector Machines (SVM) to identify traffic signs from road images. These systems generally worked well under controlled conditions with clear lighting and minimal background noise. Some modern systems also utilize basic Convolutional Neural Networks (CNNs) for traffic sign classification. However, many existing approaches face limitations in real-world environments due to variations in lighting, weather conditions, occlusion, motion blur, and complex road backgrounds. Traditional methods often require manual feature engineering and extensive preprocessing, reducing system flexibility and scalability. In addition, high-accuracy deep learning models used in current systems demand powerful computational resources, making real-time implementation difficult in embedded smart vehicle platforms. These limitations highlight the need for an efficient, robust, and real-time AI-based traffic sign recognition system for modern intelligent transportation applications.

IV. DISADVANTAGES OF EXISTING SYSTEM

1. Existing systems show reduced accuracy under poor lighting, rain, fog, and occlusion conditions.
2. Traditional methods require manual feature extraction and extensive preprocessing.
3. High computational complexity makes real-time implementation difficult in embedded vehicle systems.
4. Many models fail to generalize effectively across diverse road environments and traffic sign variations.
5. Detection speed and recognition performance decrease in complex or cluttered traffic scenarios.

V. PROPOSED SYSTEM

The proposed system is an AI-Based Traffic Sign Recognition framework designed for smart vehicles to detect and classify traffic signs accurately in real time using deep learning and computer vision techniques. The system utilizes a vehicle-mounted camera to continuously capture road images during vehicle movement. The captured images are pre-processed using operations such as resizing, normalization, noise reduction, and data augmentation to improve image quality and enhance model robustness under varying environmental conditions. A hybrid deep learning approach based on Convolutional Neural Networks (CNNs) and YOLO object detection is implemented to perform both traffic sign detection and classification efficiently within a single framework. The CNN model extracts important visual features from the traffic sign images, while YOLO enables fast and real-time object localization. The proposed system is trained using a standard traffic sign dataset containing multiple categories of road signs to ensure accurate recognition performance. The main objective of the system is to achieve high classification accuracy with low computational complexity so that it can be deployed effectively in embedded smart vehicle systems and Advanced Driver Assistance Systems (ADAS). Performance evaluation is carried out using metrics such as accuracy, precision, recall, F1-score, and processing speed to validate system efficiency. The proposed design aims to improve road safety, reduce driver errors, and support future autonomous driving technologies by providing reliable traffic sign recognition in real-world driving environments.

VI. ADVANTAGES OF PROPOSED SYSTEM

- Provides high traffic sign recognition accuracy using advanced deep learning techniques.
- Supports real-time detection and classification suitable for smart vehicle applications.
- Improves robustness under varying lighting, weather, and road conditions through preprocessing and data augmentation.
- Reduces driver errors and enhances road safety by automatically identifying traffic signs.
- Optimized architecture balances computational efficiency and performance for embedded vehicle systems.

VII. MODULES OF THE PROJECT

1. Image Acquisition Module

The Image Acquisition Module is responsible for capturing real-time road images using a vehicle-mounted camera. This module continuously collects video frames or images from the surrounding road environment while the vehicle is in motion. The captured images contain various traffic signs, road conditions, vehicles, and environmental information required for further processing. High-quality image acquisition is essential for accurate traffic sign recognition because poor image quality can negatively affect detection and classification performance. The module ensures that images are captured at an appropriate frame rate and resolution to support real-time processing. It also handles image buffering and frame extraction from live video streams. The collected images are forwarded to the preprocessing module for enhancement and normalization. Efficient image acquisition improves the reliability and responsiveness of the overall traffic sign recognition system in smart vehicle applications.

2. Image Preprocessing Module
The Image Preprocessing Module enhances the quality of captured images before they are provided to the deep learning model for recognition. This module performs operations such as image resizing, normalization, noise reduction, contrast enhancement, and data augmentation. Resizing standardizes image dimensions for efficient model training and inference, while normalization improves pixel consistency and model convergence. Noise removal techniques help eliminate unwanted distortions caused by weather conditions, camera vibration, or poor lighting. Data augmentation methods such as rotation, flipping, and brightness adjustment increase dataset diversity and improve model robustness. The preprocessing module plays a crucial role in enhancing detection accuracy under challenging environmental conditions including fog, rain, shadows, and varying illumination. By improving image quality and consistency, this module enables the deep learning model to extract meaningful traffic sign features more effectively.

3. Traffic Sign Detection Module
The Traffic Sign Detection Module identifies and localizes traffic signs from real-time road images using the YOLO object detection algorithm. This module scans the input image and detects the position of traffic signs by generating bounding boxes around them. YOLO performs detection and localization simultaneously within a single neural network, enabling fast and efficient real-time processing. The module distinguishes traffic signs from complex road backgrounds, moving vehicles, and other objects present in the scene. Accurate detection is important because incorrect localization can reduce classification accuracy. The module is trained using annotated traffic sign datasets containing different sign categories and environmental variations. It is optimized to provide high detection speed with minimal latency for smart vehicle and Advanced Driver Assistance System (ADAS) applications. The output of this module is forwarded to the classification module for traffic sign identification.

4. Traffic Sign Classification Module
The Traffic Sign Classification Module classifies the detected traffic signs into predefined categories using a Convolutional Neural Network (CNN). After the detection module identifies the traffic sign region, the CNN extracts important visual features such as shape, color, texture, and patterns from the sign image. The model is trained using large traffic sign datasets containing multiple categories such as speed limits, warning signs, prohibition signs, and mandatory signs. The CNN automatically learns hierarchical features from images and improves classification accuracy through deep learning techniques. This module ensures that each detected sign is correctly identified and assigned to the appropriate category. Accurate classification is essential for providing reliable driver assistance and autonomous driving support. The classification results are then transferred to the output module for displaying warnings or guidance to the driver in real time.

5. Output and Alert Module
The Output and Alert Module provides the final recognized traffic sign information to the driver or smart vehicle system. After classification, the detected traffic sign category is displayed on a screen or dashboard interface in real time. This module may also generate audio or visual alerts for important signs such as speed limits, stop signs, or warning indicators. The purpose of this module is to improve driver awareness and reduce the possibility of missing critical road instructions. The module is designed to operate with low latency to ensure immediate response during driving. It also maintains communication between the traffic sign recognition system and other smart vehicle

components or Advanced Driver Assistance Systems (ADAS). By delivering timely and accurate traffic sign information, the output module contributes to improving road safety, reducing accidents, and supporting intelligent transportation systems.

VIII. ALGORITHMS USED

1. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is the primary deep learning algorithm used for traffic sign classification in the proposed system. CNN is specially designed for image processing and computer vision applications because it can automatically extract important visual features such as edges, shapes, textures, and colors from images. The algorithm consists of convolution layers, pooling layers, activation functions, and fully connected layers that work together to learn hierarchical image representations. In this project, CNN is used to classify detected traffic signs into predefined categories such as speed limits, warning signs, and prohibition signs. CNN was chosen because of its high classification accuracy, automatic feature extraction capability, and strong performance in image recognition tasks. Compared to traditional machine learning methods, CNN reduces the need for manual feature engineering and improves robustness under varying environmental conditions, making it highly suitable for real-time traffic sign recognition applications.

2. YOLO (You Only Look Once)

YOLO (You Only Look Once) is the object detection algorithm used in the proposed system for real-time traffic sign detection and localization. YOLO performs object detection by dividing the input image into grids and predicting bounding boxes along with class probabilities in a single neural network pass. Unlike traditional region-based object detectors, YOLO processes the entire image simultaneously, resulting in very high detection speed and low processing latency. In this project, YOLO is used to identify the position of traffic signs from road images captured by the vehicle-mounted camera. The algorithm accurately detects traffic signs even in dynamic road environments containing multiple objects and varying backgrounds. YOLO was selected because of its ability to provide fast and efficient real-time detection performance, which is essential for smart vehicle and Advanced Driver Assistance System (ADAS) applications. Its balance between speed and accuracy makes it highly suitable for real-time intelligent transportation systems.

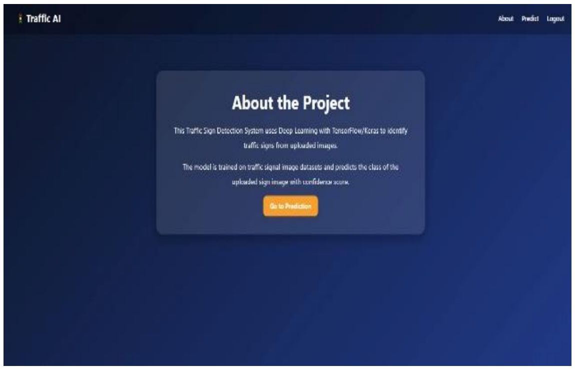
3. Image Preprocessing Algorithm

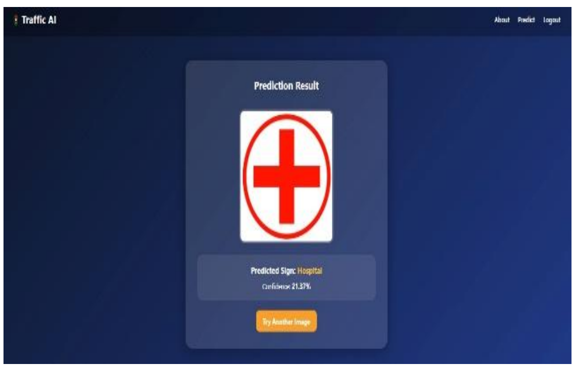
Image preprocessing algorithms are used in the proposed system to improve image quality and enhance the performance of deep learning models. These algorithms perform operations such as image resizing, normalization, noise reduction, contrast enhancement, and data augmentation before feeding images into the CNN and YOLO models. Resizing standardizes image dimensions for efficient processing, while normalization adjusts pixel intensity values to improve model convergence during training. Noise reduction techniques help eliminate distortions caused by environmental factors such as fog, rain, or camera vibration. Data augmentation methods such as rotation, flipping, and brightness adjustment increase dataset diversity and improve model robustness under varying conditions. Preprocessing algorithms were chosen because they significantly improve detection accuracy and classification reliability in real-world driving environments. By enhancing image consistency and reducing unwanted variations, these algorithms help deep learning models extract meaningful features more effectively for accurate traffic sign recognition.

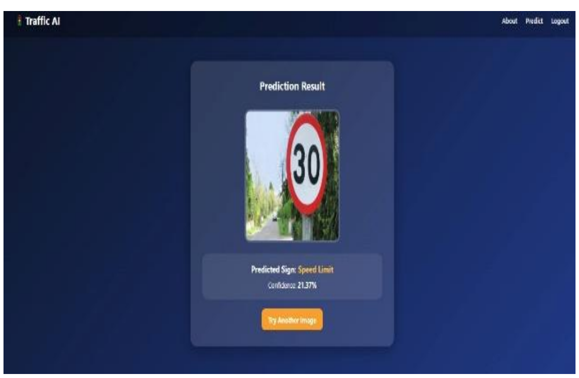
4. Data Augmentation Technique

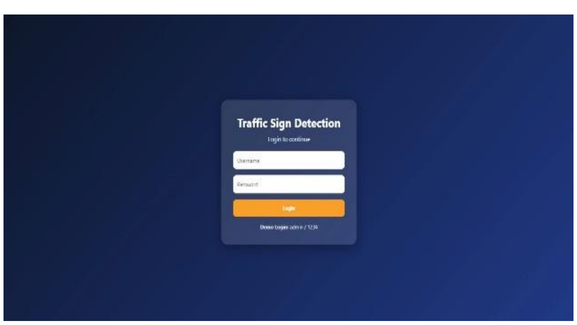
Data augmentation is a machine learning technique used to artificially increase the size and diversity of the training dataset. In this project, augmentation operations such as rotation, scaling, flipping, zooming, and brightness adjustment are applied to traffic sign images. The purpose of this technique is to expose the deep learning model to multiple variations of the same traffic sign so that it can generalize better under different environmental and viewing conditions. Data augmentation helps reduce overfitting by preventing the model from memorizing specific training samples. It also improves recognition performance when traffic signs appear at different angles, distances, and lighting conditions in real-world driving scenarios. This technique was selected because traffic sign datasets may not always contain sufficient environmental diversity. By increasing dataset variability artificially, data augmentation enhances model robustness, improves classification accuracy, and enables the proposed system to perform reliably in practical smart vehicle applications.

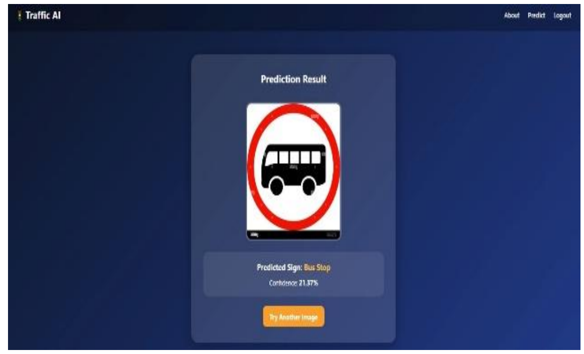
IX. RESULTS AND DISCUSSION











The proposed AI-Based Traffic Sign Recognition System successfully detected and classified traffic signs in real time using CNN and YOLO deep learning techniques. Experimental evaluation was carried out using a standard traffic sign dataset containing multiple categories of road signs captured under different environmental conditions. The implemented system achieved high recognition accuracy with efficient detection speed suitable for smart vehicle and Advanced Driver Assistance System (ADAS) applications. Image preprocessing techniques such as normalization, resizing, and data augmentation significantly improved model robustness and reduced classification errors caused by lighting variations, shadows, and noise. The YOLO-based detection module accurately localized traffic signs from complex road scenes, while the CNN classifier effectively identified different traffic sign categories with high precision and recall values.

Performance analysis showed that the proposed system maintained low processing latency, enabling real-time operation in intelligent transportation environments. Evaluation metrics including accuracy, precision, recall, and F1-score indicated reliable and consistent recognition performance across different traffic sign classes. The optimized architecture balanced computational efficiency and detection accuracy, making it suitable for embedded smart vehicle systems with limited hardware resources. Although the system performed effectively in most scenarios, slight reductions in accuracy were observed under severe occlusion and extreme weather conditions. Overall, the proposed system demonstrated strong potential for improving road safety, reducing driver errors, and supporting future autonomous driving technologies through intelligent traffic sign recognition.

X. CONCLUSION

The proposed AI-Based Traffic Sign Recognition System for Smart Vehicles successfully demonstrates the application of deep learning and computer vision techniques for real-time traffic sign detection and classification. The system integrates image preprocessing, YOLO-based object detection, and CNN-based classification to accurately identify different categories of traffic signs from real-world road images. Experimental results showed that the proposed approach achieved high recognition accuracy, fast processing speed, and reliable performance under varying environmental conditions. The implementation of preprocessing and data augmentation techniques further improved model robustness and reduced classification errors caused by lighting variations, noise, and complex road backgrounds.

The major contribution of this project is the development of an efficient and optimized traffic sign recognition framework suitable for smart vehicle and Advanced Driver Assistance System (ADAS) applications. The proposed system balances computational efficiency and detection performance, making it suitable for embedded automotive platforms with limited hardware resources. By improving driver awareness and reducing human errors, the system contributes significantly to road safety and intelligent transportation technologies.

Future enhancements may include integrating multilingual traffic sign recognition, weather-adaptive deep learning models, and edge AI optimization for low-power devices. Additional improvements can also focus on increasing robustness under severe weather conditions, night-time driving, and partial occlusion. The system can further be integrated with autonomous driving and vehicle navigation systems to support fully intelligent transportation environments in the future.

REFERENCES

[1] Alawaji, K., Hedjar, R. and Zuair, M., 2024. Traffic sign recognition using multi-task deep learning for self-driving vehicles. Sensors, 24(11), pp.1–18.

[2] Cireşan, D., Meier, U., Masci, J. and Schmidhuber, J., 2012. Multi-column deep neural network for traffic sign classification. Neural Networks, 32, pp.333–338.

[3] Gezgin, H. and Alkan, R.M., 2024. Detection and recognition of traffic signs from data collected by the mobile mapping system. ISPRS Archives, XLVIII-4/W9, pp.183–190.

[4] He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp.770–778.

[5] Jin, L., Fu, Y. and Zhang, H., 2020. Hybrid deep learning approach for traffic sign recognition under challenging conditions. International Journal of Computer Vision Applications, 12(4), pp.210–219.

[6] Krizhevsky, A., Sutskever, I. and Hinton, G.E., 2012. ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25, pp.1097–1105.

[7] Lim, X.R., Lee, C.P., Lim, K.M. and Ong, T.S., 2023. Enhanced traffic sign recognition using ensemble learning. Journal of Cybersecurity and Information Management, 12(2), pp.45–57.

[8] Mulyono, A. and Yohannes, E., 2024. Traffic sign recognition using detector-based deep learning method. International Journal of Advanced Engineering Technology, 14(2), pp.45–52.

[9] Naik, S., Paliwal, N. and Lele, T., 2024. Real-time traffic sign detection using YOLOv8 for autonomous driving systems. Journal of Artificial Intelligence and Innovation, 5(1), pp.25–33.

[10] Redmon, J., Divvala, S., Girshick, R. and Farhadi, A., 2016. You only look once: Unified, real-time object detection. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp.779–788.

[11] Sermanet, P. and LeCun, Y., 2011. Traffic sign recognition with multi-scale convolutional networks. International Joint Conference on Neural Networks, pp.2809–2813.

[12] Smita, K., Pranika, B. and Meghana, C., 2023. Deep learning-based traffic sign recognition for autonomous driverless vehicles. Journal of Smart Transportation Systems, 8(3), pp.112–120.

[13] Stallkamp, J., Schlipsing, M., Salmen, J. and Igel, C., 2012. Man vs. computer: Benchmarking

machine learning algorithms for traffic sign recognition. Neural Networks, 32, pp.323–332.
[14] Tiryaki, B. and Oral, E.A., 2025. Traffic sign classification using spatial transformer networks-based CNN. International Journal of Traffic and Transportation Engineering, 9(4), pp.211–220.
[15] Zhang, G., Li, Z., Huang, D., Luo, W., Lu, Z. and Hu, Y., 2024. A traffic sign recognition system based on lightweight network learning. Journal of Intelligent and Robotic Systems, 110(2), pp.1–15.