# Real time traffic sign recognitionsystem

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## Abstract

**Traffic Sign Recognition (TSR) systems are becoming increasingly important for making roads safer and supporting modern smart transportation. In this work, a real-time The system is designed based on deep learning methods to identify and categorize traffic signs.from images and video. The method integrates Convolutional Neural Networks (CNNs) with a YOLO-based detection model to achieve fast and accurate results. Training of the model is performed ona labeled dataset and can accurately identifydifferent types of traffic signs even under difficult conditions such as low lighting orcomplex backgrounds.**

**To make the system more practical for drivers, a voice alert feature is added, which gives instant audio feedback whenever a traffic sign is detected. The performance of the model is assessed using commonly used metrics such asprecision, recall, F1-score, mAP, and IoU, and the results show that the system performs reliably in real-time scenarios. Overall, this project presents a simple, efficient, and scalable solution that can be useful in driver assistance systems and future autonomous vehicles.**

***Keywords-***Traffic Sign Recognition, YOLO, Deep Learning, Computer Vision, Real-Time Detection, Road Safety, Autonomous Vehicles

## 1. Introduction

A real-time system for traffic sign recognition is developedis an advanced application by leveraging computer vision and deep learning methodsaimed at enhancing road safety.focuses on enabling automatic identification and categorization of traffic signs using images and live video feeds. With the increasing number of vehicles, manual monitoring related to traffic signs becomes difficult, creating a need for intelligent systems. This project uses the YOLO algorithm to achieve fast and accurate detection in real-time scenarios. The system can assist drivers by providing instant information about road signs and regulations. It further contributes significantly tothe development role in autonomous vehiclesand smart transportation systems.Alarge number for traffic sign analysis systemshave beendeveloped since the 1980's. First solutions were focusing onoptical based micro-programmed hardware in order to avoid computational complexity and other contemporary mobilecomputing related limitations [1].In the fieldofAIWith rapid progress in technology, many researchers and major companies such as Tesla, Uber, Google, Mercedes-Benz, Toyota, Ford, and Audi are actively working on autonomous and self-driving vehicles. To ensure these systems operate accurately and safely, vehicles must be capable of understanding road signs andmaking appropriate driving decisions based on them[2].Aiming to support drivers and improve both efficiency and safety, the TSRSregarded as one of the mosta key vehicle-based intelligent system developed for recognizing and analyzing road signs. It utilizes a vehicle-mounted camera to record and analyzelive road environmentsto recognize traffic signs, presenting their information to the driver in Advanced DriverAssistance Systems (ADAS), and enhancing control and safety in Autono mous Driving Systems (ADS) [4]. This capability enables a model to classify between confidently class ifiable samples and those that should be acknowledg ed for further verification or human oversight[6]. The primary objective of thissystem aims tosupport drivers by giving timely alerts about traffic signs, helping to minimize human mistakes and improve road safety. It is particularly helpful in situations where signs might be missed due to poor visibility, driver distraction, or unfamiliar roads. In addition, real-time traffic sign recognition systems have becomeimportant for the growth of autonomous vehicles, where understanding road signs automatica lly is necessary for making correct driving decisions.

Overall, such systems play a vital role increating safer driving conditions, enhancing driver assistance features, and serving as an essential component of modern intelligent transportation solutions.

## 2. Related Work

This section discusses relevantliterature related to computing, electronics, and artificial intelligence. Existing methods and their limitations are critically analyzed. The review highlights the need for improved techniques addressed by the proposed work.

[1] J. Thomas, Optimizing Real-Time Traffic sign recognition in intelligent systems Transport Systems: A comparison of deep learningtechniques Models, ResearchGate, 2024.

Earlier traffic sign detection methods relied on traditional hand-crafted feature extraction methods likecolor segmentation, shape analysis, and template matching. While effective in controlled environments, these approaches performed poorly under real-world conditions like poor lighting, occlusion, and varying sign sizes.With the advancement of deep learning, CNN-based object detection frameworks such as Faster R-CNN, SSD, and YOLO have become widely used. Among these, YOLO models gained popularity because they can perform real-time detection with high speed and accuracy.

Recent studies have concentrated onimproving YOLO architectures (YOLOv5, YOLOv6, YOLOv7, YOLOv8) by introducing attention mechanisms, better feature fusion, and anchor-free detection. However, selecting the best model for real-world ITS applications remains a challenge, especially when balancing precision, processing speed, and efficiency[1].

[2] N. Triki, M. Karray, and M. Ksantini, "A real-time traffic sign recognition method using a new attention-based deep convolutional neuralnetwork for smartvehicles," *Applied Sciences*, vol. 13, no. 8, p. 4793, 2023.

Traditional TSR systems used color-based and shape-based detection methods, which rely on features like HSV color segmentation and geometric shapes. Although computationally simple, these methods are sensitive to environmental variations such as lighting, weather, and occlusion.To overcome these limitations, researchers introduced feature descriptors such as HOG, LBP, SIFT, and SURF. However, these approaches depend on handcrafted features and lack robustness.

Recent developments focus on deep learning-based methods, particularly CNNs, that automatically extract features from data and significantly improve accuracy. Hybrid approaches combining detection and classification have also been explored.

Despite improvements, many systems still face challenges withreal-time constraints and recognition of diverse traffic sign categories, motivating the use of attention-based CNN models [4].

[3] S. W. F. Liou, H.-L. Tong, K.-W. Ng, and H. Ng, "CNN-Based Traffic Sign Recognition," in Proc. CITIC 2022, Selangor, Malaysia: Springer, 2022, pp. 195–204. doi: 10.2991/978-94-6463-094-7_16.

Traffic sign recognition has progressed from conventional machine learning methods such as SVM, Random Forest, and KD-tree to deep learning-based approaches. Traditional approaches depend on manually designed features, which are time-consuming and less reliable.Deep learning approaches, particularly CNNs and transfer learning models (e.g., VGG19), have significantly improved classification accuracy. Several studies achieved high accuracy on benchmark datasets like GTSRB using CNN-based architectures and hybrid methods.

Recent works also combine CNN with other models such as Extreme Learning Machine (ELM) to enhance performance. Despite these advancements, real-world challenges such as lighting variations, occlusion, and motion blur still affect performance [6].

[4] M. Manawadu and U. Wijenayake, Voice-Assisted Real-time traffic sign detection and recognition systemUsing Convolutional Neural Network, ResearchGate, 2021.

Traffic sign studies on recognition have developed fromcolor-based and shape-based techniques to deep learning approaches. Color-based methods are efficient but fail in poor lighting, while shape-based methods struggle with similar object shapes.Deep learning techniques, particularly CNN-based models architectures, have shown superior performance by learning features directly from data. These methods Deep learning approaches can be broadly classified intotwo-stage detectors (e.g., R-CNN) and one-stage detectors (e.g., YOLO, SSD).

Two-stage detectors provide higher accuracy but are slower, whereas one-stage detectors offer faster performance suitable for real-time applications.

Recent studies focus on using YOLO-based architectures for real-time detection due to their speed and efficiency, though they may compromise slightly on accuracy [7].

[5]A. V. S. and S. Panda, "Traffic Sign Recognition and classification based on Convolutional Neural Networks,JETIR (Journal of advanced and innovative technologies Research), vol. 6, no. 6, pp. 243–247, 2019.

Most TSR systems follow a three-stage pipeline: segmentation, detection, and classification. Early approaches relied on color-based segmentation to extract regions of interest and reduce computational complexity.Shape detection techniques such as Hough Transform and template matching were initially applied to identify theshapes of traffic signs. Later, machine learning techniques, such as Support Vector Machines (SVM),were adopted to perform classification tasks more effectively.

However, these approaches were sensitive to illumination changes, rotation, and occlusion. To address these challenges, Convolutional Neural Networks (CNNs),were adopted, enabling automatic feature extraction and improved accuracy.

Despite advancements, challenges such as low image quality, environmental variations, and computational limitations in real-time systems still persist[9].

[6] X. Bangquan and W. X. Xiong, "Real-Time Embedded traffic sign recognition using an efficient CNN model,"IEEEXplore, 2019.

Road Sign Recognitionmainly involves two key processes: detecting traffic signs (Traffic SignDetection – TSD) and identifying their categories (Traffic Sign Classification – TSC).Early methods relied on shape and color features, which lacked robustness in real-world conditions.

With the rise of deep learning, several object classification models (AlexNet, VGG, ResNet, MobileNet) have been applied to TSR. Recent research focuses on building efficient neural network models thatbalance accuracy and computational cost.

Object detection methods are classified into two-stage methods (R-CNN) and one-stage methods (YOLO). While two-stage methods provide higher accuracy, one-stage methods are preferred for real-time applications due to faster processing.

Current research emphasizes lightweight and optimized architectures employing techniques such as depthwiseseparable convolutionand multiscale processing to facilitate real-timeoperation on embedded platforms [10].

[7] R. Patil et al., "Real-time a system for detecting and recognizing traffic signs based oncomputer vision along withmachine learning," Journal of Electrical Systems, 2024.

Previous research in TSR includes Both conventional computer vision approaches and contemporary deep learning methods have been applied in this domain. In earlier systems, image processing methods such as color space conversion, thresholding, and contour detection.

With the progress in deep learning, models such as CNNs and YOLO-based architectures models are widely used to enhance accuracy, performance. Studies have also explored synthetic data generation, lightweight models (YOLOv4-Tiny), and ensemble learning techniques to enhance accuracy and efficiency.

Additionally, frameworks like TensorFlow and OpenCV have been widely applied for implementatio n. However, real-time deployment remains challenging due to hardware limitations and computational complexity[16].

[8] S Gunasekara , D Gunarathna , M B Dissanayake , S Aramith and W Muhammad , Autonomous traffic sign recognition system using deep learning for ADAS2022.

Recent TSR systems adopt end-to-end deep learning frameworks combining Detection and classification are the two main stages of the model. Models like YOLO are commonly applied for fast, real-time detection, while design such as Xception and Inception are used to accurately classify the detected traffic signs.

Earlier works introduced CNN architectures such as LeNet, followed by deeper models like VGG and Inception, which improved accuracy through increased network depth. Techniques like dropout, transfer learning, and feature distillation were proposed to reduce overfitting and improve performance.

However, many studies mainly concentrate onclassification or detection separately, with limited integration of both in real-time systems. Additionally, performance depends heavily on dataset size and quality[21].

[9] IsraNaz , Jamal Hussain Shah , Ali Tahir, Mahatma Reddy Marri, RabiaSaleem, MutazElradi S. Saeed Attention to detail: A conditional multi-head transformer in traffic sign recognition2025.

Previous research in road sign detection and classification has been largely dominated by CNN-based deep learning models, which achieved high accuracy on datasets such as GTSRB. However, CNN-based models struggle with global feature extraction and are sensitive to real-world challenges like occlusion, illumination changes, and motion blur.To address these challenges, researchers introducedVision Transformers (ViTs), which use self-attention mechanisms to capture long-range dependencies in images. Variants such as Tokens-to-Token ViT and adaptive token sampling methods improved efficiency and performance.

In addition, models integrating CNNs with other techniquesand transformers have been investigated to improve generalization. Techniques like data aug mentation, adversarial training, and attention-based Localization approaches have been introduced to improve thesystem more reliable.

Nevertheless, most current approaches are based onstatic attention mechanisms and are unable to dynamically adapt to different traffic sign conditions, leading to misclassification in safety-critical scenarios. This limitation motivates the development of adaptive transformer-based models[22].

[10] Zsolt T. Kardkov´ acs, Zsombor Par´ oczi, EndreVarga,Ad´amSiegler, P´ eterLucz,Real-Live traffic sign recognition system2011.

Road sign recognition has studied for decades, evolvi ng from hardware-based optical systems to modern AI-based solutions. Early systems relied on low-resolution images and simple algorithms due to computational constraints.ModernTSR systems must address complex real-world challenges such as:Lighting and weather variations . Occlusions and distortions. Rotation and perspective changes Differe nces in traffic sign designs across regions .

Various strategies, including feature extraction, normalization, and adaptive algorithms, have been proposed to handle these challenges. Yet, reaching high accuracy withreal-time performance remains a significant research problem [23].

## 3. Materials and Methods

The development and implementation of a real-time TSR system system involved the use of software resources along with a structured methodology. The primary materials include a custom traffic sign image dataset, a computer system with GPU support for training, and a camera for real-time video input. The dataset was collected from various sources and annotated using labeling tools to mark different traffic sign classes, ensuring high-quality supervised learning data [16].

The project follows a supervised learning approach where the annotated dataset is utilized to train a deep learning model based on the YOLO (You Only Look Once) algorithm, well-known for its effectiveness in real-time object detection, was employed in this work. The The implementation was carried out using Python., utilizing libraries such as OpenCV for image processing and Ultralytics YOLOv8 for object detection. The dataset was divided into training, validation, and testing sets to ensure proper model evaluation. testing sets to ensure proper model evaluation [1].

The proposed system utilizes deep learning and computer vision methods to detect and classify traffic signs from images and video streams. A custom dataset consisting of board sign images was collected from Roboflow, containing multiple classes of Indian The system can recognize traffic signs under various environmental conditions. All dataset images were acquired and labeled using bounding boxes to label the position and category of each traffic sign [5].

Preprocessing steps were performed toincrease model performance and generalization. These include
resizing images to a uniform resolution, normalizatio n, and approaches for augmenting data such asrotation, flipping, scaling, and brightness adjustment. These steps help the model adapt to real-world variations such as lighting changes and occlusions [13].

The system employs the YOLOv8 deep learning detection model,known for its real-time processing and high accuracy. YOLO-based architectures are single-stage detectors that simultaneously predict bounding boxes along with class probabilities, rendering them suitable for time-critical applications like traffic sign recognition [14].

During training, the annotated dataset was fed into the model using supervised learning. The training process involved optimizing The loss function accounted for classification, localization, and confidence errors, while model hyperparameters such as learning rate, batch size, andepochs were optimized to enhance performance.[6].

The trained model was evaluated using standardobject detection metrics, including Precision, Recall, F1-score, and The model was assessed using MeanAverage Precision (mAP), computed at different IoU levels to measure performance.thresholds ranging from 0.5 to 0.95 to assess both detection and localization performance [15].

The system was developed in Pythonalong with OpenCV and the Ultralytics YOLOv8 framework for both model training and inference. After training, the modelwas tested on both images and real-time video streams to simulate practical deployment scenarios [8].

In the system workflow, the incoming image or video frameis first preprocessed and passed through the trained YOLOv8. The system detects traffic signs by generating object bounding boxes and corresponding class labelsare displayed together withconfidence scores to enable real-time interpretation and decision-making [11].

To enhance user interaction and safety, a voice alertmechanism was added to the proposed model. Once
a sign is detected and classified, the corresponding
label is converted into speech output to alert the driver in real time. This feature is particularly useful in assisting drivers who may miss visual cues due to distractions or poor visibility conditions. The voice alert module was implemented using text-to-speech libraries in Python, enabling seamless incorporation with the detection pipeline. Similar voice-assisted TSR systems have demonstrated improved driver awareness and response time in real-world scenarios [2], [7].

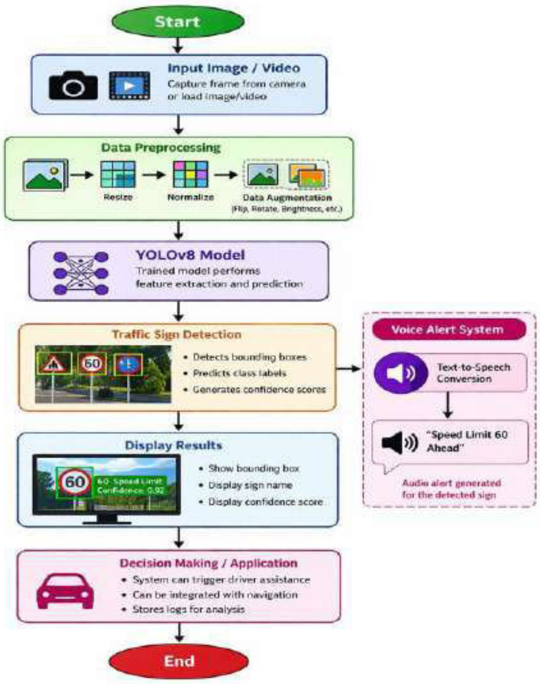


Fig: 3.1 Workflow chart

System Workflow:

The procedure starts with the Start block, followed by Input Image/Video, where the system captures real-time frames captured by a camera or processes pre-recorded images or videos. Real-time image capture is a vital step in traffic sign recognition systems and plays an important role in embedded platforms and intelligent transportation applications. [8].

Following this, the input data is preprocessed, whichincludes resizing the images, normalization, and applying augmentation techniques such as flipping,
rotation, and brightness adjustment. These preproce ssing steps improve model robustness and generalization under different environmental and lighting conditions [13].

The preprocessed data is then fed to the YOLOv8 Model, which performs extraction of features and prediction. YOLO-based deep learning neural network models are known for their live object detection capability and high efficiency in detecting multiple objects within a single frame [14].

In a Sign Detection stage, the model generates bounding boxes around detected signs, assigns class labels, and provides confidence scores for each detection. Such identification and classification techniques are extensively adopted in modern deep learning-based TSR systems [1], [16].

Simultaneously, the detected output is fed to the Voice Alert System, where a text-to-speech (TTS) module converts the recognized traffic sign into an audible alert (e.g., "Speed Limit 60 Ahead").This enhancesdriver awareness and reduces dependency on visual attention, improving safety in real-world driving conditions [2], [7].

The results are then shown in the Display Results stage, where bounding boxes, sign names, and confidence scores are visually presented on the screen for real-time interpretation [11].

Further, in the Decision Making/Application stage, the system can assist drivers by triggering alerts, integrating with navigation systems, or storing detection logs for future analysis. Such intelligent decision-support features are essential key parts of driver assistance technologies (ADAS)and smart transportation solutions [18], [19].

## 4. Results and Discussion

This part presents the experimental results collected using the proposed method. Performance metrics are analyzed and compared with existing approaches, and the discussion highlights the efficiency of deep learning–basedtraffic sign recognition systems [1], [15].

The performance evaluationof the developed real-time traffic sign recognition systemdemonstrates strong detection and classification capability across multiple metrics. The model achieved a precision of 84.17%, showing that most ofdetected traffic signs are correctly identified, with relatively few false positives. The recall value of 91.55% reflects the model's effectiveness in capturing most of the actual traffic signs present in the input, which is critical for safety-oriented applications [16]. The resulting F1-score of 87.7% shows a well-balanced highlighting the balance between precision and recall, which confirms the system'srobustness.Furthermore, the model attained a high mAP@50 score of 91.75%, suggesting excellent detection performance at a standard IoU threshold of 0.5. The mAP@50–95 value of 87.37%, computed over a more stringent IoU range of 0.5 to 0.95, indicates consistent performance even under stricter localization requirements. This demonstrates that the model not only detects traffic signs accurately but also localizes them precisely within the image. Similar improvements in detection accuracy using YOLO-based architectures have been reported in recent studies [14].

The approximate detection accuracy of 91.75% further supports the reliability for the system in livescenarios. These results from the use of awell-annotated dataset, effective training using the YOLOv8 architecture, and proper tuning of hyperpar ameters. Prior research also emphasizes that dataset quality and modeloptimizationsignificantly influence TSR performance [13], [17].

However, the slightly lower precision compared to recall indicates the presence of some false positive detections, which may occur due to similarities between certain traffic sign classes or challenging environmental conditions such as poor lighting, occlusions, or motion blur. Addressing these limitations through advanced techniques such as attention-based models [4] or transformer-based approaches [22] can further enhance system performance in future work.

## 5. Conclusion

The proposed Real-Time Road sign recognition framework successfully showcases the effectiven ess of deep learning techniquesto achieve precise and precise identification of traffic signs from images and videosBy leveraging the YOLOv8 model, the system achieves strong performance regarding precision andrecall, ensuring reliable identification of various traffic signs across various environmental conditions. The high mAP score further indicates the model's consistencyin handling multiple classes with precise localization, which aligns with recent advancements in YOLO-based detection frameworks [14], [1].

The project effectively addresses the drawbacks ofmanual traffic sign monitoring by providing an aut omated solution that can assist drivers and support intelligent transportation systems. The integration of computer vision techniques with a well-annotated dataset enables instantaneous processing usingmini mal latency, enabling the system to be used forpractical deployment in driver assistance technolo gies [11], [18].

Despite its effectiveness, the system may encounter challenges in extreme conditions such as poor lighting, occlusion, and complex backgrounds. Similar limitations have been discussed in prior studies, emphasizing the need for improved model generalization and robustness [15], [17]. Future work can focus on enhancing dataset diversity, incorporating advanced architectures such as attention-based or transformer-based models [4], [22], andoptimizing the system designed for edge devices.

Overall, this work highlights the significant potential of AI-driven road sign recognition systems inimproving road safety and enabling smarter transportation solutions. It also provides a strong foundation for future research in autonomous driving and intelligent traffic management systems [19], [20].

## References

[1] J. Thomas, Optimizing Real-Time Traffic Sign Recognition for Intelligent Transport Systems: A Comparative Study of Deep Learning Models, ResearchGate, 2024.

[2] ShilpaShahapur, Nyamatulla Patel, and M. Z. Choudhari, "CNN-Based Traffic Sign Recognition with Voice Alerts," Int. J. Embedded Syst. Emerg. Technol., vol. 10, no. 2, pp. 1–9, 2024, doi: 10.37628/IJESET.

[3] H. K. Sharma and A. Jamwal, "Traffic Sign Recognition System using CNN," Int. J. Innov. Sci. Res. Technol., vol. 8, no. 11, pp. 339–345, Nov. 2023.

[4] N. Triki, M. Karray, and M. Ksantini, "A Real-Time Traffic Sign Recognition Method Using a New Attention-Based Deep Convolutional Neural Network for Smart Vehicles," Applied Sciences, vol. 13, no. 8, p. 4793, 2023.

[5] N. T. L., A. K. A., A. Sanman, G. J., and P. A. Y., "Traffic Sign Recognition System Using Machine Learning," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 4, no. 2, pp. –, 2022.

[6] S. W. F. Liou, H.-L. Tong, K.-W. Ng, and H. Ng, "CNN-Based Traffic Sign Recognition," in Proc. CITIC 2022, Selangor, Malaysia: Springer, 2022, pp. 195–204. doi: 10.2991/978-94-6463-094-7_16.

[7] M. Manawadu and U. Wijenayake, "Voice-Assisted Real-Time Traffic Sign Recognition System Using Convolutional Neural Network," ResearchGate, 2021.

[8] I. S. B. M. Isa, C. J. Yeong, and N. L. A. M. S. Azyze, "Real-time traffic sign detection and recognition using Raspberry Pi," Int. J. Electr. Comput. Eng. (IJECE), vol. 12, no. 1, pp. 331–338, Feb. 2022, doi: 10.11591/ijece.v12i1.pp331-338.

[9] A. V. S. and S. Panda, "Traffic Sign Recognition and Classification Employing Convolutional NeuralNetwork," JETIR (Journal of Emerging Technologies and Innovative Research), vol. 6, no. 6, pp. 243–247, 2019.

[10] X. Bangquan and W. X. Xiong, "Real-Time Embedded Traffic Sign Recognition Using Efficient Convolutional Neural Network," IEEE Xplore, 2019.

[11] G. Kumar N. G., A. Kishore, and A. J. Krishna, "Real-time traffic sign recognition and autonomous vehicle control system using convolutional neural networks," *Multimedia Tools and Applications*, vol. 84, no. 34, pp. 43119–43154, Apr. 2025.

[12] S. Maldonado-Bascón, S. Lafuente-Arroyo, P. Gil-Jiménez, H. Gómez-Moreno, and F. López-Ferreras, "Road-sign detection and recognition based on support vector machines," *IEEE Transactions on IntelligentTransportation Systems*, vol. 8, no. 2, pp. 264–278, 2014.

[13] Y. Zhu and W. Q. Yan, "Traffic sign recognition based on deep learning," *Multimedia Tools and Applications*, vol. 81, pp. 17779–17791, 2022.

[14] Y. Gu and B. Si, "A novel lightweight real-time traffic sign detection integration framework based on YOLOv4," *Entropy*, vol. 24, no. 4, p. 487, 2022.

[15] C. Liu, S. Li, F. Chang, and Y. Wang, "Machine vision based traffic sign detection methods: Review, analyses and perspectives," *IEEE Access*, vol. 7, pp. 86578–86596, 2019.

[16] R. Patil *et al.*, "Real-time traffic sign detection and recognition system using computer vision and machine learning," *Journal of Electrical Systems*, 2024.

[17] V. Golgire, "Traffic sign recognition using machine learning: A review," *International Journal of Engineering Research & Technology (IJERT)*, vol. 10, no. 05, pp. 1–5, 2021.

[18] M. Drobiniak*et al.*, "Traffic sign recognition for advanced driver assistance systems: A neural network and computer vision approach," *International Journal of Computing*, 2025.

[19] X. Chen, "Technological evolution of traffic sign recognition," *Applied and Computational Engineering*, 2025.

[20] "Real-time traffic sign detection and recognition," in *Proc. IEEE High Performance Extreme Computing Conference (HPEC)*, 2014.

[21] "S Gunasekara , D Gunarathna , M B Dissanayake , S Aramith and W Muhammad , Deep Learning Based Autonomous Real-Time Traffic Sign Recognition System for Advanced Driver Assistance , 2022."

[22] "IsraNaz , Jamal Hussain Shah , Ali Tahir, Mahatma Reddy Marri, RabiaSaleem, MutazElradi S. Saeed Attention to detail: A conditional multi-head transformer for traffic sign recognition 2025."

[23] "Zsolt T. Kardkov´ acs, Zsombor Par´ oczi, EndreVarga,Ad´amSiegler, P´ eterLucz,Real-time Traffic Sign Recognition System 2011."