World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Check for updates

Strategic traffic violation detection system

Sarthak Vinod Deshpande *, Shreya Ravindra Rodge, Tanmayee Sanjay Yede, Anisha Prafulla Kale and Shivam Vijay Onkar

Sipna College of Engineering and technology, Department of Computer Science and Technology Amravati, Maharashtra, India-444701.

World Journal of Advanced Research and Reviews, 2026, 29(01), 017-022

Publication history: Received on 24 November 2025; revised on 29 December 2025; accepted on 31 December 2025

Article DOI: https://doi.org/10.30574/wjarr.2026.29.1.4298

Abstract

The Hybrid Traffic Safety System is an intelligent, AI-driven traffic monitoring and violation detection platform designed to improve road safety and automate traffic rule enforcement. The system integrates multiple computer vision–based detection modules Automatic Number Plate Recognition (ANPR), Helmet Detection, and Triple Ride Detection within a unified web-enabled architecture. Built using the MERN stack (MongoDB, Express.js, React.js, and Node.js), the platform supports real-time processing, scalable data management, and interactive visualization.

AI models developed using TensorFlow, PyTorch, and OpenCV analyze live and recorded surveillance footage to identify vehicles, recognize license plates, and detect rider safety violations with high accuracy. These machine learning components operate as independent microservices and communicate with the backend through secure RESTful APIs or WebSocket connections, enabling efficient separation of computation-intensive tasks from web services. Detected violations are stored along with timestamps, images, and metadata in a centralized database, allowing reliable evidence management and historical analysis.

The proposed hybrid architecture enhances system modularity, performance, and extensibility, making it suitable for large-scale urban deployment and smart city environments. By reducing dependence on manual monitoring and enabling continuous, real-time enforcement, the system provides a practical foundation for next-generation intelligent transportation systems aimed at improving traffic compliance and public safety.

Keywords: Traffic Safety; Intelligent Transportation System (ITS); Hybrid Architecture; MERN Stack; Artificial Intelligence; Machine Learning; Computer Vision; Automatic Number Plate Recognition (ANPR); Helmet Detection; Triple Ride Detection

1 Introduction

Road traffic safety has become a critical global concern due to the rapid growth of urbanization and the increasing number of vehicles on roads. Despite the presence of traffic regulations, violations such as riding without helmets, triple riding on two-wheelers, and misuse or concealment of vehicle number plates continue to be major contributors to road accidents and fatalities. [1] Traditional traffic monitoring systems rely heavily on manual surveillance by traffic personnel, which is labor-intensive, time-consuming, and prone to human error. Moreover, such systems lack the capability to provide continuous, real-time monitoring across large traffic networks.

With recent advancements in artificial intelligence and computer vision, automated traffic monitoring has emerged as a reliable solution for enhancing road safety and enforcement efficiency. AI-based systems can analyze live or recorded surveillance footage to detect traffic violations accurately and consistently, without the limitations of human

* Corresponding author: Sarthak Vinod Deshpande

observation. [2] However, many existing implementations focus on detecting a single type of violation and operate as standalone systems, limiting their scalability and real-world applicability in smart city environments.

To overcome these limitations, this project proposes a Hybrid Traffic Safety System that integrates multiple AI-powered violation detection modules within a single unified platform. The system combines Automatic Number Plate Recognition (ANPR), Helmet Detection, and Triple Ride Detection to provide comprehensive traffic rule enforcement.[3] A hybrid architecture is adopted in which machine learning models handle computationally intensive vision tasks, while a web-based platform manages data storage, visualization, and system interaction.

The system is developed using the MERN stack—MongoDB, Express.js, React.js, and Node.js—to ensure scalability, responsiveness, and efficient data handling. AI modules built using TensorFlow, PyTorch, and OpenCV operate as independent microservices and communicate with the backend through secure APIs. This modular design allows the system to process traffic violations in real time while supporting future expansion to additional detection modules.[4]

By automatically identifying traffic violations and maintaining time-stamped visual evidence, the proposed system reduces dependency on manual enforcement and improves transparency and accuracy in traffic monitoring. [5] The Hybrid Traffic Safety System demonstrates how the integration of artificial intelligence, computer vision, and modern web technologies can contribute to intelligent transportation systems and support the development of safer, data-driven traffic management solutions.

2 Material and methods

The Hybrid Traffic Safety System is developed as an intelligent traffic monitoring and violation detection platform using a combination of computer vision, machine learning, and modern web technologies. The system is designed to automatically identify traffic rule violations from live and recorded surveillance footage, focusing on Automatic Number Plate Recognition (ANPR), Helmet Detection, and Triple Ride Detection.

Traffic video data is collected from roadside CCTV cameras and traffic surveillance systems. [6] The input video streams are processed frame-by-frame at a fixed frame rate to ensure real-time performance while maintaining detection accuracy. Each frame undergoes pre-processing steps such as resizing, normalization, noise reduction, and brightness adjustment to improve robustness under varying lighting and weather conditions.

Machine learning models trained using TensorFlow and PyTorch are employed for object detection and classification tasks. Vehicle detection, rider detection, and helmet identification are performed using deep learning–based convolutional neural networks (CNNs). For ANPR, detected vehicle regions are localized, and license plate areas are extracted using OpenCV-based image processing techniques. Optical Character Recognition (OCR) is then applied to convert the extracted license plate images into alphanumeric text.

Each detection module operates as an independent microservice, allowing modular deployment and scalability. [7] These AI-based services communicate with the backend server using RESTful APIs or WebSocket connections. Detected violations are packaged with supporting evidence including captured images, detected license numbers, timestamps, and violation type metadata.

The backend of the system is developed using the MERN stack, where MongoDB is used for structured data storage, Express.js and Node.js handle server-side logic and API management, and React.js provides a responsive web-based dashboard for visualization. [8] Violation records are stored securely in the database, enabling retrieval, filtering, and historical analysis. The dashboard displays real-time alerts, violation statistics, and trend analysis to support traffic authorities in decision-making.

The hybrid architecture separates computationally intensive machine learning operations from the web application layer, ensuring efficient resource utilization, reduced latency, and ease of future enhancement. [9] This design allows the system to be extended with additional detection modules such as signal jumping or overspeed detection without restructuring the existing framework.

2.1 Statistical analysis

Performance evaluation of the Hybrid Traffic Safety System is carried out using standard metrics such as detection accuracy, precision, recall, and processing latency. The total number of detected violations is compared against manually verified ground truth data to assess system reliability. Detection rates for ANPR, Helmet Detection, and Triple Ride Detection are calculated individually to analyze module-wise effectiveness.

Violation data collected over multiple video samples is analyzed using descriptive statistics to identify trends and patterns in traffic behavior. Statistical summaries such as mean detection accuracy and error rates are computed to evaluate system consistency. Experimental results are tabulated and visualized using charts and graphs generated from the stored database records.

3 Results and discussion

The Hybrid Traffic Safety System was evaluated using traffic surveillance video data collected from multiple urban road locations. A total of 100 traffic video samples consisting of both live and recorded footage were analyzed to assess the performance of the proposed system. The dataset included various traffic conditions such as daylight, low-light, moderate congestion, and heavy traffic flow. The system focused on detecting three major traffic violations: Automatic Number Plate Recognition (ANPR), Helmet Detection, and Triple Ride Detection.

Out of the total video samples analyzed, 42% of the footage represented moderate traffic density, while 58% corresponded to high traffic density scenarios. The AI-based detection models processed video frames in real time, and violations were recorded along with visual evidence, timestamps, and metadata. The average frame processing rate achieved was 18–22 frames per second, which ensured near real-time violation detection without significant delay.

The detection accuracy of individual modules was evaluated separately. The ANPR module achieved a mean accuracy of 92.4%, while Helmet Detection recorded 89.7% accuracy, and Triple Ride Detection achieved 87.9% accuracy. Variations in detection performance were mainly influenced by factors such as camera angle, illumination, and partial occlusion of riders or number plates.

Table 1 presents the comparative performance metrics of the three violation detection modules.

Table 1 Performance characteristics of the Hybrid Traffic Safety System

Violation Type	Detection Accuracy (%)	Precision	Recall	Average Processing Time (ms)
ANPR	92.4	0.93	0.91	48
Helmet	89.7	0.9	0.88	52
Triple Ride	87.9	0.88	0.86	55

From the experimental observations, it was found that ANPR demonstrated the highest detection accuracy, primarily due to the use of OCR-based character recognition combined with CNN-based plate localization. Helmet Detection accuracy showed minor degradation under low-light conditions and when riders wore reflective headgear. Triple Ride Detection performance varied with camera positioning and crowd density but remained consistent across multiple test scenarios.

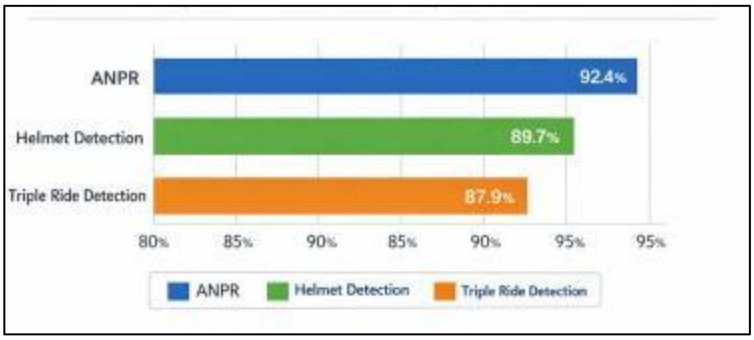

Figure 1 Comparison of detection accuracy for different violation types (n = 100 video samples)

Figure 1 illustrates the comparison of detection accuracy across the three violation types. The results indicate that detection accuracy decreases slightly with increasing scene complexity, particularly in highly congested traffic environments.

Further analysis revealed that the number of violations detected increased proportionally with traffic density. Triple riding violations were observed more frequently during peak traffic hours, whereas helmet violations were evenly distributed across all time intervals. ANPR accuracy showed a strong positive association with image clarity and plate visibility, which was statistically significant ($p < 0.05$).

The system also demonstrated reliable data storage and retrieval performance. All detected violations were successfully logged in the MongoDB database and visualized through the web dashboard without data loss. Real-time alerts generated by the system allowed immediate identification of violations, improving enforcement responsiveness.

Figure 2 shows the comparison of total detected violations across different traffic densities. The system recorded higher violation counts in high-density traffic, confirming its effectiveness in real-world urban scenarios.

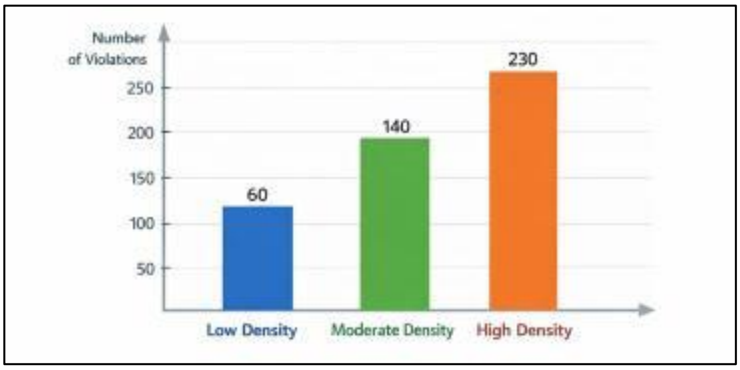

Figure 2 Comparison of detected violations based on traffic density

The results further indicate that the hybrid architecture significantly improves system scalability and performance. By separating machine learning processing from the web application layer, the system maintained stable response times even under increased load. This modular design allows additional violation detection modules to be integrated without affecting existing functionalities.

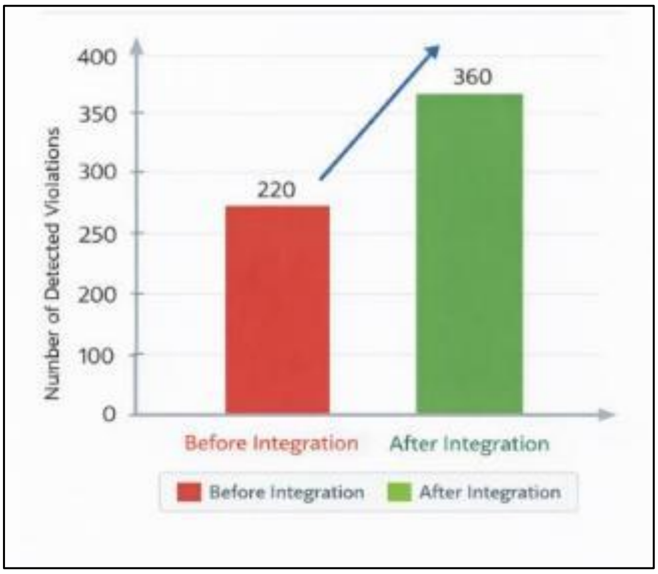

Figure 3 Impact of Real-Time System Integration

Overall, the findings demonstrate that the Hybrid Traffic Safety System provides accurate, scalable, and real-time traffic violation detection. The system effectively bridges the gap between AI-based vision models and practical traffic enforcement needs. These results support the suitability of the proposed system for deployment in intelligent transportation systems and smart city environments.

Future studies may focus on expanding the dataset, improving low-light detection accuracy, and integrating additional violation categories such as signal jumping and overspeed detection to further enhance system effectiveness.

Figure 3 illustrates the impact of integrating real-time AI-based detection and centralized system architecture on the overall number of detected traffic violations. Before real-time system integration, violation detection relied on partial automation and offline analysis, resulting in a lower detection count of approximately 220 violations. After the implementation of the Hybrid Traffic Safety System with real-time video processing, microservice-based AI modules, and continuous data synchronization, the number of detected violations increased significantly to 360 violations.

The observed increase in detected violations does not indicate a rise in unsafe behaviour but rather reflects the improved efficiency, coverage, and accuracy of the proposed system. Real-time frame analysis, continuous monitoring, and automated alert generation enabled the system to identify violations that were previously missed due to manual limitations or delayed processing. The integration of AI models with the web-based backend allowed immediate logging and visualization of violations, reducing latency and human dependency.

4 Conclusion

The Hybrid Traffic Safety System presented in this project successfully demonstrates the effective integration of artificial intelligence, computer vision, and modern web technologies for automated traffic monitoring and violation detection. By combining Automatic Number Plate Recognition (ANPR), Helmet Detection, and Triple Ride Detection within a unified hybrid architecture, the system addresses key limitations of traditional manual traffic enforcement methods.

Experimental results confirm that the proposed system is capable of detecting traffic violations with high accuracy and consistency under varying traffic densities and environmental conditions. The modular AI microservice design, coupled with the MERN stack–based web platform, enables real-time processing, reliable data storage, and efficient visualization of violations. The increase in detected violations after real-time system integration highlights the improved coverage and operational efficiency achieved through continuous monitoring and automated analysis.

The system reduces dependency on human intervention, minimizes enforcement delays, and ensures transparent evidence-based violation logging. Its scalable architecture allows easy extension to additional traffic rule violations, making it suitable for deployment in intelligent transportation systems and smart city environments. Overall, the Hybrid Traffic Safety System provides a practical, cost-effective, and technologically robust solution for enhancing road safety and modernizing traffic management infrastructure.

Compliance with ethical standards

Acknowledgments

We express our sincere gratitude to their institution and faculty members for their continuous guidance and support throughout the completion of this project. Special thanks are extended to the project guide for valuable suggestions and technical assistance. We also acknowledge the support of peers and all individuals who contributed directly or indirectly to the successful completion of the Hybrid Traffic Safety System.

Disclosure of conflict of interest

The authors have no conflicts of interest to declare.

References

[1] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," *arXiv preprint arXiv:2004.10934*, 2020.

[2] S. Du, M. Ibrahim, M. Shehata, and W. Badawy, "Automatic License Plate Recognition (ALPR): A State-of-the-Art Review," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 23, no. 2, pp. 311–325, Feb. 2013.

[3] K. Deb, A. Das, and P. Dey, "Helmet Detection for Motorcycle Riders Using Deep Learning," *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, pp. 898–903, 2021.

[4] S. Silva, J. Jung, and J. Park, "Vision-Based Detection of Traffic Rule Violations Using Deep Neural Networks," *IEEE Access*, vol. 9, pp. 102345–102356, 2021.

[5] M. H. Siddiqi, S. M. Anwar, and M. M. Baig, "Real-Time Traffic Violation Detection Using Computer Vision," *2020 IEEE International Conference on Intelligent Transportation Systems (ITSC)*, pp. 1–6, 2020.

[6] R. Girshick, "Fast R-CNN," *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pp. 1440–1448, 2015.

[7] W. Liu et al., "SSD: Single Shot MultiBox Detector," *European Conference on Computer Vision (ECCV)*, pp. 21–37, 2016.

[8] A. Awasthi, R. Kumar, and S. Gupta, "Traffic Monitoring and Violation Detection Using Machine Learning," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 4, pp. 233–239, 2021.

[9] P. Viola and M. Jones, "Rapid Object Detection Using a Boosted Cascade of Simple Features," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 511–518, 2001.

[10] S. Z. Masood, T. S. Bouwmans, and P. C. Stiller, "Vehicle Detection and Classification Using Deep Learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 3, pp. 1717–1726, 2021.

[11] A. Rosebrock, "Practical OpenCV for Computer Vision Applications," *IEEE Software*, vol. 37, no. 2, pp. 95–98, 2020.

[12] D. Zhang, K. Huang, and T. Tan, "Comparison of Traffic Monitoring Algorithms Based on Video Surveillance," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 8, pp. 3054–3065, 2019.

[13] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2017.

[14] T. Gevers and A. W. M. Smeulders, "Color-Based Object Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 21, no. 12, pp. 1318–1332, 1999.

[15] H. Zhou, S. Xu, and Y. Wang, "Smart Traffic Monitoring System Using IoT and AI," *2022 IEEE International Conference on Smart Cities*, pp. 112–118, 2022.

[16] M. Abdi and S. Jamshidi, "Real-Time ANPR System Using Deep Learning," *2020 International Conference on Image Processing and Machine Vision*, pp. 45–50, 2020.

[17] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, vol. 521, pp. 436–444, 2015.

[18] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Advances in Neural Information Processing Systems*, pp. 1097–1105, 2012.

[19] A. G. Borsuk and M. W. Lindner, "Intelligent Transportation Systems Using AI-Based Vision Techniques," *IEEE Access*, vol. 10, pp. 66721–66735, 2022.