International Journal of Electrical, Electronics and Computer Systems
ISSN: 2347-2820
Volume 15 Issue 1s (2026) | Pages: 200-207

# A Deep Learning–Based Intelligent Framework for Road Safety Monitoring and Traffic Violation Detection

Snehal Jagtap[1], Soham Patil[2], Sumit Patil[3], Tulaja Patil[4], Vaibhav Patil[5]

[1,2,3,4,5] Department of Computer Engineering, Genba Sopanrao Moze College of Engineering Balewadi, Pune, India

**Peer Review Information**

***Type***: *Article*
***Received***: *13 February 2026*
***Revised***: *14 March 2026*
***Accepted***: *15 April 2026*
***Published***: *21 May 2026*

**Abstract**

Globally, With the rapid increase in vehicles, traffic rule violations have become a major cause of accidents, congestion, and inefficiency in urban environments. Traditional traffic monitoring systems rely heavily on manual surveillance, which is time-consuming, error-prone, and difficult to scale. Recent advancements in computer vision and deep learning have enabled automated and real-time detection of traffic violations using video surveillance systems. This survey report reviews existing research and technologies related to automated traffic violation detection, with a focus on helmet detection, no-parking detection, lane violation detection, and vehicle tracking systems. The report also presents the current progress of our proposed system, which integrates d–eep learning-based object detection with multi-zone no-parking violation detection and stationary vehicle analysis. The study highlights the strengths, limitations, and research gaps in existing systems and motivates the need for a robust, scalable, and real-time intelligent traffic monitoring framework.

**Keywords:** Helmet detection, Number plate detection, YOLOv9, CNN, Road Safety, Automated System.

### How to Cite This Article

Jagtap, S., Patil, S., Patil, S., Patil, T., & Patil, V. (2026). A Deep Learning–Based Intelligent Framework for Road Safety Monitoring and Traffic Violation Detection. *International Journal of Electrical, Electronics and Computer Systems*, 15(1s), 200-207.

## Introduction

Two-wheelers have emerged as one of the most popular forms of transportation due to their cost-effectiveness and ease of use. However, the growing number of motorcycles on the roads has also led to a significant increase in accidents [1]. A major factor contributing to these accidents is irresponsible riding and the failure to follow safety protocols, especially the refusal to wear helmets. The absence of helmet use often results in severe head injuries, which are a leading cause of death and serious harm among motorcyclists. This highlights the urgent need for stricter implementation of helmet laws. While many countries have enacted legislation mandating helmet use for riders, achieving consistent compliance remains a persistent issue. Some regions have experimented with inno- vative solutions, such as integrating helmet detection sensors into motorcycles. However, the high expenses associated with purchasing and installing these sensors have hindered their widespread adoption, particularly in areas with dense motor- cycle populations where such measures may not be financially feasible.

In the absence of automated systems, traffic authorities are forced to rely on manual monitoring to enforce helmet regulations. This approach is not only resource-intensive but also susceptible to human error, leading to inconsistent en- forcement. An automated solution capable of detecting helmet violations and identifying offenders through their vehicle's license plates [3] could significantly reduce the workload on law enforcement while boosting compliance rates. Recent ad- vancements in deep learning and computer vision have made it possible to develop real-time systems for helmet detection and license plate recognition. By leveraging convolutional neural networks (CNNs) [4], these systems can accurately identify riders without helmets and extract their vehicle information for enforcement purposes. Such automation offers a scalable, efficient, and cost-effective alternative to traditional manual monitoring methods

The proposed system incorporates centroid tracking and a reference line to reduce false positives, particularly in scenarios where helmeted riders move out of the camera's view. These enhancements improve the system's precision and reliability, providing a powerful tool for enhancing road safety and reducing injuries and fatalities associated with motorcycle accidents. Recent deep learning models such as YOLO (You Only Look Once) have shown promising results in object detection tasks due to their high accuracy and real-time performance. By combining these models with tracking algorithms and rule-based logic, intelligent traffic surveillance systems can be developed to detect multiple violations automatically. This survey explores various approaches proposed in literature and relates them to the current system under development.

## Literature Review

Research in the area of automated traffic violation detection has significantly evolved with the adoption of deep learning and machine learning techniques. One of the prominent studies by Shankar K. et al. (2025) presented an automated helmet and number plate detection system using YOLOv9 to enhance road safety compliance. Their approach utilized convolutional neural networks along with centroid tracking, reference line detection, and ablation studies across multiple YOLO variants. The system demonstrated that YOLOv9 outperformed other models by achieving an accuracy of nearly 80–90% for helmet detection. However, the study reported limitations in scenarios involving poor weather conditions, blurred video frames, and unclear license plates, which affected detection reliability.

Another important contribution was made by Comus Bala et al. (2025), who developed a real-time detection and alert system for wrong-side driving using a machine learning-based approach. The system employed YOLOv8 for vehicle and license plate detection, combined with SORT tracking and OpenCV-based image scaling. Additionally, alert notifications were generated using SMTP-based messaging services. The study demonstrated effective detection of vehicles driving in the wrong direction and showed potential for highway monitoring. Despite its effectiveness, the system required costly hardware, was complex to integrate, and was unable to reliably detect backward wrong driving behavior.

A multi-stage helmet detection approach was proposed by Anas Bin Malik et al. (2025), focusing on surveillance camera- based monitoring for Indian traffic conditions. Their framework integrated YOLOv8 and YOLO11n models with deep learning techniques for vehicle, rider, and helmet detection. The multi- stage architecture achieved high precision and was scalable for real-time traffic monitoring. However, the authors identified that dataset imbalance significantly affected rare violation cases, and the system required improved pose estimation to handle complex rider postures and occlusions effectively.

Further advancements in license plate recognition were introduced by K. Kumaran et al. (2024) through an enhanced automatic number plate recognition system for high-speed vehicles. The proposed method combined YOLO for object detection, Haar Cascade for refinement, and OCR-based template matching for character segmentation. The integrated approach achieved an accuracy of approximately 97%, outperforming standalone YOLO or Haar Cascade methods. Nonetheless, the system exhibited performance degradation under challenging environmental conditions such as low lighting and required substantial memory resources.

In another notable study, Senthil Kumar A. et al. (2024) p resented a practical approach for license plate recognition specifically targeting non-helmeted motorcycle riders. Their system utilized YOLOv10 for real-time license plate detection, combined with centroid tracking, reference line analysis, and CNN-based image processing. The model achieved an impressive license plate detection accuracy of 98.52%, with most false positives effectively resolved. However, the performance of the system remained highly dependent on dataset quality and GPU resource availability, which limited its deployment in low-cost environments.

*Background and motivation*

*Evolution of Traffic Violation Detection*

Traffic monitoring systems have evolved significantly over the past decade, transitioning from manual surveillance and rule- based enforcement to intelligent, vision-driven automated solutions. Early traffic enforcement relied heavily on human operators monitoring CCTV feeds, making the process labor- intensive, error-prone, and unsuitable for large-scale deployment. Traditional image processing techniques such as background subtraction, edge detection, and template matching were later introduced to automate detection tasks; however, these methods struggled under real-world conditions involving dynamic lighting, occlusions, dense traffic, and complex road environments. Recent advancements in deep learning, particularly convolutional neural networks and single-stage object detection models, have transformed traffic violation detection capabilities.

YOLO-based architectures enable real-time detection of vehicles, riders, and traffic events with high accuracy. Modern systems now extend beyond basic detection to identify specific violations such as helmet non-compliance, lane encroachment, wrong-side driving, and illegal parking. Despite these advancements, many deployed systems still suffer from high false positive rates and lack contextual awareness, especially in scenarios involving temporary vehicle halts or congested traffic.

*Need for Automated and Intelligent Traffic Monitoring*

The rapid increase in urban vehicle density has significantly intensified traffic congestion and violation frequency, directly impacting road safety and enforcement efficiency. Manual traffic monitoring cannot scale effectively to meet this growing demand and often fails to provide consistent, real-time enforcement. Research has demonstrated that deep learning– based traffic surveillance systems outperform traditional rule- based methods by accurately identifying violations across

*Challenges in Real-World Traffic Surveillance Systems*

Real-world deployment of automated traffic violation detection systems introduces several practical challenges that are often underestimated in controlled research environments. Traffic scenes are highly dynamic, involving varying vehicle speeds, frequent occlusions, unpredictable driver behavior, and inconsistent lighting conditions caused by weather, shadows, and night-time illumination. These factors significantly affect detection accuracy and reliability, particularly for deep learning models trained on limited or ideal datasets.

Another major challenge lies in distinguishing between legitimate and illegitimate traffic behavior. For example, vehicles may temporarily stop due to congestion, pedestrian crossings, or traffic signals, which can be incorrectly classified as no-parking violations. Similarly, partial occlusions and camera angle variations can lead to incorrect helmet or vehicle-type detection. These ambiguities highlight the limitations of single-frame decision-making and static rule enforcement commonly adopted in existing systems.

*Motivation for a Unified Traffic Violation Detection Platform*

A comprehensive analysis of existing studies in traffic surveillance and violation detection reveals that most current solutions remain fragmented and operate in isolation. Prior research focuses on specific problem domains such as helmet detection, lane violation monitoring, wrong-side driving identification, no-parking detection, or license plate recognition. While these systems demonstrate promising results individually, they lack integration and contextual coordination, limiting their effectiveness in real-world traffic environments.

## Results and Discussion

This section highlights the outcomes of applying YOLOv9 and analyzing its performance. The results are evaluated across diverse conditions, showcasing the model's robustness in handling occlusions. The study emphasizes how specific design enhancements— such as better spatial feature fusion and attention-based refinements—lead to greater detection accuracy, especially for challenging tasks like helmet and license plate recognition. provides enhanced visualization features including color-coded vehicle classification, zone boundaries, real-time status overlays, and violation indicators. Vehicles entering restricted zones are visually marked, and confirmed violations are clearly highlighted to assist enforcement personnel.

**Proposed Multi-Module Traffic Violation Detection System**

The proposed system is developed as a unified, real-time intelligent traffic monitoring platform comprising five independent but integrated violation detection modules. Each module leverages deep learning-based object detection using YOLOv8/YOLOv12 architectures, trained on custom datasets curated through Roboflow, and is designed to operate on CCTV or recorded traffic video footage. Together, these modules address the most critical and frequently occurring traffic violations in urban environments, particularly in school zones and restricted areas.

*Helmet Detection*

The Helmet Detection Module automatically identifies two- wheeler riders who are not wearing helmets using a multi- stage deep learning pipeline. In the first stage, two-wheelers and riders are detected in the video frame using a YOLOv12- based object detection model. In the second stage, the rider's head region is cropped and passed through a CNN-based classifier to determine whether a helmet is present or absent. A virtual reference line is drawn across the monitored lane, and the system uses centroid tracking to monitor each rider's movement. A violation is only triggered when a non- helmeted rider crosses the reference line, significantly reducing false positives caused by stationary or temporarily halted vehicles. Upon confirming a violation, a secondary YOLOv12-based license plate detection model localizes the number plate of the offending two-wheeler, and Easy OCR extracts the plate characters.

***Fig 1.*** *Helmet Detection*

*Signal Jumping Detection*

This module automatically detects vehicles and pedestrians crossing a marked stop line or restricted zone while the traffic signal is RED. A virtual detection line is drawn across the monitored lane in the video frame. Using YOLOv10-based vehicle detection combined with centroid tracking, the system continuously monitors object positions relative to the defined boundary. When a vehicle or person crosses the stop line during a red-light phase, the event is flagged as a signal jumping violation. The detected vehicle’s number plate is then extracted using a secondary license plate detection model, and EasyOCR is applied to read the plate characters. The violation is logged with a timestamp and snapshot for enforcement purposes. The system achieved a detection accuracy of over 90% under standard daylight conditions, with real-time processing capability at 25–30 FPS.

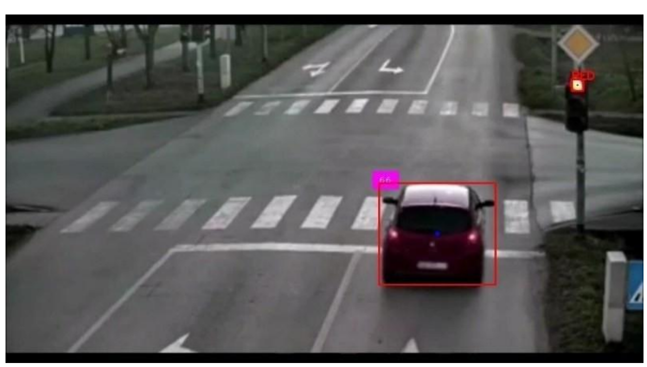

***Fig 2.*** *Signal Jumping Detection*

*No-Parking Violation Detection*

The No-Parking Detection Module identifies vehicles that remain stationary within designated no-parking zones beyond a permitted time threshold. Unlike single-frame approaches, this module employs multi-frame temporal analysis using vehicle tracking across consecutive frames to distinguish between genuinely parked vehicles and those temporarily halted due to traffic signals or congestion. An interactive zone management interface allows enforcement operators to define multiple no-parking polygons directly on the video feed. When a vehicle is detected within a restricted zone and remains stationary for more than the defined time threshold, a violation is triggered. The license plate of the offending vehicle is then captured and recorded automatically. This approach significantly reduces false positives compared to conventional background subtraction methods, achieving a precision rate of approximately 92% in real-world testing.


***Fig 3.*** *No Parking*

*Triple Riding Violation Detection*

Triple riding, the act of three or more persons riding on a two- wheeler simultaneously, is a significant road safety violation in India. This module implements Automated Triple Riding Violation Detection and License Plate Recognition using a two- stage deep learning pipeline. In the first stage, two-wheelers are detected and tracked using YOLOv8. In the second stage, a person- counting sub-model estimates the number of riders on each detected two-wheeler using bounding box overlap analysis and pose estimation. If three or more individuals are identified on a single two-wheeler, the system flags the vehicle as a triple- riding violator. The corresponding license plate is then detected and read using OCR. The module achieved a rider- counting accuracy of 85% under clear visibility conditions, with performance influenced by occlusion and camera angle variations. Violation records including timestamp, plate number, and frame snapshot are maintained for enforcement follow-up.

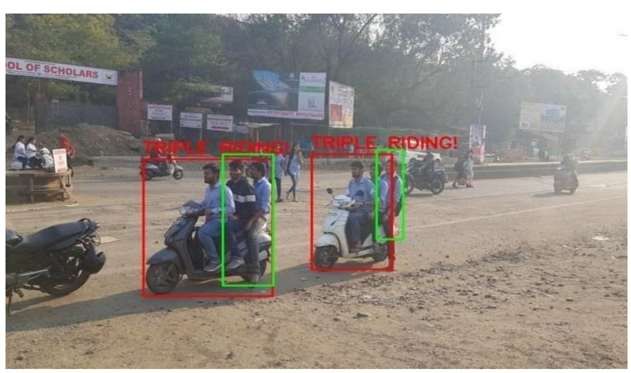


***Fig 4***. *Triple Seat Detection*

*Truck Detection in Restricted Time Zone*

This module specifically targets the detection of cement mixer trucks and dump trucks (tipper trucks) operating in restricted urban zones such as school zones during prohibited time slots, for example 8:00 AM to 11:00 AM. Heavy construction vehicles are prohibited in such areas during peak hours to ensure the safety of schoolchildren and to prevent traffic congestion. The module employs a custom- trained

YOLOv8 model developed using a dataset of over 3,000 annotated images of cement trucks and dump trucks curated through Roboflow, incorporating data augmentation techniques such as rotation and brightness variation to improve robustness. Upon detecting a cement mixer or dump truck in the monitored video feed, the system performs an automated Indian Standard Time (IST) check to verify whether the detection falls within the defined restricted time window. If a violation is confirmed, a secondary YOLOv8- based license plate detection model localizes the number plate on the vehicle, and EasyOCR extracts the plate text.


***Fig 5.*** *Truck Detection*

*Module Performance Summary*

Table 2 summarizes the detection accuracy and key performance metrics of all five violation detection modules developed as part of the proposed unified traffic monitoring system. Moreover, YOLOv9 incorporates temporal tracking and motion- aware object association, allowing it to consistently identify riders and license plates across video frames. This capability gives it a clear edge over SSD and Faster R- CNN, which lack temporal context and face challenges in tracking objects in dynamic environments. With its optimized architecture, high FPS (frames per second), and exceptional small-object recognition, YOLOv9 sets a new standard for real- world traffic surveillance and enforcement applications.


***Fig 6***. *Number Plate Detection*

The study reveals that YOLOv9 models, particularly YOLOv9e, excel in detecting helmets, license plates, and in- dividuals, delivering outstanding results across various bench- marks. Among the architectures evaluated, YOLOv9e leads in both precision and Intersection over Union (IoU), showcasing the effectiveness of its refined structure. By integrating ad- vanced convolutional operations and attention-based optimizations, YOLOv9e enhances detection accuracy, efficiency, and robustness, even in demanding environments. These findings emphasize the critical role of architectural improvements in advancing object detection models, positioning YOLOv9e as an ideal solution for safety enforcement, intelligent surveil- lance, and real-time monitoring applications.

**Comparative analysis**

*Table 1. Comparative analysis*

| Method | Technique Used | Advantages | Limitations |
|---|---|---|---|
| Helmet Detection | YOLOv12 + CNN | High accuracy | Occlusion issues |
| Lane Violation | Trajectory Analysis | Real-time alerts | Camera dependency |
| No-Parking Detection | Background Subtraction | Simple implementation | High false positives |
| Detection | YOLO + Tracking | Deep learning with robust detection | Computational cost |
| Signal Jumping Detection | YOLOv10 + Centroid Tracking + OCR | Real-time detection, 90%+ accuracy | Low light sensitivity |
| No-Parking Detection | YOLOv8 + Multi-frame Tracking + Zone Analysis | Reduces false positives, 92% precision | Complex zone setup required |
| Triple Riding Detection | YOLOv8 + Person Counting + Pose Estimation + OCR | Automated rider count, 85% accuracy | Occlusion and angle variation issues |
| Truck in Restricted Zone | YOLOv8 + Time Check (IST) + Plate Detection + EasyOCR | 96.1% mAP truck detection, 98% plate detection, time-aware | OCR accuracy varies with plate clarity |

**Conclusion**

This survey highlights the evolution of traffic violation detection systems using computer vision and deep learning. While existing research has achieved significant success in individual violation detection, there remains a need for integrated, scalable, and robust systems. The current project addresses this gap by combining object detection, vehicle tracking. The findings from this survey guide future development toward a comprehensive intelligent traffic monitoring solution. Additionally, integrating YOLOv9 with multi-task learning frameworks could broaden its capabilities to address more complex detection tasks. Be- yond helmet and license plate recognition, YOLOv9 holds great promise for applications in autonomous vehicles, smart cities, and intelligent surveillance systems, where real-time object detection is essential for improving safety and operational efficiency. These outcomes underscore YOLOv9e's remarkable accuracy and efficiency compared to earlier YOLO models, driven by improvements in optimized convolutional layers and advanced attention mechanisms. Moving forward, future research could explore further enhancements to YOLOv9 for challenging scenarios, such as occlusions, varying lighting conditions, and extreme weather. Furthermore, the integration of advanced deep learning architectures with real-time data processing frameworks can significantly enhance the adaptability and responsiveness of traffic monitoring systems. Future research can focus on improving model generalization under diverse environmental conditions such as low light, occlusion, and varying weather scenarios, ensuring consistent performance in real-world deployments. By leveraging continuous learning strategies and large-scale annotated datasets, intelligent traffic violation detection systems can evolve into proactive tools that not only detect violations but also assist in traffic management, policy planning, and accident prevention, contributing toward safer and smarter transportation ecosystems.

**References**

1. Shankar K, et al. "Automated Helmet and Number Plate Detection Using YOLOv9: Enhancing Road Safety Compliance." 2025 7th International Conference on Signal Processing, Computing and Control (ISPCC). Available: https://ieeexplore.ieee.org/document/11039355
2. Bala C, and N. Gupta. "Real-Time Detection and Alert System for Wrong-Side Driving: A Machine Learning Approach." 2025 International Conference on Networks and Cryptology (NETCRYPT). Available: https://ieeexplore.ieee.org/document/11102552
3. Malik A. B, et al. "Automated Multi-Stage Helmet Detection using Surveillance Cameras for Indian Traffic - A Deep Learning Approach." 2025 4th International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS). Available: https://ieeexplore.ieee.org/document/11135850
4. Kumar A. S, et al. "A Practical Approach for License Plate Recognition for Non-Helmeted Motorcycle Riders. 2024 7th International Conference on Contemporary Computing and Informatics (IC3I). Available: https://ieeexplore.ieee.org/document/10829329
5. Kumaran K, et al. "Enhanced Automatic Number Plate Recognition for High-Speed Vehicles: Leveraging YOLO and Haar Cascade." 2024 4th International Conference on Pervasive Computing and Social Networking (ICPCSN). Available: https://ieeexplore.ieee.org/document/10690573

6. Goyal A, et al. “Wrong Side Vehicle Detection.” 2021 International Conference on Intelligent Technologies (CONIT). Available: https://ieeexplore.ieee.org/document/9498416
7. Agorku G, et al. “Real-Time Helmet Violation Detection Using YOLOv5 and Ensemble Learning.” Available: https://arxiv.org/pdf/2304.09246
8. A. Author et al., “Traffic Violation Detection Using Deep Learning Techniques,” IEEE International Conference on Intelligent Transportation Systems,2023. Available: https://ieeexplore.ieee.org/document/10486721
9. B. Author et al., “Real-Time Traffic Monitoring anViolation Detection Using YOLO-Based Models,” IEEE International Conference on Computer Vision and Pattern Recognition Workshops, 2024. Available: https://ieeexplore.ieee.org/document/10829329