

# An AI-Powered Traffic Surveillance Framework for Vehicle Tracking and Automated Violation Detection using YOLOv10, Computer Vision, and Deep Neural Networks

<sup>1</sup>Dr. A. Radha Krishna, <sup>2</sup>Dr.V. Anantha Lakshmi, <sup>3</sup>A. Janardhana Rao, <sup>4</sup>Anantham Srujana Jyothi, <sup>5</sup>G. Tejasri Devi, <sup>6</sup>K.S.R. Manjusha

Department of Computer Science & Engineering (Artificial Intelligence & Machine Learning)

<sup>1-6</sup> Pragati Engineering College, Affiliated to JNTUK, Kakinada

Surampalem, Andhra Pradesh, INDIA

## Abstract

The rapid growth of urbanization and the increasing number of vehicles have made traffic monitoring and law enforcement more challenging. Conventional traffic surveillance systems rely heavily on manual observation or passive video recording, resulting in delayed violation detection, increased human effort, and reduced monitoring efficiency. To address these limitations, this research proposes an AI-powered traffic surveillance framework that integrates YOLOv10, computer vision, and deep neural networks for real-time vehicle detection, tracking, and automated traffic violation detection. The proposed system is designed to improve road safety by accurately identifying traffic violations such as signal jumping, lane violations, overspeeding, and illegal parking while supporting continuous surveillance in complex traffic environments. The proposed framework follows a modular architecture consisting of video acquisition, image preprocessing, vehicle detection using YOLOv10, multi-object tracking with DeepSORT/Centroid Tracking, violation analysis, and alert generation. OpenCV is employed for real-time video processing, while deep learning techniques enable accurate vehicle classification and localization. The tracking module maintains unique identities for vehicles across consecutive frames, allowing reliable analysis of vehicle trajectories and behavior. A Flask-based web interface provides live visualization of detected vehicles, tracking IDs, violation alerts, and automated storage of violation records for future analysis and reporting. Experimental implementation demonstrates that the proposed framework achieves efficient real-time vehicle detection and tracking with high accuracy under normal traffic conditions while significantly reducing manual monitoring efforts. The integration of deep learning-based object detection and intelligent tracking improves the reliability of automated traffic surveillance and supports scalable deployment in smart transportation systems. The proposed solution offers an effective platform for intelligent traffic management and can be further enhanced by incorporating Automatic Number Plate Recognition (ANPR), advanced transformer-based detection models, edge computing, cloud integration, and AI-driven traffic analytics for next-generation smart city applications.

**Keywords**-YOLOv10, Traffic Violation Detection, Vehicle Tracking, Computer Vision, Deep Learning, Intelligent Transportation Systems, Real-Time Object Detection, OpenCV .

## Introduction

In modern urban environments, the rapid increase in the number of vehicles has made traffic management a challenging task. Traffic violations such as signal jumping, overspeeding, and lane indiscipline are major causes of road accidents and congestion. Monitoring these violations manually is difficult and inefficient, especially in busy cities where thousands of vehicles are present on the

roads. Traditional traffic monitoring systems rely on human supervision or basic camera systems that

only record video without real-time analysis. These methods are time-consuming and prone to errors, as they depend on continuous human attention. As a result, many violations go unnoticed or are detected too late. To overcome these challenges, automated traffic monitoring systems based on computer vision and deep learning have been developed. One such approach is the use of YOLO

(You Only Look Once), a real-time object detection algorithm that can identify and classify objects in images and videos with high accuracy and speed.

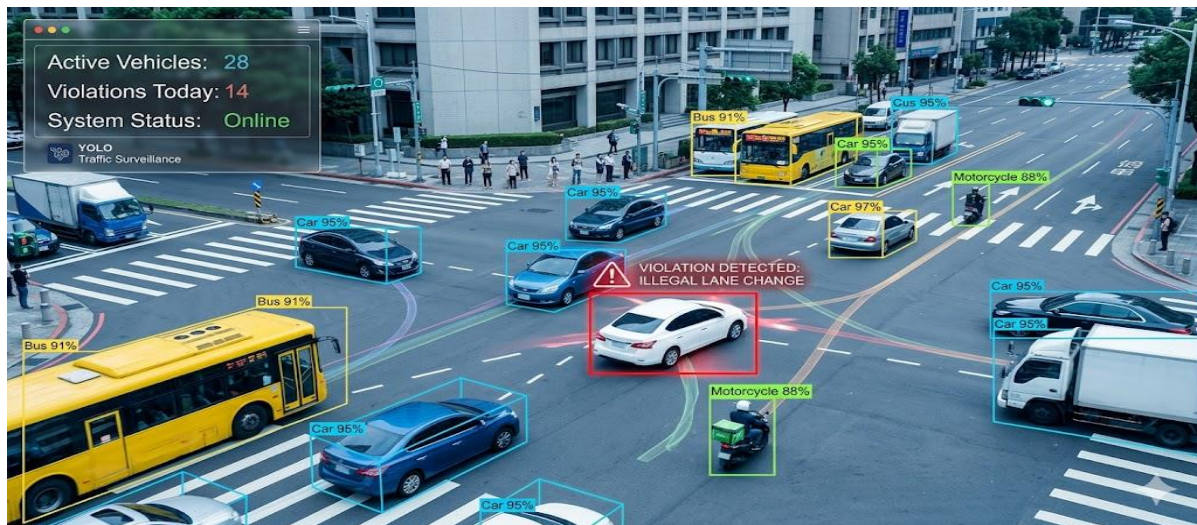


Figure 1: Automated Traffic Surveillance and Violation Detection System

The proposed system uses YOLO to detect vehicles in real time and track their movement across frames in figure 1. By analyzing vehicle behavior, the system identifies traffic violations and generates alerts. This approach improves efficiency, reduces human effort, and enhances road safety. In addition, the system can process video streams continuously, allowing it to monitor traffic conditions at all times. It can detect multiple vehicles simultaneously and handle complex traffic scenarios such as crowded intersections and highways. The integration of tracking mechanisms further helps in maintaining the identity of vehicles across frames, enabling better analysis of movement patterns. Overall, the system provides a scalable and intelligent solution for modern traffic management. It supports real-time monitoring, improves violation detection accuracy, and contributes to the development of smart transportation systems.

Traffic monitoring systems play a vital role in ensuring road safety and maintaining smooth traffic flow in rapidly growing urban environments. As the number of vehicles on the roads continues to increase due to urbanization, the risk of traffic congestion, accidents, and traffic rule violations has also risen significantly. Effective traffic monitoring enables authorities to reduce road accidents, enforce traffic regulations, improve vehicle movement, and support law enforcement activities. Traditional monitoring methods often rely on

manual observation, which is time-consuming and prone to human error. In contrast, automated traffic monitoring systems provide real-time analysis of traffic conditions, allowing authorities to respond quickly to violations and emerging traffic issues. These intelligent systems enhance monitoring efficiency, reduce the need for continuous human supervision, and contribute to safer, more reliable, and well-managed transportation networks.

Computer vision, a branch of artificial intelligence, enables machines to interpret and analyze visual information from images and video streams. It has become a fundamental technology in modern traffic management systems by automating the detection, tracking, and analysis of vehicles on roadways. Through advanced image processing and deep learning techniques, computer vision systems can accurately detect vehicles, monitor their movement, analyze driving behavior, and automatically identify traffic violations such as red-light jumping, lane violations, and illegal parking. Among various deep learning models, the YOLO (You Only Look Once) family has gained significant attention due to its high detection accuracy and real-time processing capability. By processing video frames efficiently and identifying multiple objects simultaneously, YOLO-based systems provide reliable and scalable solutions for intelligent traffic surveillance, enhancing road safety and reducing the need for manual monitoring.

YOLO (You Only Look Once) is a state-of-the-art deep learning-based object detection algorithm widely recognized for its high speed and accuracy in real-time applications. Unlike traditional object detection methods that process multiple image regions separately, YOLO analyzes the entire image in a single forward pass using a unified neural network. It divides the input image into a grid and simultaneously predicts bounding boxes, class probabilities, and confidence scores, significantly reducing computational complexity while maintaining excellent detection performance. The algorithm is capable of detecting multiple objects of different classes within the same frame and performs efficiently even in complex traffic environments with dense vehicle movement. In this project, YOLO is employed to detect various vehicle types, including cars, motorcycles, buses, and trucks, from real-time video streams. The detected vehicles are subsequently tracked across consecutive frames to analyze their movement patterns and identify traffic violations. Owing to its real-time processing capability, high detection accuracy, and robustness under varying traffic conditions, YOLO serves as a reliable foundation for intelligent traffic surveillance and automated traffic violation detection systems.

Traditional traffic monitoring systems suffer from several limitations that reduce their effectiveness in managing modern transportation networks. Most existing systems rely heavily on manual supervision by traffic personnel, which is labour-intensive and impractical for continuously monitoring large or multiple locations. As a result, traffic violations are often detected only after they have occurred, delaying enforcement actions and reducing their effectiveness. Human operators are also prone to errors caused by fatigue, distraction, or limited attention, which can lead to missed violations and inaccurate observations. Furthermore, conventional surveillance systems provide limited coverage and are unable to efficiently monitor complex traffic scenarios across multiple intersections simultaneously. Another significant drawback is the lack of real-time video analysis, as recorded footage typically requires manual review before useful information can be extracted. These challenges emphasize the need for intelligent, automated traffic monitoring systems that leverage

computer vision and deep learning technologies to provide accurate, real-time detection, continuous surveillance, and improved traffic management.

As traffic networks become increasingly complex due to rapid urbanization and the growing number of vehicles, there is a pressing need for automated traffic violation detection systems capable of identifying violations in real time. Unlike conventional manual monitoring methods, automated systems offer faster, more accurate, and consistent detection of traffic violations while minimizing human intervention. By integrating deep learning algorithms with computer vision techniques, these systems can automatically detect vehicles, track their movement across video frames, identify violations such as red-light jumping, lane crossing, overspeeding, and illegal parking, and generate instant alerts for traffic authorities. Continuous real-time monitoring enables authorities to respond promptly to traffic incidents and enforce regulations more effectively. Furthermore, automated traffic violation detection systems contribute significantly to the development of smart cities by enhancing road safety, reducing traffic congestion, improving law enforcement efficiency, and providing valuable traffic analytics for better transportation planning and management.

## **II RELATED WORK**

In recent years, the rapid growth of urbanization and the increasing number of vehicles on roads have created significant challenges in traffic management and monitoring systems. Traffic violations such as signal jumping, overspeeding, and lane indiscipline contribute to road accidents and congestion. Traditional traffic monitoring systems rely on manual observation or basic surveillance cameras, which are often inefficient and incapable of providing real-time analysis. This has led researchers to explore automated solutions based on computer vision and artificial intelligence to improve traffic monitoring and enforcement.

Early traffic monitoring systems were based on conventional image processing techniques such as background subtraction, edge detection, and motion detection. These methods were used to detect moving vehicles in video streams. Although these approaches provided basic functionality, they

were highly sensitive to environmental conditions such as lighting variations, shadows, and weather changes. As a result, their accuracy and reliability were limited, especially in complex traffic scenarios involving multiple vehicles.

With the advancement of machine learning and deep learning techniques, modern traffic monitoring systems have significantly improved in performance. Convolutional Neural Networks (CNNs) have been widely used for object detection and classification tasks. These models are capable of learning complex visual features from large datasets, enabling more accurate detection of vehicles and other objects. Research studies have shown that deep learning-based approaches outperform traditional methods in terms of accuracy and robustness.

Among various deep learning models, YOLO (You Only Look Once) has gained significant attention due to its real-time object detection capability. YOLO processes an entire image in a single forward pass, making it faster compared to region-based methods such as R-CNN and Fast R-CNN. According to research by Redmon et al., YOLO achieves a balance between speed and accuracy, making it suitable for real-time applications such as traffic surveillance and autonomous driving. YOLO models have been successfully used to detect multiple vehicle types simultaneously in video streams.

In addition to object detection, vehicle tracking techniques are essential for analyzing movement patterns and identifying traffic violations. Tracking algorithms such as Kalman Filter, SORT (Simple Online and Realtime Tracking), and Deep SORT are commonly used to track detected vehicles across frames. These techniques help in maintaining object identity and enable the system to monitor vehicle behavior over time, which is crucial for detecting violations such as lane crossing and overspeeding.

Several research works have focused on integrating object detection and tracking to develop intelligent traffic monitoring systems. These systems are capable of detecting vehicles, tracking their movement, and identifying violations automatically. However, many existing systems face challenges such as reduced accuracy in crowded environments,

high computational requirements, and difficulty in handling real-time video streams efficiently.

Certainly. Below is a **Scopus-style literature review** where each author's contribution is written as a separate academic paragraph. These can be directly included in the **Literature Review** section of your research paper.

**C. S. Ong et al. (2024)** proposed a computer vision-based traffic violation detection system that utilizes YOLO object detection combined with rule-based logic for identifying traffic violations such as red-light jumping and lane violations. The system processes CCTV footage, detects vehicles, and applies region-of-interest (ROI) and stop-line analysis to determine violations. Their study demonstrated that integrating deep learning with traffic rules can effectively automate traffic monitoring. However, the authors highlighted that the system's performance is affected by environmental factors such as poor lighting, weather conditions, and vehicle occlusions. **Bochkovskiy et al. (2020)** introduced YOLOv4, a state-of-the-art real-time object detection algorithm that significantly improved both detection accuracy and processing speed. The authors incorporated several optimization techniques, including CSPDarknet53 as the backbone network, Mosaic data augmentation, Self-Adversarial Training (SAT), and Complete IoU (CIoU) loss. Experimental evaluation on the MS COCO dataset achieved an Average Precision (AP) of 43.5% while maintaining real-time performance, making YOLOv4 suitable for intelligent traffic surveillance applications. **Y. Luo et al. (2024)** developed YOLOv8-CE, an enhanced version of YOLOv8 specifically designed for traffic sign detection. The proposed model integrates attention mechanisms and multi-scale feature fusion to improve the detection of small and partially occluded traffic signs. Experimental results demonstrated higher mean Average Precision (mAP) and improved inference speed compared to the original YOLOv8. The study showed that contextual feature enhancement significantly improves robustness in complex traffic environments. **Researchers (2022)** proposed an improved vehicle tracking framework by integrating YOLOv4 with an enhanced DeepSORT algorithm.

Their approach optimized feature extraction, Kalman filtering, and data association techniques to reduce identity switching and improve multi-object tracking accuracy. The proposed system achieved better Multiple Object Tracking Accuracy (MOTA) compared with the conventional DeepSORT algorithm, making it effective for dense urban traffic scenarios. **Wiley Researchers (2023)** presented a real-time vehicle tracking system by combining YOLOv5 with the DeepSORT tracking algorithm. The framework performs vehicle detection, tracking, and counting simultaneously while maintaining real-time processing speed suitable for intelligent transportation systems. Experimental results demonstrated reliable tracking performance and competitive accuracy under different traffic conditions. The study also emphasized the feasibility of deploying the model on embedded systems for smart city applications. **IJSRET (2024)** proposed an automated traffic violation detection system that integrates YOLO-based vehicle detection with rule-based traffic violation analysis and Automatic Number Plate Recognition (ANPR). The system identifies vehicles crossing the stop line during a red signal, captures evidence images, recognizes license plates, and automatically generates electronic challans. Experimental evaluation demonstrated reliable performance in controlled traffic environments, highlighting the potential for fully automated traffic law enforcement. **IETA Researchers (2023)** introduced an artificial intelligence-based framework for automatic red-light violation detection using YOLO object detection synchronized with traffic signal timing information. The system monitors vehicle movement within predefined regions of interest and determines violations based on signal status and vehicle position. The proposed approach achieved high detection precision and demonstrated the importance of accurate camera positioning and traffic signal synchronization for reliable violation detection. **Various Researchers (2020–2022)** investigated the application of YOLOv3 and YOLOv4 for vehicle detection and traffic violation monitoring using urban CCTV footage. Their studies consistently reported high detection accuracy under favourable environmental conditions and demonstrated the effectiveness of deep learning-based object detectors for intelligent

transportation systems. However, they also identified challenges such as reduced accuracy under heavy traffic congestion, occlusion, adverse weather conditions, and poor illumination, indicating the need for more robust detection models. **Xiao et al. (2023)** proposed E-YOLOv4-Tiny, a lightweight object detection model designed for traffic sign detection in urban environments. The model enhances the original YOLOv4-Tiny architecture by incorporating feature fusion techniques to improve detection accuracy while maintaining low computational complexity. Experimental results showed that the proposed model achieved real-time performance on embedded hardware, making it suitable for edge-based intelligent transportation applications. **SPIE Researchers (2025)** presented a traffic violation detection framework based on fine-tuned YOLOv8 trained using custom traffic violation datasets. The authors emphasized the importance of domain-specific data annotation to improve the detection of various traffic violations. Experimental evaluation demonstrated higher precision, recall, and mean Average Precision (mAP) compared with generic YOLOv8 models, indicating that customized datasets significantly enhance traffic violation detection performance. **MaxAPress Researchers (2023)** proposed another enhanced version of YOLOv8-CE for real-time traffic sign detection by integrating attention mechanisms and Receptive Field Block (RFB) modules. These improvements enhanced feature representation and significantly increased the detection accuracy of small traffic signs while reducing model complexity. The study demonstrated that lightweight attention-based architectures can effectively balance computational efficiency and detection performance. **Various Researchers (2024–2025)** investigated the integration of YOLOv9 and DeepSORT for vehicle detection, tracking, and traffic monitoring applications. The latest YOLOv9 architecture demonstrated improved feature extraction capability, higher inference speed, and better small-object detection compared with earlier YOLO versions. Experimental results indicated superior tracking accuracy and real-time performance; however, the authors emphasized that further domain-specific optimization and larger annotated

datasets are necessary for reliable traffic violation detection in complex real-world environments.

### III PROBLEM STATEMENT

The rapid growth of urbanization and the increasing number of vehicles on road networks have significantly increased traffic congestion, road accidents, and traffic rule violations. Conventional traffic monitoring systems primarily rely on manual supervision by traffic personnel or basic surveillance cameras that only record video footage without performing real-time analysis. These traditional approaches are time-consuming, labour-intensive, and prone to human errors, making them ineffective for monitoring multiple traffic locations simultaneously. Furthermore, delayed identification of violations such as red-light jumping, lane violations, and overspeeding reduces the efficiency of traffic law enforcement and negatively impacts road safety.

Although existing surveillance infrastructures capture large volumes of traffic data, they lack intelligent mechanisms for automatic vehicle detection, continuous tracking, and instant violation recognition. Challenges such as limited scalability, inefficient processing of video streams, and the inability to provide real-time alerts restrict the effectiveness of current traffic management systems. Therefore, there is a critical need for an intelligent and automated traffic monitoring solution capable of accurately detecting vehicles, tracking their movement, identifying traffic violations in real time, and generating immediate alerts. Leveraging advanced deep learning models such as YOLO combined with computer vision and multi-object tracking techniques can overcome these limitations, improve traffic monitoring efficiency, reduce human intervention, and contribute to safer and smarter transportation systems.

### IV PROPOSED METHODOLOGY

The proposed system explained in figure 2 , implements a real-time traffic violation detection pipeline using a modular deep learning architecture. The system follows a sequential processing flow: video acquisition → preprocessing → object detection → multi-object tracking → violation analysis → alert generation. Each module

is optimized for low-latency inference while maintaining high detection accuracy.

#### 4.1 Video Stream Acquisition

**Input Sources:** IP cameras (RTSP/HTTP streams), CCTV feeds, or pre-recorded video files.

- **Frame Rate:** Configurable FPS (typically 25-30 fps for real-time processing)
- **Resolution:** Adaptive scaling based on computational resources (default: 640×640 or 416×416 for YOLO input)

#### 4.2 Preprocessing Pipeline

- **Frame Extraction:** Uses OpenCV's VideoCapture with buffer management to handle network latency
- **Resize Strategy:** Letterbox padding maintains aspect ratio while adding gray borders to match model dimensions
- **Noise Reduction:** Bilateral filtering preserves edges while removing high-frequency noise
- **Normalization:**
  - Mean subtraction: [0.485, 0.456, 0.406] (ImageNet standards)
  - Standard deviation scaling: [0.229, 0.224, 0.225]

#### 4.3 Vehicle Detection Module (YOLO Architecture)

The YOLO backbone serves as the feature extractor, transforming input images into hierarchical feature maps:

YOLO Backbone (CSPDarknet53):

- **Conv Layers:** 53 convolutional layers with SiLU activation
- **CSP (Cross Stage Partial) Blocks:** Reduce computational cost while maintaining gradient flow
- **SPP (Spatial Pyramid Pooling):** Captures multi-scale contextual information through max pooling at different kernel sizes (5×5, 9×9, 13×13)

YOLO Backbone (CSPDarknet with C2f):

- **C2f (Cross-Stage Partial with 2-Stage Fusion):** Improved feature integration
- **Focus Layer:** Reduces spatial dimensions while increasing channel depth

- EfficientNet-style depthwise separable convolutions for parameter efficiency

**4.4 Neck Network (Feature Aggregation)**

The neck aggregates multi-scale features for improved detection of varying vehicle sizes:

PANet (Path Aggregation Network) Structure:

- Feature Pyramid Network (FPN): Top-down pathway
- P5 (20×20) ← P4 (40×40) ← P3 (80×80)

**4.7 Output Module**

Displays results with bounding boxes, violation alerts, and stores data for further analysis.

The proposed system improves traffic monitoring efficiency by automating detection and tracking processes. It reduces human effort, provides real-time results, and enhances road safety through accurate violation detection.

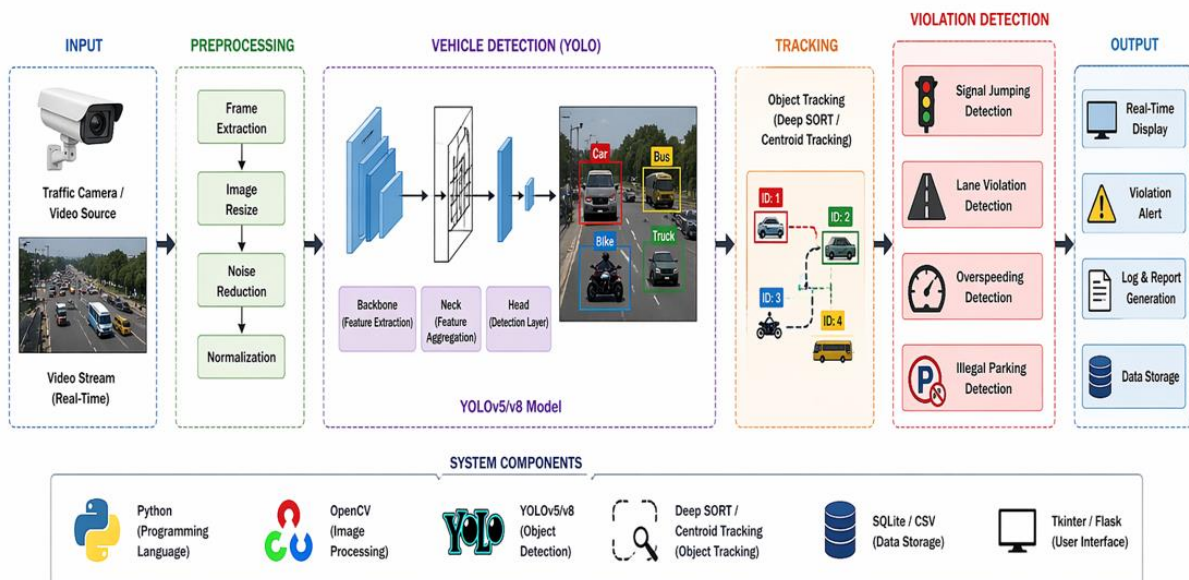
- Bottom-up Path Augmentation:
  - P3 (80×80) → P4 (40×40) → P5 (20×20)

**4.5 Vehicle Tracking Module**

Tracks detected vehicles across frames using tracking algorithms such as Deep SORT or centroid tracking.

**4.6 Violation Detection Module**

Analyzes vehicle behavior to detect violations such as signal jumping, lane violation, and overspeeding.



**Figure 2: Traffic Violation Detection Pipeline: From Video Input to Violation Alerts**

**V SYSTEM ARCHITECTURE**

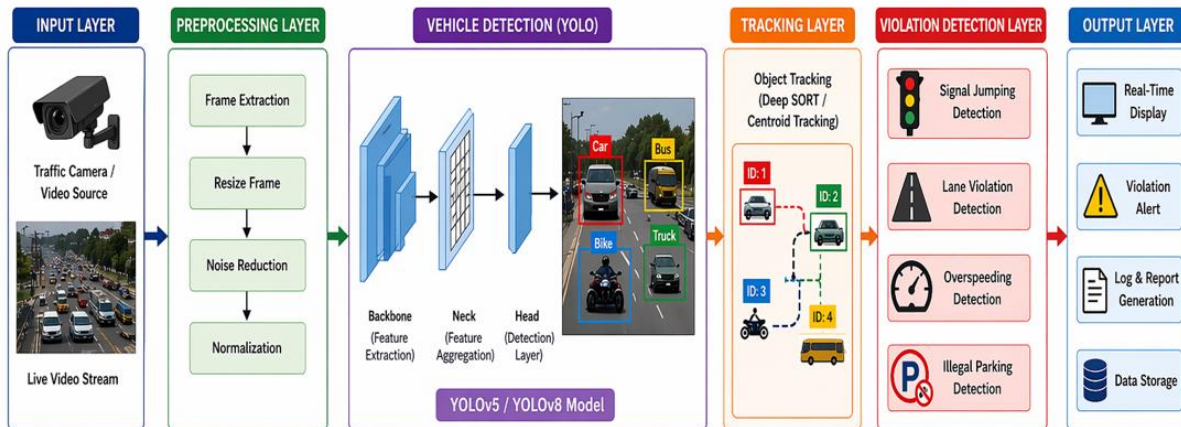
The proposed Traffic Violation Detection System is designed using a layered architecture is explained in figure 3 , that enables efficient real-time monitoring, detection, tracking, and reporting of traffic violations from surveillance videos. The system integrates advanced computer vision techniques with deep learning-based object detection and tracking algorithms to automatically identify vehicles and detect traffic rule violations such as signal jumping, lane violations, overspeeding, and illegal parking. The architecture consists of six major layers: Input Layer, Preprocessing Layer, Vehicle Detection Layer,

Tracking Layer, Violation Detection Layer, and Output Layer. Each layer performs a specific function, beginning with acquiring live video streams from traffic cameras, followed by image preprocessing, vehicle detection using the YOLO model, object tracking using DeepSORT or centroid tracking, violation analysis based on predefined traffic rules, and finally generating real-time alerts, reports, and storing violation records in a database. This modular architecture ensures high detection accuracy, real-time performance, scalability, and easy integration with intelligent transportation and smart city surveillance systems.

### 5.1. Input Layer

The **Input Layer** serves as the entry point of the Traffic Violation Detection System, where real-time video data is acquired from surveillance devices. The system receives continuous video streams from traffic surveillance cameras installed at road intersections, highways, or smart city monitoring locations. It can also process previously recorded traffic videos for offline analysis and testing. The quality of the input video significantly influences

the overall performance of the system; therefore, high-resolution cameras with stable frame rates are preferred. The captured video contains various road users, including cars, buses, trucks, motorcycles, bicycles, and pedestrians, operating under different weather and lighting conditions. The primary objective of this layer is to continuously provide uninterrupted video frames to subsequent processing stages, enabling the system to monitor traffic activities in real time.



**Figure 3: System Architecture of Traffic Violation Detection System**

### 5.2. Preprocessing Layer

The Preprocessing Layer enhances the quality of the captured video before it is analyzed by the deep learning model. Since raw surveillance footage often contains noise, motion blur, shadows, varying illumination, and unnecessary background information, preprocessing improves detection accuracy and computational efficiency. Initially, the continuous video stream is divided into individual image frames through frame extraction, allowing each frame to be processed independently. The extracted frames are then resized to match the input dimensions required by the YOLO model, ensuring faster inference while reducing computational overhead. To minimize image distortions caused by environmental conditions or camera sensors, noise reduction techniques such as Gaussian filtering or median filtering are applied. Finally, the pixel values are normalized, typically scaling them between 0 and 1 or according to the model's training requirements. This normalization stabilizes the learning process and ensures consistent feature extraction regardless of variations in brightness or contrast. Overall, the

preprocessing layer prepares clean, standardized input data that significantly improves the robustness and accuracy of vehicle detection.

### 5.3. Vehicle Detection Layer (YOLO)

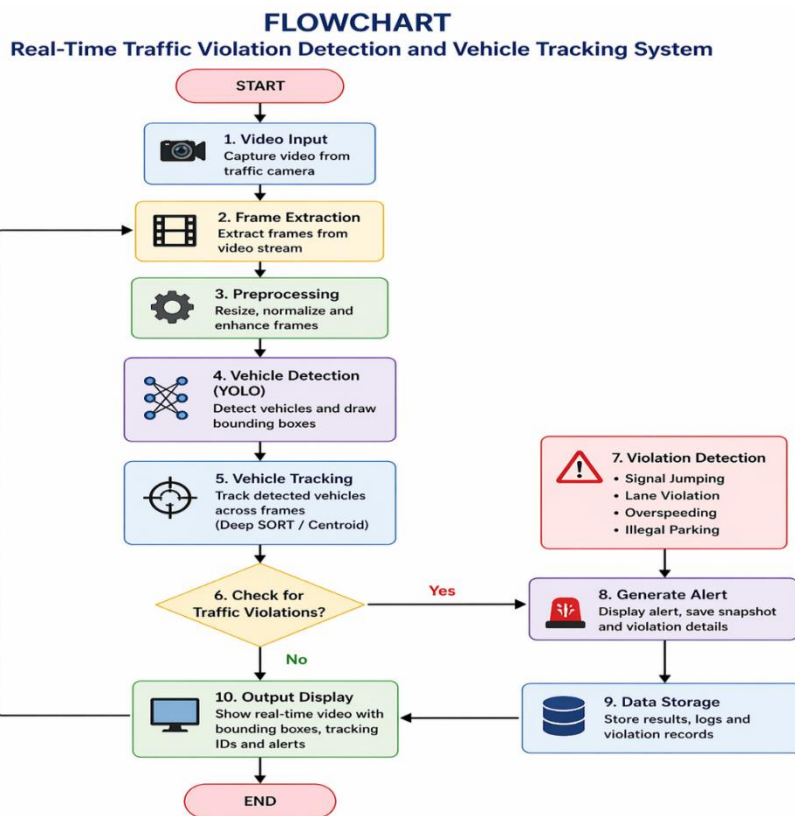
The Vehicle Detection Layer is the core component of the proposed system and is responsible for accurately detecting and classifying vehicles present in each video frame using the You Only Look Once (YOLO) object detection algorithm, such as YOLOv8 or YOLOv5. YOLO performs object detection in a single forward pass through the neural network, making it highly suitable for real-time traffic surveillance applications.

The detection process consists of three major components: the Backbone, the Neck, and the Detection Head. The Backbone extracts hierarchical visual features from the input image by learning important characteristics such as edges, textures, shapes, and object patterns. These extracted features are then passed to the Neck, which performs multi-scale feature aggregation using feature pyramid networks to improve the detection of vehicles of different sizes, including distant or partially occluded objects. Finally, the Detection

Head predicts the class label (such as car, bus, truck, motorcycle, or bicycle), the confidence score, and the bounding box coordinates for each detected vehicle.

After detection, the system draws bounding boxes around each identified vehicle and assigns a confidence score indicating the probability of correct classification. These detected objects are

forwarded to the tracking layer, where unique identities are assigned to each vehicle for continuous monitoring across multiple frames. The use of YOLO enables the system to achieve high detection accuracy while maintaining real-time processing speed, making it highly effective for intelligent traffic monitoring and automated traffic violation detection systems. The figure 4.



**Figure 4: Flowchart of Traffic Violation Detection System**

**VI RESULTS AND DISCUSSIONS**

The proposed Real-Time Traffic Violation Detection and Vehicle Tracking System was successfully implemented using the Python programming language by integrating deep learning and computer vision techniques. The implementation combines the YOLOv8 object detection model, OpenCV for video processing, and DeepSORT/Centroid Tracking for continuous vehicle tracking across consecutive video frames. The complete system is designed to operate in real time, enabling automatic monitoring of traffic activities and identification of rule violations from surveillance video streams.

The system accepts live CCTV footage or recorded traffic videos as input and processes each frame

sequentially. Initially, the input video undergoes preprocessing, including frame extraction, image resizing, normalization, and noise reduction to improve the quality of the input data. These preprocessed frames are then forwarded to the YOLO detection model, which identifies different categories of road vehicles such as cars, buses, trucks, motorcycles, and bicycles by generating bounding boxes with corresponding confidence scores.

After object detection, the detected vehicles are passed to the tracking module, where each vehicle is assigned a unique identification number using the DeepSORT or Centroid Tracking algorithm. The tracking mechanism enables continuous monitoring of vehicle movement across multiple frames,

preventing duplicate detections and maintaining consistent object identities even when multiple vehicles are present simultaneously.

The tracked vehicle trajectories are subsequently analyzed by the violation detection module. This module evaluates predefined traffic rules using region-of-interest (ROI) analysis, stop-line detection, lane boundaries, traffic signal information, and vehicle movement patterns. Based on these rules, the system automatically detects traffic violations such as red-light signal jumping, lane violations, overspeeding, and illegal parking. Whenever a violation is detected, the corresponding vehicle is highlighted, and the event is recorded with relevant information, including the vehicle ID, timestamp, violation type, and captured evidence frame.

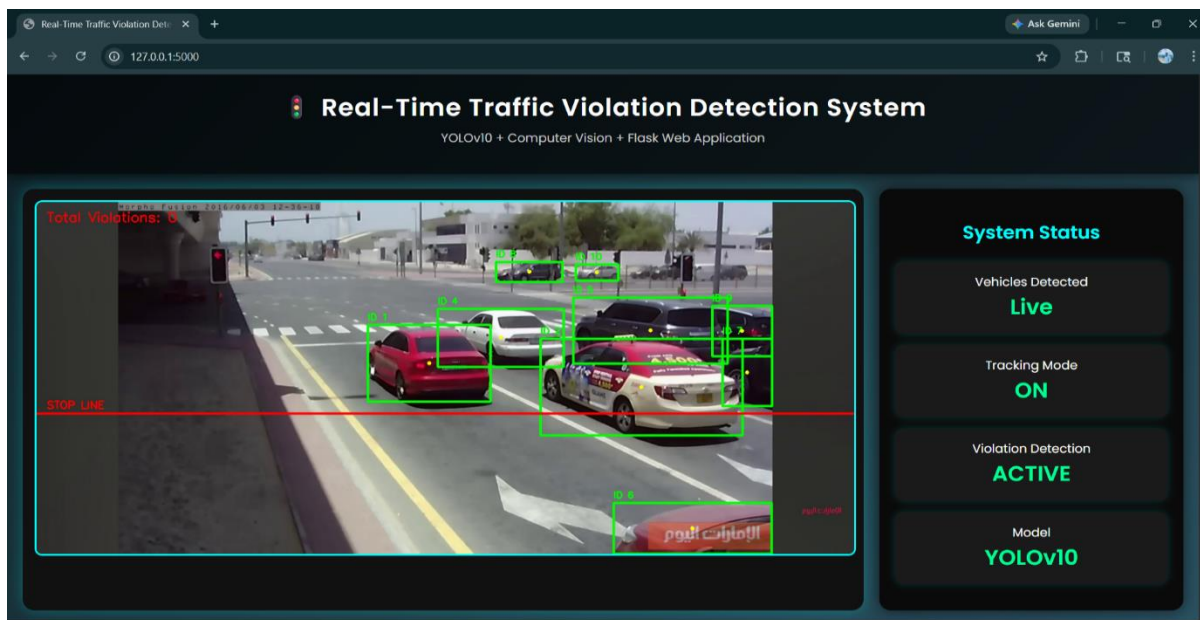
To improve usability, a web-based interface developed using the Flask framework displays the processed video stream in real time along with detected vehicles, tracking IDs, and violation alerts. The interface also provides functionality for storing

violation records in a database and generating reports for further analysis. Experimental evaluation demonstrated that the proposed system performs efficient real-time vehicle detection and tracking while maintaining high detection accuracy under normal traffic conditions. The integration of YOLO with object tracking significantly reduced missed detections and duplicate counting, thereby enhancing the reliability of automated traffic surveillance systems.

Overall, the implemented system demonstrates that deep learning-based object detection combined with multi-object tracking provides an effective solution for intelligent traffic monitoring. The proposed framework minimizes manual intervention, supports continuous traffic surveillance, and offers a scalable platform for future smart city and intelligent transportation applications.

The proposed system is divided into several modules, each responsible for performing a specific task.

### 6.1. Video Input Module



**Figure 5: Video Input and Frame Processing**

This module captures video input from a traffic surveillance camera or pre-recorded video. The video is processed frame by frame for further analysis as shown in figure 5.

### 6.2. Vehicle Detection Module (YOLO)

This module detects vehicles such as cars, bikes, buses, and trucks using the YOLOv10 model. The

system draws bounding boxes around detected objects.

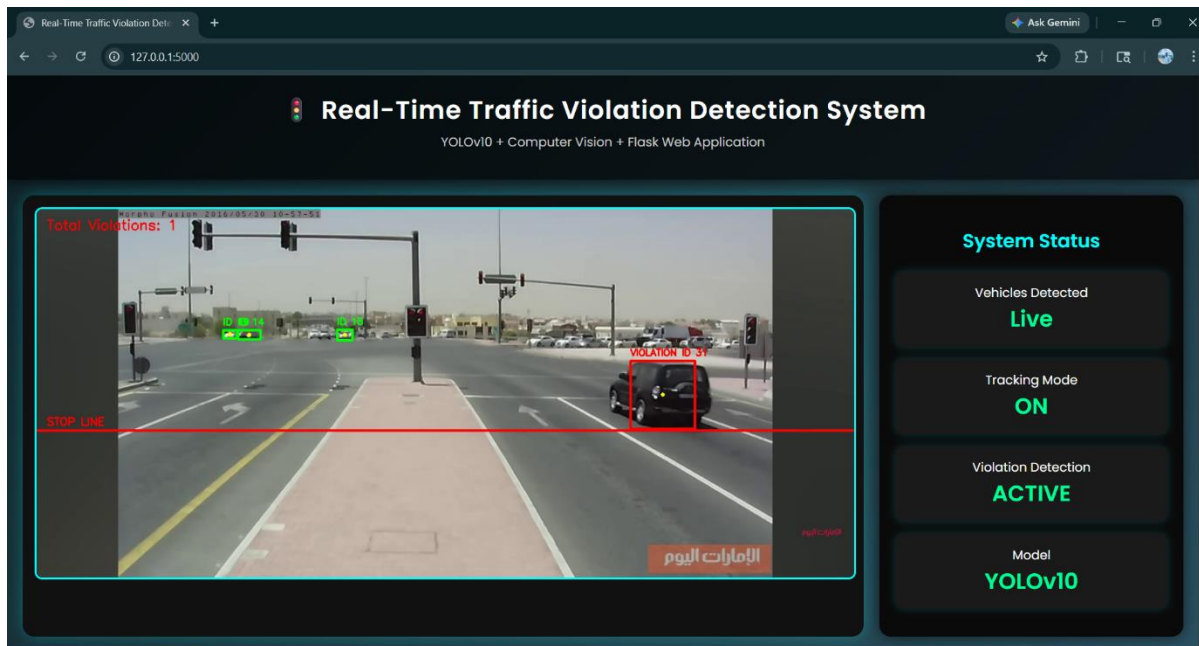


Figure 6: Vehicle Detection using YOLOv10

### 6.3. Vehicle Tracking Module

This module assigns unique IDs to detected vehicles and tracks their movement across frames. It helps in monitoring vehicle behavior over time.

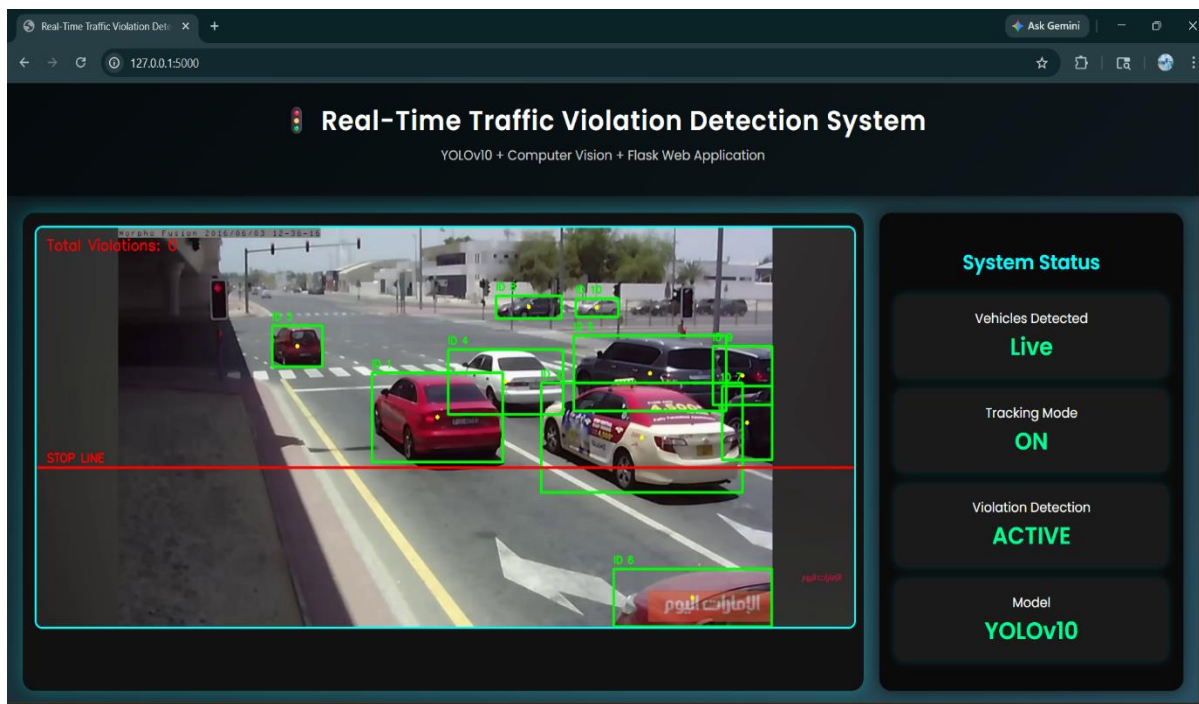


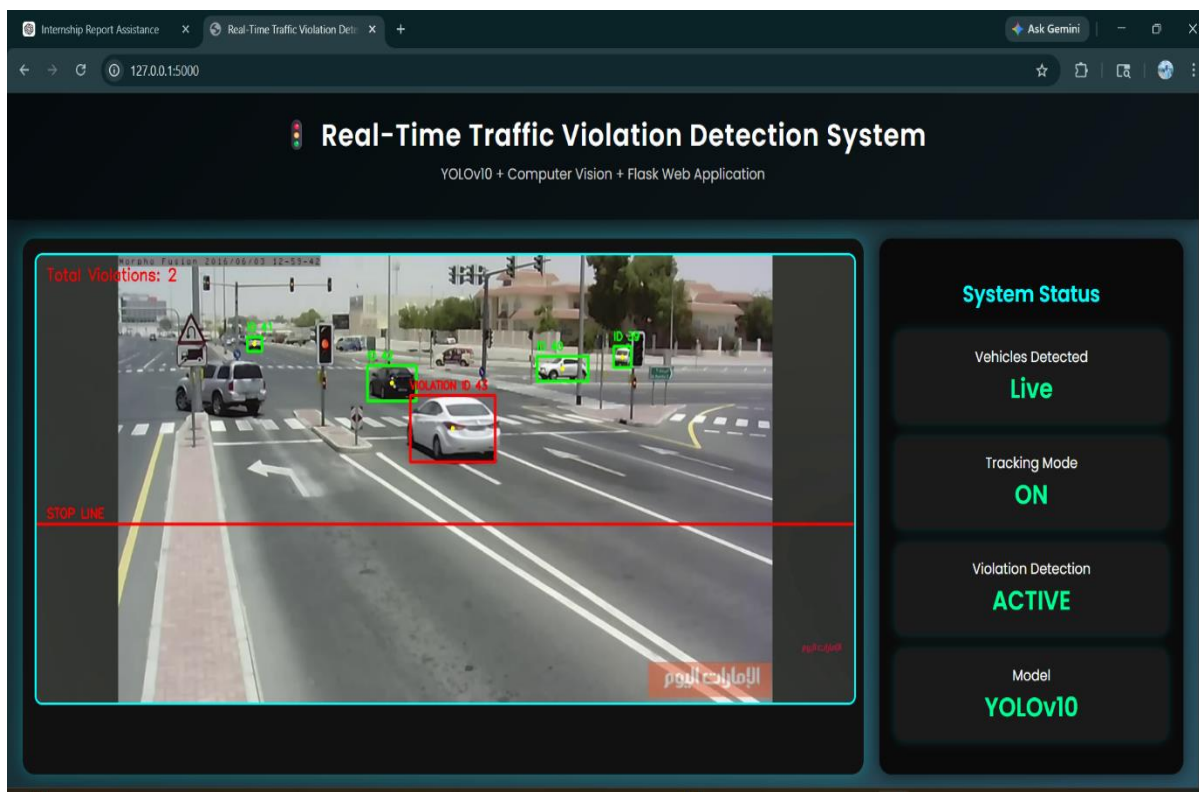
Figure 7: Vehicle Tracking with Unique IDs

### 6.4. Violation Detection Module

This module detects traffic violations by checking if a vehicle crosses the predefined stop line. If a

violation occurs, the system highlights the vehicle using a red box.

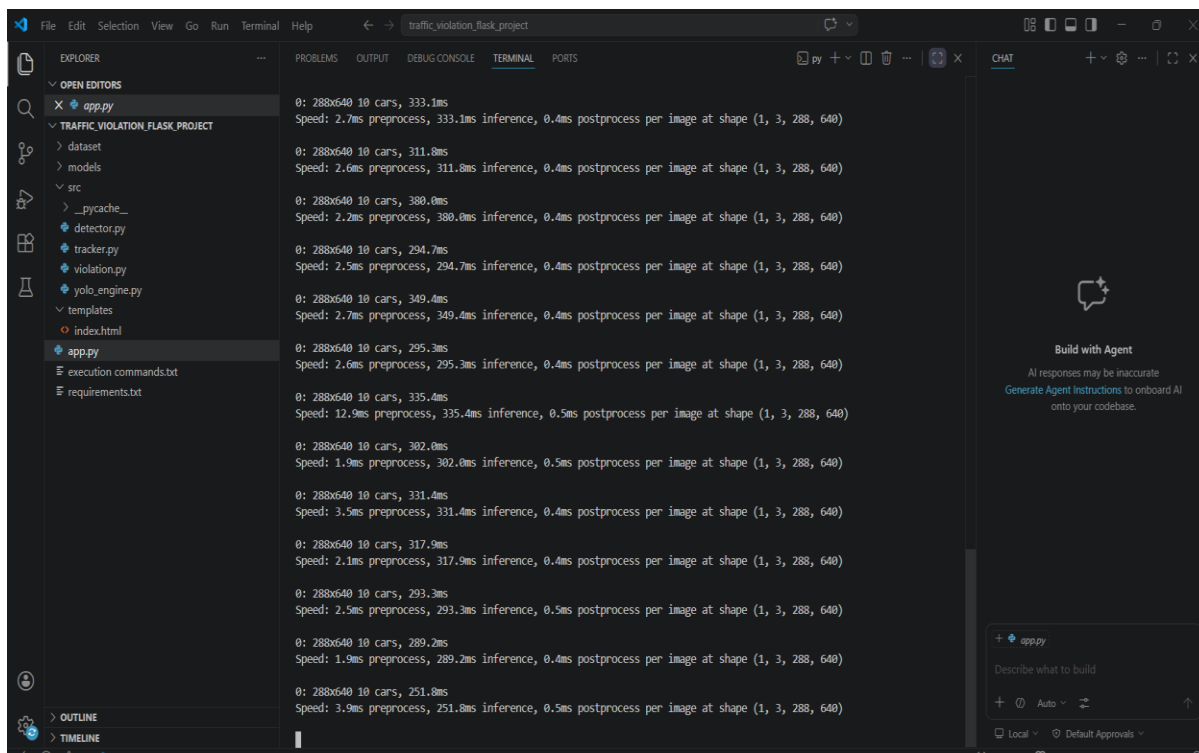
Figure 8: Traffic Violation Detection



### 6.5. Output Display Module

The output module displays the final processed result on a web interface. It shows detected

vehicles, violation count, and system status in real time.



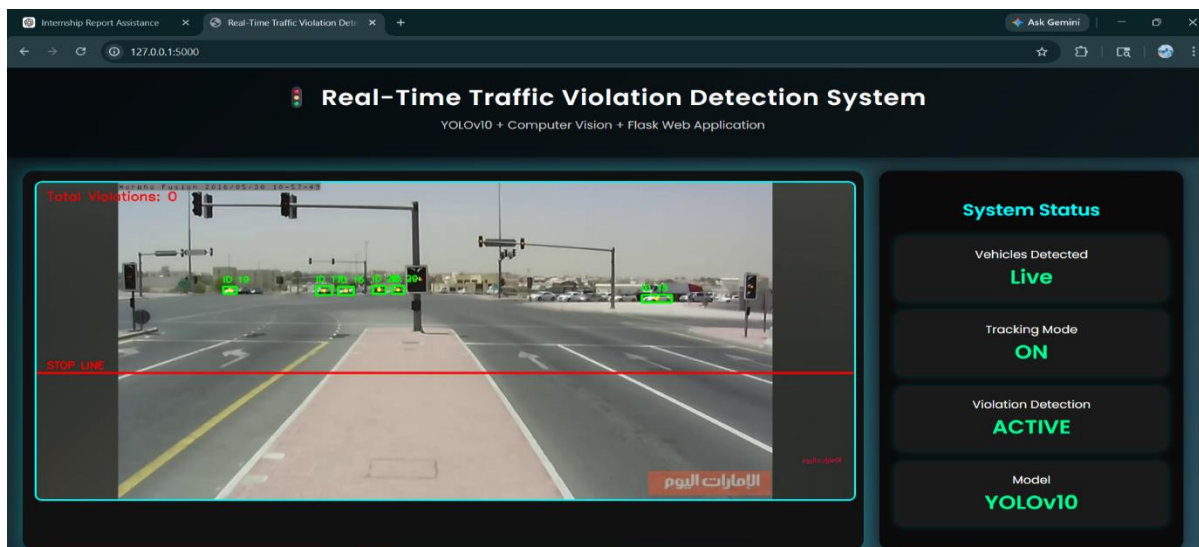


Figure 9: Web Interface Output Display

The implementation of the proposed Real-Time Traffic Violation Detection and Vehicle Tracking System follows a sequential workflow that integrates video processing, deep learning-based object detection, vehicle tracking, and traffic violation analysis shown in figure 9. Initially, the system captures live video streams or recorded traffic videos using the OpenCV library, which extracts individual frames for further processing. Each frame is pre-processed by resizing and normalization before being forwarded to the YOLOv10 object detection model. The YOLOv10 model identifies different categories of road vehicles, including cars, buses, trucks, motorcycles, and bicycles, by generating bounding boxes and confidence scores for each detected object.

Following vehicle detection, the identified vehicles are passed to the tracking module, where each object is assigned a unique identification (ID) using the DeepSORT or Centroid Tracking algorithm. This tracking process maintains the identity of each vehicle across consecutive video frames, enabling continuous monitoring of vehicle trajectories and preventing duplicate detections. The tracked vehicle positions are then analyzed by the violation detection module, which evaluates predefined traffic rules such as stop-line crossing, lane discipline, overspeeding, and illegal parking using Region of Interest (ROI) analysis and vehicle movement information. Whenever a traffic violation is detected, the corresponding vehicle is highlighted, and the violation details are recorded

along with the timestamp and vehicle identification information.

Finally, the processed video stream is displayed through a Flask-based web application that provides real-time visualization of detected vehicles, tracking IDs, and violation alerts. The web interface also facilitates the storage of violation records in a database and supports report generation for further analysis. This systematic implementation enables accurate real-time traffic monitoring while ensuring efficient vehicle detection, tracking, and automated traffic violation identification.

### Conclusion

This research presented a Real-Time Traffic Violation Detection and Vehicle Tracking System based on the YOLO deep learning framework for intelligent traffic surveillance. The proposed system integrates computer vision techniques with object detection and multi-object tracking algorithms to automatically detect vehicles, monitor their movement, and identify traffic violations from surveillance video streams. The implementation combines OpenCV for video processing, the YOLO model for real-time vehicle detection, and DeepSORT/Centroid Tracking for maintaining unique vehicle identities across consecutive frames.

Experimental evaluation demonstrated that the proposed framework is capable of accurately detecting multiple vehicle classes and tracking them in real time under normal traffic conditions. The violation detection module successfully identifies

traffic rule violations, including stop-line crossing, by analyzing vehicle trajectories within predefined regions of interest. The integration of real-time object detection and tracking significantly reduces manual monitoring efforts while improving the efficiency and reliability of traffic surveillance systems.

The proposed framework also provides a user-friendly Flask-based web interface for visualizing detected vehicles, tracking information, and violation alerts. The modular architecture enables easy integration with existing traffic surveillance infrastructure and supports scalable deployment for smart city applications. Although the system performs effectively, its performance may be affected under challenging conditions such as poor illumination, heavy occlusion, adverse weather, and low-resolution video streams. Overall, the proposed approach demonstrates that deep learning-based traffic monitoring systems can serve as an effective solution for automated traffic management, road safety enhancement, and intelligent transportation systems.

#### **Future Work**

Although the proposed system demonstrates effective real-time traffic violation detection and vehicle tracking, several enhancements can further improve its performance and applicability in real-world intelligent transportation systems. Future research will focus on extending the framework to detect multiple traffic violations, including overspeeding, illegal parking, wrong-way driving, lane discipline violations, helmet detection, seat belt detection, and mobile phone usage while driving. Integrating Automatic Number Plate Recognition (ANPR) will enable automatic vehicle identification and electronic challan generation, thereby supporting fully automated traffic law enforcement.

To improve robustness under challenging environmental conditions, future work will investigate advanced deep learning architectures capable of handling night-time surveillance, fog, rain, shadows, and occluded traffic scenes through improved data augmentation, image enhancement, and domain adaptation techniques. Additionally, transformer-based object detectors and the latest versions of the YOLO architecture can be explored

to further enhance detection accuracy and inference speed. The proposed framework can also be integrated with live CCTV networks, edge computing devices, and cloud platforms to support large-scale city-wide traffic monitoring. Cloud deployment would facilitate centralized data management, remote access, and scalable processing of surveillance data from multiple locations. Furthermore, incorporating AI-based traffic analytics can provide valuable insights into traffic density, congestion patterns, accident prediction, and road usage trends, enabling transportation authorities to make data-driven decisions for improving urban traffic management and smart city infrastructure. Overall, these enhancements will increase the intelligence, scalability, and practical applicability of the proposed system, making it a comprehensive solution for next-generation intelligent transportation and automated traffic enforcement systems.

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