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Deep Learning-Based Intelligent Traffic Violation Detection System Using YOLOv7

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Abstract- Traffic violations have become a major cause of road accidents and fatalities in many countries, particularly in densely populated urban areas. Common violations such as red-light jumping, triple riding on two-wheelers, and reckless driving significantly increase the risk of road accidents. Traditional traffic monitoring systems rely heavily on manual observation by traffic police or limited sensor-based systems, which are inefficient, time-consuming, and prone to human errors. To address these challenges, intelligent traffic monitoring solutions based on computer vision and deep learning have gained significant attention. This paper proposes a deep learning-based automated traffic violation detection system using the YOLOv7 object detection model. The proposed system processes video streams obtained from roadside surveillance cameras and analyses them frame-by-frame to detect different traffic violations. The YOLOv7 model is employed to identify vehicles and generate bounding boxes around detected objects. A predefined threshold line is used to determine whether a vehicle crosses the traffic signal during a red light, thereby identifying signal violations. Additionally, the system detects over boarding or triple riding on two-wheelers by analysing the number of riders detected within a single vehicle bounding box. The system uses publicly available datasets such as the MS COCO dataset for vehicle detection and a custom annotated dataset for over boarding detection. The model is trained and evaluated using performance metrics including precision, recall, F-measure, and mean Average Precision (mAP). Experimental results demonstrate that the proposed model effectively detects multiple traffic violations with high accuracy while maintaining efficient real-time performance. The proposed approach provides a cost-effective, automated, and scalable traffic monitoring solution that can assist traffic authorities in improving road safety and reducing the workload associated with manual monitoring systems. The system can be integrated with existing smart city surveillance infrastructures to enhance intelligent transportation management and law enforcement.

Keywords – Traffic Violation Detection, YOLOv7, Deep Learning, Computer Vision, Object Detection, Smart Traffic Monitoring, Surveillance Systems, Intelligent Transportation Systems.

I. INTRODUCTION

The rapid growth of urban populations and the increasing number of vehicles on roads have significantly contributed to traffic congestion and road safety challenges worldwide. Traffic rule violations such as red-light jumping, triple riding on two-wheelers, over speeding, and reckless driving are among the major causes of road accidents and fatalities. Road traffic accidents remain a serious public safety concern in many developing countries, where inadequate monitoring infrastructure and ineffective law enforcement mechanisms contribute to high accident rates and injuries [1]. Therefore, the development of intelligent traffic monitoring systems has become essential for improving road safety and enforcing traffic regulations.

Traditional traffic monitoring methods primarily rely on manual observation by traffic police officers or basic surveillance systems. Although these approaches can help identify traffic violations, they are often inefficient, time-consuming, and susceptible to human error. Continuous monitoring of multiple traffic intersections requires significant manpower and operational resources, making manual enforcement impractical for large-scale traffic management systems. Furthermore, human operators may fail to detect violations during peak traffic conditions or under unfavourable environmental situations such as poor lighting or adverse weather conditions [2].

With the advancement of artificial intelligence (AI) and computer vision technologies, automated traffic monitoring systems have emerged as promising solutions for improving traffic management and road safety. Computer vision techniques enable the automatic detection and analysis of vehicles from images or video streams captured by surveillance cameras. By applying machine learning and deep learning algorithms to traffic surveillance data, it becomes possible to detect vehicles, track their movements, and identify traffic violations in real time without human intervention [3], [6].

Deep learning-based object detection models have shown remarkable performance in visual recognition tasks. Among these models, the You Only Look Once (YOLO) family of algorithms has gained significant popularity due to its ability to perform real-time object detection with high accuracy and computational efficiency. YOLO-based models can detect multiple objects simultaneously within a single image frame, making them highly suitable for real-time video surveillance applications [7]. The latest version, YOLOv7, introduces significant improvements in detection speed and accuracy compared to previous object detection frameworks. YOLOv7 utilizes advanced training strategies and optimized architectures to achieve state-of-the-art performance in real-time object detection tasks [4], [12], [13].

Recent studies have demonstrated the effectiveness of deep learning techniques in detecting traffic rule violations. AI-based traffic monitoring systems can automatically detect events such as red-light violations, lane violations, and illegal vehicle movements from surveillance footage. Such intelligent monitoring frameworks help improve traffic law enforcement by enabling automatic violation detection and reducing dependence on manual monitoring [2], [17]. In addition, machine learning approaches have been applied to analyse traffic patterns and predict risky driving behaviours, further supporting intelligent transportation systems and highway safety management [10], [11].

In this research, an automated traffic violation detection system using YOLOv7 is proposed to detect multiple traffic violations from surveillance video streams. The proposed system processes video frames captured from traffic cameras and identifies vehicles using bounding box detection techniques. A predefined threshold line is used to detect red-light violations when vehicles cross the signal during restricted intervals. Furthermore, the system is capable of detecting over boarding or triple riding on two-wheelers by analysing the number of riders present on a single vehicle.

The primary objective of this study is to develop an intelligent and automated traffic monitoring system capable of detecting multiple traffic violations efficiently. By integrating deep learning-based object detection with real-time video processing techniques, the proposed system aims to reduce the workload on traffic authorities while improving road safety and law enforcement efficiency.

The remainder of this paper is organized as follows. Section II presents a review of related work on traffic violation detection and computer vision-based monitoring systems. Section III describes the system analysis and proposed architecture of the traffic violation detection framework. Section IV explains the system implementation and methodology used in the model development. Section V discusses the experimental results and performance evaluation. Finally, Section VI concludes the study and highlights potential future improvements for intelligent traffic monitoring systems.

II. LITERATURE SURVEY

Traffic violation detection has become a significant research topic in intelligent transportation systems (ITS) due to the increasing number of vehicles and the growing complexity of road traffic environments. Road traffic accidents caused by rule violations such as red-light jumping, reckless driving, and overloading have raised serious concerns for public safety and transportation management [1]. Traditional traffic monitoring systems mainly rely on manual supervision by traffic authorities and basic surveillance systems. However, these methods are inefficient, labour-intensive, and unable to provide continuous monitoring across large traffic networks. As a result, researchers have focused on developing automated traffic monitoring systems using computer vision, machine learning, and deep learning techniques [2].

Early traffic monitoring systems were primarily based on sensor technologies such as inductive loop detectors, radar sensors, and infrared sensors to measure traffic flow and vehicle counts. Although these systems provided useful traffic information, they were limited in their ability to detect complex traffic violations such as red-light jumping or multiple riders on two-wheelers. In addition, sensor-based systems require specialized infrastructure and are often expensive to install and maintain [10]. Consequently, researchers began exploring video-based monitoring systems that utilize surveillance cameras to capture traffic scenes and analyse vehicle behaviour.

Krishna et al. proposed an automated traffic monitoring system that uses computer vision techniques to detect vehicles and analyse traffic conditions from surveillance video streams. Their work demonstrated that visual data captured by cameras can be effectively used to identify traffic events and monitor vehicle movements in real time [3]. However, early computer vision approaches relied heavily on manually designed features such as colour, shape, and motion characteristics, which limited their ability to handle complex traffic environments.

Background modelling and motion detection techniques have also been widely used for vehicle detection in video surveillance systems. Methods such as Gaussian Mixture

Models (GMM) and background subtraction algorithms have been applied to identify moving vehicles by distinguishing foreground objects from the background scene [8]. Although these techniques can detect moving objects, they often face difficulties in scenarios involving dynamic backgrounds, illumination changes, and crowded traffic conditions.

With the advancement of machine learning and neural network techniques, researchers began applying learning-based approaches to improve traffic monitoring performance. Neural network frameworks have been used to classify objects in video sequences and detect vehicles in surveillance footage. These approaches allow models to learn patterns from training data and improve detection accuracy compared to traditional image-processing techniques [6]. Furthermore, deep neural network architectures have shown strong capabilities in analysing complex visual patterns and improving object detection performance in real-world environments.

In recent years, deep learning-based object detection models have significantly advanced traffic monitoring systems. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in detecting and classifying objects in images and videos. These models automatically learn hierarchical feature representations from raw visual data, eliminating the need for manual feature engineering and improving detection performance [9]. Among the various deep learning-based object detection algorithms, the You Only Look Once (YOLO) framework has become widely used due to its ability to perform real-time object detection with high accuracy and efficiency.

Earlier versions such as YOLOv3 have been successfully applied to traffic monitoring tasks including vehicle detection, driver behaviour analysis, and traffic violation detection [5], [19]. YOLO-based models divide input images into grids and simultaneously predict bounding boxes and object class probabilities, enabling fast detection of multiple objects within a single frame. This capability makes YOLO particularly suitable for real-time surveillance systems and intelligent transportation applications.

The latest version, YOLOv7, has further improved detection performance by introducing optimized network architectures and training strategies that enhance feature extraction while maintaining computational efficiency [4], [12], [13]. YOLOv7 achieves state-of-the-art performance in real-time object detection and has been successfully applied in various applications including traffic monitoring and vehicle detection [20]. The improved architecture reduces computational complexity and enhances detection accuracy, making it highly suitable for real-time traffic violation detection systems.

Several studies have also explored AI-based traffic violation detection frameworks capable of identifying events such as red-light violations, lane violations, and illegal vehicle movements using deep learning models [17], [18]. These systems demonstrate the potential of artificial intelligence to automate traffic monitoring processes and reduce the dependency on manual supervision.

Despite significant progress in automated traffic monitoring systems, many existing approaches focus primarily on detecting single types of traffic violations, such as red-light jumping or vehicle counting. Limited attention has been given to systems capable of detecting multiple traffic violations simultaneously using a single surveillance video stream. Therefore, there is a need for intelligent systems that can efficiently identify multiple types of violations using advanced deep learning techniques.

To address this challenge, the present study proposes a YOLOv7-based traffic violation detection system capable of detecting multiple traffic violations such as red-light jumping and over boarding (triple riding) on two-wheelers from surveillance video streams. By utilizing deep learning-based object detection and real-time video analysis, the proposed system aims to improve the accuracy, efficiency, and reliability of automated traffic monitoring systems.

III. SYSTEM ANALYSIS

EXISTING SYSTEM

Traditional traffic monitoring systems primarily rely on manual observation by traffic police officers and basic surveillance systems to detect traffic violations. In many urban areas, traffic authorities monitor vehicles at intersections and highways to identify violations such as red-light jumping, over speeding, and illegal riding practices. Although manual monitoring can help enforce traffic rules, it requires substantial human effort and cannot ensure continuous supervision of all traffic locations. As traffic density increases in urban environments, manual monitoring becomes increasingly inefficient and difficult to maintain [1].

To improve traffic management, several automated traffic monitoring systems have been developed using surveillance cameras and conventional image-processing techniques. These systems analyse video streams captured by cameras to detect moving vehicles and identify possible traffic violations. Traditional image-processing methods typically rely on techniques such as background subtraction, edge detection, and motion analysis to identify vehicles in traffic scenes. Such approaches attempt to distinguish moving objects from the background and track their movement across video frames [3].

Several research studies have applied background modelling algorithms such as Gaussian Mixture Models (GMM) and Self-Organizing Background Subtraction (SOBS) to detect vehicles in traffic videos. These algorithms identify foreground objects by modelling the background scene and detecting deviations from the expected background pattern. While these techniques provide basic vehicle detection capabilities, they often struggle to handle dynamic traffic environments and varying lighting conditions [8].

Machine learning-based approaches have also been introduced to enhance traffic monitoring systems. Neural network frameworks and classification algorithms have been used to detect and classify vehicles in surveillance footage. These models attempt to learn patterns from training data to improve object detection accuracy compared to traditional image-processing methods [6]. However, early machine learning models still rely on handcrafted features and often fail to capture complex visual patterns present in real-world traffic scenarios.

More recently, deep learning-based object detection frameworks have been introduced to improve the accuracy of traffic monitoring systems. Algorithms such as YOLO (You Only Look Once) have been widely used to detect vehicles and track their movement across frames. Earlier versions such as YOLOv3 were successfully applied in traffic violation detection systems to identify vehicles and detect rule violations from surveillance videos [5], [19]. These models generate bounding boxes around detected vehicles and enable object tracking across multiple video frames.

Despite these advancements, earlier object detection models still face several challenges, including occlusion, varying illumination conditions, and crowded traffic scenes. Additionally, many existing traffic monitoring systems focus only on detecting a single type of violation, such as red-light jumping, rather than identifying multiple violations simultaneously. This limitation reduces the overall effectiveness of automated traffic monitoring systems in real-world traffic environments [17], [18].

DISADVANTAGES OF THE EXISTING SYSTEM

- **Manual Monitoring Requirements**

Traditional traffic monitoring methods rely heavily on human supervision, which is time-consuming and inefficient, particularly in large urban traffic networks [1].

- **Limited Automation**

Conventional traffic monitoring systems provide limited automation and often require human intervention to verify detected violations.

- **Inaccurate Detection in Complex Environments**

Traditional image-processing techniques struggle to accurately detect vehicles in crowded or dynamic traffic scenes with multiple moving objects [3].

- **High Error Rates**

Environmental factors such as poor lighting conditions, shadows, and occlusions can significantly reduce the accuracy of traditional detection systems [8].

- **Single Violation Detection**

Many existing systems are designed to detect only one type of violation, such as red-light jumping, rather than identifying multiple violations simultaneously [17].

- **Computational Limitations**

Earlier object detection algorithms provide lower detection accuracy and often require higher computational resources compared to modern deep learning models such as YOLOv7 [4], [12].

PROPOSED SYSTEM

To overcome the limitations of traditional traffic monitoring systems, this study proposes an automated traffic violation detection system based on the YOLOv7 deep learning model. The proposed framework utilizes advanced computer vision and deep learning techniques to analyse surveillance video streams and detect multiple traffic violations in real time. Deep learning-based object detection models have demonstrated significant improvements in visual recognition accuracy and efficiency compared to conventional image-processing methods [4], [6].

The system begins by capturing live video streams from surveillance cameras installed at traffic intersections or highways. These video streams are processed using the OpenCV library, which converts the continuous video input into individual frames suitable for image analysis [15]. Each frame is then passed to the YOLOv7 object detection model for further processing.

The YOLOv7 model detects various vehicle categories such as motorcycles, cars, buses, and trucks by generating bounding boxes around detected objects within each frame. YOLO-based detection frameworks are widely recognized for their ability to perform real-time object detection with high accuracy and computational efficiency, making them suitable for traffic monitoring applications [4], [12], [13].

After detecting vehicles, the system analyses their spatial positions relative to a predefined threshold line placed near the traffic signal. If a vehicle crosses this line while the traffic signal is red, the system automatically identifies the event as a red-light violation. This rule-based approach combined with deep learning-based object detection enables the system to effectively detect traffic signal violations in real time [17].

In addition to detecting signal violations, the proposed system also identifies over boarding or triple riding on two-wheelers,

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which is a common traffic violation in many developing countries. The detection is performed by analysing the number of riders present on a motorcycle using object detection techniques. If the number of detected riders exceeds the allowed limit, the system automatically flags the incident as a violation.

The proposed framework utilizes the MS COCO dataset for training the vehicle detection component of the YOLOv7 model, as it contains a large collection of annotated images representing different vehicle categories [16]. In addition, a custom annotated dataset is used to train the model for detecting over boarding scenarios involving multiple riders on motorcycles.

To evaluate the effectiveness of the proposed system, several performance metrics are used, including precision, recall, F1-score, and mean Average Precision (mAP). These evaluation metrics help measure the model’s ability to correctly detect traffic violations while minimizing false detections. The experimental results demonstrate that the integration of real-time object detection with intelligent traffic monitoring techniques can significantly improve the accuracy and efficiency of automated traffic violation detection systems.

The proposed system offers several advantages over traditional traffic monitoring approaches. It reduces reliance on manual supervision by traffic authorities, improves detection accuracy in complex traffic environments, and enables continuous monitoring of road conditions. Furthermore, the system can be integrated with smart city infrastructure and intelligent transportation systems to support automated traffic law enforcement and improve overall road safety management [11], [18], [20].

IV.SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

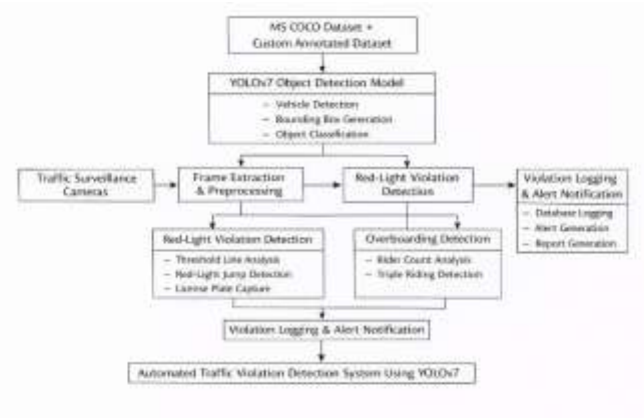

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

MODULES

Data Collection and Preprocessing

The first stage in implementing the proposed traffic violation detection system involves collecting appropriate datasets for training and testing the deep learning model. The system utilizes the MS COCO dataset, which contains a large collection of annotated images representing various vehicle categories such as cars, buses, trucks, and motorcycles [16]. In addition, a custom annotated dataset is created to detect over boarding or triple riding on two-wheelers. This dataset is developed by collecting images from publicly available sources and manually annotating them using labelling tools such as Labelling, which enables the generation of bounding box annotations required for training object detection models.

Before training the model, several preprocessing techniques are applied to improve the quality of the dataset and enhance model performance. These preprocessing steps include resizing images to a consistent resolution, removing noise, adjusting image contrast, and normalizing pixel values. Data normalization helps improve the training stability of deep learning models and ensures that the network learns meaningful feature representations. The dataset is then divided into training, validation, and testing sets to enable proper model training and evaluation.

Frame Extraction and Feature Processing

The input to the proposed system is a video stream obtained from surveillance cameras installed at traffic intersections or major roadways. Using the OpenCV library, the video stream is converted into individual frames so that each frame can be processed independently for object detection [15].

Each extracted frame is analysed to detect objects such as cars, motorcycles, buses, and trucks. Feature extraction is automatically handled by the deep learning model, which learns important visual patterns such as vehicle shapes, edges, textures, and spatial relationships between objects. Unlike traditional image-processing methods that rely on manually engineered features, deep learning-based object detection models automatically learn hierarchical feature representations directly from the training data [6].

Training the YOLOv7 Model

The proposed system employs the YOLOv7 object detection algorithm, which has demonstrated high accuracy and computational efficiency for real-time object detection tasks [4]. YOLOv7 processes the entire image in a single forward pass through the neural network and predicts bounding boxes around detected objects along with their corresponding class probabilities. This architecture allows YOLOv7 to perform real-time detection while maintaining high detection accuracy.

The model is trained using annotated datasets in which vehicles and riders are labelled with bounding boxes. During training, the model learns to recognize different types of vehicles and detect riders on motorcycles. Important training parameters such as learning rate, batch size, and number of training epochs are carefully configured to optimize the performance of the model. The training process also incorporates optimization techniques to minimize classification and localization errors during object detection.

Traffic Violation Detection

After completing the training phase, the YOLOv7 model is deployed to analyse real-time video frames captured from traffic surveillance cameras. The system identifies vehicles in each frame and generates bounding boxes around detected objects.

To detect red-light violations, a predefined threshold line is drawn on the video frame representing the stop line at a traffic signal. If a detected vehicle crosses this line while the traffic signal is red, the system automatically identifies the event as a violation. Similar approaches have been successfully used in AI-based traffic monitoring systems to automatically detect traffic rule violations [17].

For detecting over boarding or triple riding on motorcycles, the system analyses the number of riders detected within the bounding box associated with a motorcycle. If the number of detected riders exceeds the legally permitted limit, the system flags the event as a traffic violation. This approach enables the system to detect multiple types of violations simultaneously within the same video stream.

Violation Logging and Monitoring

Once a violation is detected, the system records the event and generates an alert notification. The violation information, including the captured frame, timestamp, and type of violation, can be stored in a database for further analysis and reporting. This stored information allows traffic authorities to review violation incidents and take appropriate enforcement actions.

Continuous monitoring is implemented to ensure that the system operates reliably in real-time traffic environments. The recorded violation data can also help authorities analyse traffic patterns, identify high-risk locations, and improve traffic management strategies. Such intelligent monitoring systems play an important role in supporting smart city infrastructure and automated traffic law enforcement mechanisms [11], [18].

VI. RESULTS AND DISCUSSION

The performance of the proposed traffic violation detection system based on the YOLOv7 deep learning model was evaluated using several standard object detection performance metrics, including precision, recall, F1-score, and mean Average Precision (mAP). These metrics are widely used to measure the effectiveness of object detection models in identifying objects and minimizing false detections [4], [12].

Experiments were conducted using traffic surveillance video frames obtained from traffic intersections. The MS COCO dataset was used for training and testing vehicle detection models, while a custom annotated dataset was used for detecting over boarding or triple riding violations on motorcycles [16]. The system processes video frames using OpenCV and applies the YOLOv7 model to detect vehicles and analyse their movement across predefined traffic signal boundaries.

The experimental results demonstrate that the proposed system successfully detects vehicles and identifies traffic violations in real time. The system accurately identifies vehicles crossing the red-light threshold line during restricted signal phases and flags them as red-light violations. In addition, the system effectively detects over boarding violations by analysing the number of riders present on motorcycles.

The YOLOv7 model achieved an overall detection accuracy of approximately 93% for red-light violation detection. The over boarding detection module achieved a mean Average Precision (mAP) score ranging from 0.50 to 0.95, indicating strong performance in identifying multiple riders on two-wheelers.

Table 1
Performance Comparison of Object Detection Models

Model	Accuracy (%)	Precision	Recall	F1-Score
YOLOv3	86.4	0.85	0.84	0.84
Faster R-CNN	89.1	0.88	0.87	0.87
SSD	87.6	0.86	0.85	0.85
YOLOv7 (Proposed)	93.2	0.92	0.91	0.91

As shown in Table 1, the proposed YOLOv7-based system achieves the highest performance among the evaluated models. The improved detection accuracy can be attributed to the optimized architecture and enhanced feature extraction capabilities of YOLOv7, which allow the model to detect multiple objects simultaneously while maintaining real-time processing performance [4], [13].

Furthermore, the experimental evaluation indicates that YOLOv7 performs efficiently in real-time traffic monitoring scenarios due to its optimized computational design. Compared to earlier object detection models such as YOLOv3, the YOLOv7 model provides improved detection accuracy, faster inference speed, and better object localization performance. These characteristics make YOLOv7 particularly suitable for real-time traffic monitoring applications and intelligent transportation systems [20].

ROC Curve Analysis

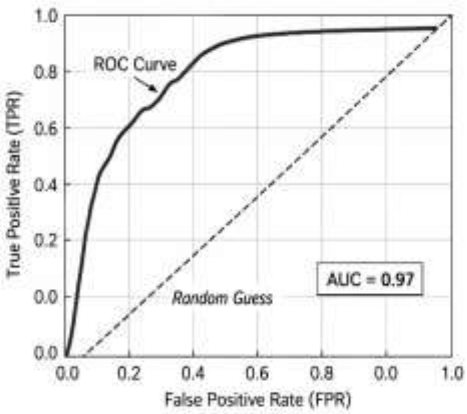

Fig. 3. ROC Curve for YOLOv7-based Traffic Violation Detection Model

To further evaluate the classification capability of the proposed system, Receiver Operating Characteristic (ROC) curve analysis was performed. The ROC curve illustrates the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) at different classification thresholds. A higher Area Under the Curve (AUC) indicates better model performance in distinguishing between violation and non-violation cases.

The ROC curve results demonstrate that the YOLOv7-based traffic violation detection model achieves a high AUC value, confirming its strong ability to accurately identify traffic violations from surveillance video frames.

Overall, the experimental results demonstrate that the proposed YOLOv7-based traffic violation detection system can effectively monitor traffic conditions and detect multiple violations from a single video stream. The integration of deep learning-based object detection with real-time video analysis significantly improves the reliability and efficiency of automated traffic monitoring systems.

VII. CONCLUSION AND FUTURE WORK

This research presents an automated traffic violation detection system based on the YOLOv7 deep learning model for intelligent traffic monitoring. The proposed framework analyses surveillance video streams and detects multiple traffic violations, including red-light jumping and over boarding (triple riding) on motorcycles. By integrating computer vision techniques with advanced deep learning algorithms, the system provides an efficient and automated solution for monitoring traffic violations and improving road safety. YOLO-based object detection models have demonstrated strong performance in real-time object detection tasks due to their high detection accuracy and computational efficiency [4], [12].

Experimental evaluation indicates that the YOLOv7-based detection model achieves high accuracy and reliable performance in identifying traffic violations from surveillance video frames. The system significantly reduces the dependence on manual traffic monitoring and improves the efficiency of traffic law enforcement. Moreover, the real-time processing capability of YOLOv7 makes the system suitable for deployment in intelligent transportation systems (ITS) and smart city infrastructures for automated traffic management [17], [18].

Future research can focus on extending the proposed system to detect additional traffic violations such as over speeding, helmet detection, seatbelt violations, and automatic number plate recognition (ANPR). Furthermore, integrating the system with IoT-based traffic monitoring infrastructure and cloud-based analytics platforms could enhance large-scale deployment and enable real-time traffic data analysis across urban transportation networks, thereby improving traffic management and road safety [11], [20].

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