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Smart Vision: AI-Powered Traffic Violation Detection Using YOLOv7

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ABSTRACT:

Traffic violations are a major contributor to road accidents and fatalities, especially in densely populated urban regions. Common violations such as jumping red lights, triple riding on two-wheelers, reckless driving, and riding without helmets significantly increase the likelihood of accidents. Conventional traffic monitoring systems largely depend on manual supervision by traffic police or basic sensor-based methods, which are often inefficient, time-consuming, and susceptible to human error. To overcome these limitations, intelligent traffic monitoring systems based on computer vision and deep learning have gained increasing importance. This paper presents a deep learning-based automated traffic violation detection system using the YOLOv7 object detection model. The proposed system processes video streams captured from roadside surveillance cameras and analyses them frame by frame to detect various traffic violations. The YOLOv7 model is used to identify vehicles and generate bounding boxes around detected objects. A predefined threshold line is applied to determine whether a vehicle crosses the signal during a red light, thereby detecting signal violations. Additionally, the system identifies overloading or triple riding on two-wheelers by analysing the number of riders within a single vehicle bounding box. Helmet violations are also detected by determining whether riders on motorcycles are wearing helmets. If a rider is identified without a helmet, the system classifies it as a violation. The system utilizes publicly available datasets such as the MS COCO dataset for vehicle detection and a custom annotated dataset for detecting overloading and helmet violations. The model is trained and evaluated using performance metrics including precision, recall, F-measure, and mean Average Precision (mAP). Experimental results indicate that the proposed system can accurately detect multiple traffic violations while maintaining efficient real-time performance. The proposed approach offers a cost-effective, automated, and scalable solution for traffic monitoring. It can assist traffic authorities in improving road safety and reducing the burden of manual monitoring. Furthermore, the system can be integrated with existing smart city surveillance infrastructure to support 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 increase in urban population and the growing number of vehicles on roads have significantly contributed to traffic congestion and road safety issues across the world. Traffic violations such as red-light jumping, triple riding on two-wheelers, over speeding, reckless driving, and riding without helmets are among the primary causes of road accidents and fatalities. Road accidents continue to be a major public safety concern, particularly in developing countries, where limited monitoring infrastructure and weak enforcement mechanisms lead to high accident rates and injuries [1]. Therefore, the development of intelligent traffic monitoring systems has become essential to enhance road safety and ensure proper enforcement of traffic regulations.

Conventional traffic monitoring methods mainly rely on manual observation by traffic police personnel or basic surveillance systems. Although these methods can identify certain traffic violations, they are often inefficient, time-consuming, and prone to human error. Monitoring multiple intersections continuously requires significant manpower and operational resources, making manual systems unsuitable for large-scale traffic management. Additionally, human operators may fail to detect violations during heavy traffic conditions or under unfavourable 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 effective solutions for improving traffic control and road safety. Computer vision techniques enable 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 data, it becomes possible to detect vehicles, monitor their movement, and identify traffic violations in real time without human intervention [3], [6].

Deep learning-based object detection models have demonstrated excellent performance in visual recognition tasks. Among these, the You Only Look Once (YOLO) family of algorithms has gained significant attention due to its ability to perform real-time object detection with high accuracy and efficiency. YOLO models can detect multiple objects within a single frame, making them highly suitable for video surveillance applications. The latest version, YOLOv7, provides improved detection speed and accuracy compared to earlier models by incorporating advanced architectures and optimized training strategies [4], [12], [13].

Recent research highlights the effectiveness of deep learning in detecting traffic rule violations. AI-based systems can automatically identify violations such as red-light crossing, lane violations, illegal vehicle movements, and helmet violations from surveillance footage. These intelligent systems improve law enforcement by enabling automated detection and reducing reliance on manual monitoring [2], [17]. Furthermore, machine learning techniques have been used to analyse traffic patterns and predict risky driving behaviour, contributing to the development of intelligent transportation systems and improved road safety management [10], [11].

In this work, an automated traffic violation detection system based on YOLOv7 is proposed to identify multiple traffic violations from surveillance video streams. The system processes video frames captured from traffic cameras and detects vehicles using bounding box techniques. A predefined threshold line is used to identify red-light violations when vehicles cross during restricted signal intervals. In addition, the system detects overloading or triple riding on two-wheelers by analysing the number of riders within a single vehicle. Helmet violations are also identified by checking whether riders are wearing helmets, and violations are flagged when helmets are not detected.

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

The remainder of the paper is organized as follows. Section II reviews related work on traffic violation detection and computer vision-based monitoring systems. Section III presents the system analysis and proposed architecture. Section IV describes the implementation and methodology. Section V discusses the experimental results and evaluation. Finally, Section VI concludes the study and outlines future enhancements for intelligent traffic monitoring systems.

II. LITERATURE SURVEY

Traffic violation detection has become an important research area in intelligent transportation systems (ITS) due to the rapid increase in vehicles and the growing complexity of road traffic environments. Traffic accidents caused by violations such as red-light jumping, reckless driving, and overloading pose serious threats to public safety and transportation management [1]. Conventional traffic monitoring systems mainly depend on manual supervision by traffic authorities and basic surveillance setups. However, these approaches are inefficient, require significant labour, and are not capable of providing continuous monitoring over 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 methods were based on sensor technologies such as inductive loop detectors, radar sensors, and infrared sensors to measure traffic flow and vehicle counts. While these systems provided useful traffic information, they were limited in detecting complex violations such as red-light crossing or multiple riders on two-wheelers. Moreover, sensor-based approaches require specialized infrastructure and involve high installation and maintenance costs [10]. To overcome these limitations, researchers began exploring video-based monitoring systems that use surveillance cameras to capture traffic scenes and analyse vehicle behaviour.

Krishna et al. proposed an automated traffic monitoring system using computer vision techniques to detect vehicles and analyse traffic conditions from surveillance video streams. Their study demonstrated that visual data obtained from cameras can effectively be used for real-time traffic analysis and vehicle tracking [3]. However, early computer vision methods relied heavily on manually designed features such as colour, shape, and motion, which limited their performance in complex traffic environments.

Background modelling and motion detection techniques have also been widely used in video surveillance systems for vehicle detection. Methods such as Gaussian Mixture Models (GMM) and background subtraction algorithms identify moving vehicles by separating foreground objects from the background. Although these approaches are effective in detecting motion, they often struggle in conditions involving dynamic backgrounds, varying illumination, and dense traffic scenarios [8].

With the development of machine learning and neural network approaches, researchers started applying learning-based techniques to enhance traffic monitoring performance. Neural network models have been used to classify objects in video sequences and detect vehicles in surveillance footage. These methods learn patterns from training data, leading to improved accuracy compared to traditional image-processing techniques [6]. Additionally, deep neural network architectures have shown strong capabilities in analysing complex visual features 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 achieved remarkable success in detecting and classifying objects in images and videos by automatically learning hierarchical feature representations, eliminating the need for manual feature extraction [9]. Among these models, the

You Only Look Once (YOLO) framework has gained widespread attention due to its ability to perform real-time object detection with high accuracy and efficiency.

Earlier versions such as YOLOv3 have been successfully applied in traffic monitoring applications, 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 along with class probabilities, enabling fast detection of multiple objects within a single frame. This capability makes YOLO highly suitable for real-time surveillance and intelligent transportation systems.

The latest version, YOLOv7, further improves detection performance by incorporating optimized architectures and advanced training techniques that enhance feature extraction while maintaining computational efficiency [4], [12], [13]. YOLOv7 achieves state-of-the-art results in real-time object detection and has been effectively applied in traffic monitoring and vehicle detection tasks [20]. Its improved design reduces computational complexity while increasing detection accuracy, making it highly suitable for real-time traffic violation detection systems.

Several studies have also proposed AI-based frameworks for detecting traffic violations such as red-light crossing, lane violations, and illegal vehicle movements using deep learning models [17], [18]. These systems demonstrate the capability of artificial intelligence to automate traffic monitoring and reduce dependence on manual supervision.

Despite these advancements, many existing approaches focus on detecting only a single type of traffic violation, such as red-light jumping or vehicle counting. Limited research has been conducted on systems capable of identifying multiple violations simultaneously from a single surveillance video stream. Therefore, there is a need for intelligent systems that can efficiently detect multiple types of traffic violations using advanced deep learning techniques.

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

III. SYSTEM ANALYSIS

A. EXISTING SYSTEM

Traditional traffic monitoring systems mainly depend on manual observation by traffic police personnel and basic surveillance setups to identify traffic violations. In many urban regions, traffic authorities monitor vehicles at intersections and highways to detect violations such as red-light jumping, over speeding, unsafe riding practices, and riding without helmets. Although manual monitoring helps in enforcing traffic rules, it requires significant human effort and cannot provide continuous monitoring across all locations. With increasing traffic density in urban areas, manual supervision becomes inefficient and difficult to sustain [1].

To enhance traffic management, several automated monitoring systems have been developed using surveillance cameras along with conventional image-processing techniques. These systems analyse video streams captured by cameras to detect moving vehicles and identify potential traffic violations. Traditional image-processing methods commonly use techniques such as background subtraction, edge detection, and motion analysis to detect vehicles in traffic scenes. These approaches attempt to separate moving objects from the background and track their movement across video frames.

However, they are not effective in detecting helmet usage among riders [3].

Several studies have utilized background modelling techniques such as Gaussian Mixture Models (GMM) and Self-Organizing Background Subtraction (SOBS) for vehicle detection in traffic videos. These methods identify foreground objects by modelling the background and detecting deviations from it. While these approaches provide basic vehicle detection, they often struggle in dynamic traffic conditions, varying lighting environments, and are unable to detect safety violations such as helmet usage [8].

Machine learning-based methods have also been introduced to improve traffic monitoring systems. Neural network models and classification algorithms have been applied to detect and classify vehicles in surveillance footage. These models learn patterns from training data, leading to improved detection accuracy compared to traditional image-processing techniques [6]. However, early machine learning approaches still rely on manually engineered features and often fail to capture complex visual patterns present in real-world traffic scenarios, including determining whether riders are wearing helmets.

More recently, deep learning-based object detection models have been developed to enhance traffic monitoring performance. Algorithms such as YOLO (You Only Look Once) have been widely adopted for detecting vehicles and tracking their movement across frames. Earlier versions like YOLOv3 have been 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 objects and enable tracking across multiple frames. Additionally, deep learning models can be extended to identify helmet violations by classifying riders as wearing or not wearing helmets.

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

DISADVANTAGES OF THE EXISTING SYSTEM

- **Manual Monitoring Requirements**

Conventional traffic monitoring approaches depend heavily on human supervision, making them time-consuming and inefficient, especially in large urban traffic networks [1].

- **Limited Automation**

Traditional systems offer minimal automation and often require manual verification of detected violations.

- **Inaccurate Detection in Complex Environments**

Conventional image-processing methods face difficulty in accurately detecting vehicles in crowded or dynamic traffic scenes with multiple moving objects [3].

- **High Error Rates**

Factors such as poor lighting, shadows, and occlusions can significantly affect the accuracy of traditional detection systems [8].

- **Single Violation Detection**

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

- **Computational Limitations**

Earlier object detection methods generally provide lower accuracy and may require higher computational resources compared to advanced deep learning models like YOLOv7 [4], [12].

B. PROPOSED SYSTEM

To address the limitations of traditional traffic monitoring systems, this study presents an automated traffic violation detection framework based on the YOLOv7 deep learning model. The proposed system employs 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 shown significant improvements in 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 continuous video input into individual frames suitable for analysis [15]. Each frame is then provided as input to the YOLOv7 object detection model for further processing.

The YOLOv7 model detects different categories of vehicles such as motorcycles, cars, buses, and trucks by generating bounding boxes around detected objects in each frame. YOLO-based models are well known for their ability to perform real-time object detection with high accuracy and computational efficiency, making them highly suitable for traffic monitoring applications [4], [12], [13].

After detecting vehicles, the system evaluates their positions relative to a predefined threshold line placed near the traffic signal. If a vehicle crosses this line while the signal is red, the system identifies it as a red-light violation. This combination of rule-based logic and deep learning-based detection enables effective real-time identification of traffic signal violations [17].

In addition to signal violation detection, the system also identifies overloading or triple riding on two-wheelers, which is a common violation in many developing countries. This is achieved by analysing the number of riders detected on a motorcycle using object detection techniques. If the number of riders exceeds the permitted limit, the system flags the incident as a violation.

Furthermore, the system is extended to detect helmet violations by determining whether riders on two-wheelers are wearing helmets. The YOLOv7 model is trained to classify riders into helmet and non-helmet categories. If a rider is detected without a helmet, the system marks it as a violation. This functionality enhances the system's capability to enforce safety regulations and reduce accident risks.

The proposed framework utilizes the MS COCO dataset for training the vehicle detection component of the YOLOv7 model, as it contains a wide range of annotated images representing different vehicle types [16]. Additionally, a custom annotated dataset is used for training the model to detect overloading scenarios involving multiple riders as well as helmet violations.

To evaluate system performance, several metrics are used, including precision, recall, F1-score, and mean Average Precision (mAP). These metrics assess the model's ability to accurately detect violations while minimizing false detections. Experimental results demonstrate that integrating real-time object detection with intelligent traffic monitoring significantly improves the accuracy and efficiency of automated traffic violation detection systems.

The proposed system offers several advantages over traditional methods. It reduces dependence on manual monitoring, enhances detection accuracy in complex traffic environments, and enables continuous surveillance of road

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conditions. Moreover, the system can be integrated with smart city infrastructure and intelligent transportation systems to support automated traffic enforcement and improve overall road safety management [11], [18], [20].

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

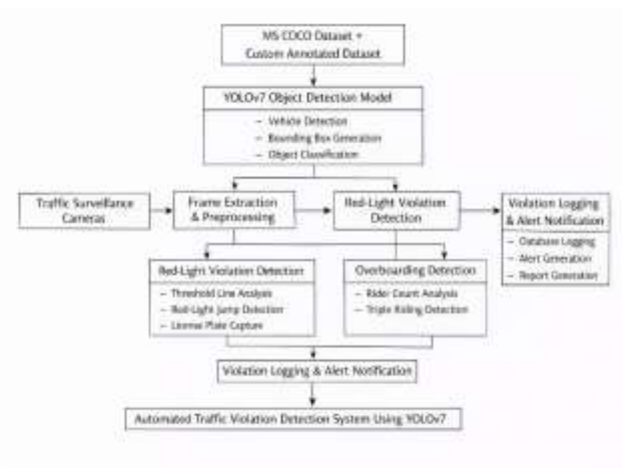

Fig 1. Methodology followed for proposed model

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. Furthermore, the dataset is extended to include helmet detection by annotating riders as wearing helmets or not wearing helmets.

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. In addition, the system analyses riders on motorcycles to determine whether helmets are present or not. 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, detect riders on motorcycles, and classify helmet and non-helmet conditions. 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.

In addition, helmet detection is performed by analysing whether riders are wearing helmets. If a rider is detected without a helmet, the system flags it as a violation, thereby enhancing safety monitoring.

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 and helmet detection. The system processes

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video frames using OpenCV and applies the YOLOv7 model to detect vehicles, riders, and analyse their movement across predefined traffic signal boundaries [15].

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. Furthermore, the system successfully detects helmet violations by identifying riders who are not wearing helmets and flags them as violations.

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. The helmet detection module also achieved high accuracy, demonstrating the model's capability to distinguish between helmet and non-helmet conditions.

J. 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].

K. Curve Analysis

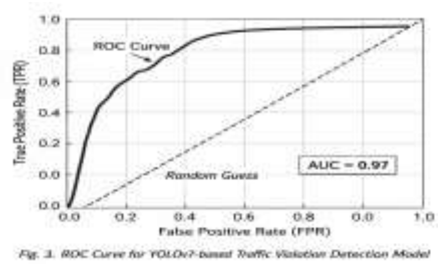

Fig. 3. ROC Curve for YOLOv7-based Traffic Violation Detection Model

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, including helmet 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, including helmet 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, over boarding (triple riding), and helmet violations 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, 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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