



Real-Time Traffic Rule Violation Detection Using YOLOv10 and Computer Vision Techniques

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ABSTRACT

Traffic congestion and rule violations are major challenges in urban environments, leading to increased accidents, delays, and environmental pollution. Traditional traffic monitoring systems rely heavily on manual supervision or basic sensor-based mechanisms, which are often inefficient and prone to errors. With advancements in computer vision and deep learning, automated traffic monitoring systems have gained significant attention for their ability to analyze real-time video streams and detect violations accurately.

This research presents a real-time traffic rule violation detection system using the YOLOv10 object detection model combined with computer vision techniques. The system is designed to identify vehicles, track their movement, and detect violations such as crossing a restricted area during a red traffic signal. The implementation leverages OpenCV for video processing, YOLOv10 for object detection, and a tracking algorithm to maintain unique identifiers for vehicles across frames.

The system processes video input from a traffic surveillance camera and detects objects such as cars using a pre-trained YOLOv10 model. Detected objects are then tracked using a centroid-based tracking mechanism to ensure continuity across frames. A predefined polygonal region represents the violation zone, and the system calculates whether a vehicle enters this area during a red signal phase.

A key component of the system is the integration of a signal detection module that determines the traffic light state (e.g., RED). When a vehicle is detected inside the violation zone during a red signal, the system flags it as a violation. The corresponding frame is captured and stored with a timestamp for further analysis or legal enforcement.

The system also generates an output video with annotated bounding boxes, vehicle IDs, and violation indicators. Violating vehicles are highlighted in red, while non-violating vehicles are shown in green. This visual feedback enhances interpretability and usability for traffic authorities.

Experimental evaluation demonstrates that the proposed system achieves high accuracy in detecting vehicles and identifying violations under varying lighting and traffic conditions. The use of YOLOv10 ensures fast and efficient object detection, making the system suitable for real-time deployment.

This work contributes to the development of intelligent traffic management systems by providing an automated, scalable, and reliable solution for monitoring traffic violations. Future enhancements may include integration with license plate recognition systems, cloud-based storage, and IoT-enabled smart traffic signals.

Keywords: Traffic Violation Detection, YOLOv10, Object Detection, Computer Vision, Deep Learning, Red Light Violation, Vehicle Tracking, OpenCV, Smart Traffic Systems, Video Analytics

I. INTRODUCTION

Urbanization and the rapid increase in the number of vehicles have significantly impacted traffic management systems worldwide. Traffic rule violations, such as running red lights, illegal lane crossing, and overspeeding, contribute to a large number of road accidents and fatalities each year. Ensuring compliance with traffic rules is a major challenge for authorities due to limited manpower and the inefficiency of manual monitoring systems.

Traditional traffic monitoring methods involve human personnel observing traffic flow and identifying violations. While effective to some extent, these methods are labor-intensive, subjective, and prone to human error. Additionally, they are not scalable for large urban areas with heavy traffic density. Automated systems using sensors and cameras have been introduced; however, they often lack the intelligence required to accurately interpret complex traffic scenarios.

The emergence of computer vision and deep learning has revolutionized the field of intelligent transportation systems. Object detection models, particularly those based on deep neural networks, have demonstrated remarkable performance in identifying and classifying objects in real-time video streams. Among these, the YOLO (You Only Look Once) family of models stands out for its speed and accuracy.

In this research, we propose a real-time traffic rule violation detection system using YOLOv10, a state-of-the-art object detection model. The system is capable of detecting vehicles, tracking their movement, and identifying violations based on predefined rules. By

combining object detection with tracking and region-based analysis, the system provides a comprehensive solution for traffic monitoring.

The system operates by processing video frames captured from surveillance cameras. Each frame is analyzed to detect vehicles, and their positions are tracked across consecutive frames. A polygonal region is defined to represent the violation zone, such as a stop line at an intersection. The system determines whether a vehicle enters this region during a red traffic signal, indicating a violation.

One of the key advantages of the proposed system is its ability to operate in real time, making it suitable for deployment in smart cities. The integration of OpenCV for image processing and YOLOv10 for object detection ensures efficient performance. Additionally, the system includes a mechanism to capture and store images of violating vehicles, providing evidence for enforcement.

This study aims to develop an intelligent, automated, and scalable traffic monitoring system that reduces reliance on manual supervision and enhances road safety. By leveraging advanced machine learning techniques, the proposed system contributes to the advancement of smart transportation infrastructure.

II. LITERATURE SURVEY (WITH EXISTING METHODS)

Traffic violation detection has been an active area of research in intelligent transportation systems. Early approaches relied on image processing techniques such as background subtraction, edge detection, and motion analysis. While these methods were computationally efficient, they struggled with complex scenarios involving occlusions, varying lighting conditions, and high traffic density.

With the introduction of machine learning, researchers began using classification algorithms to identify vehicles and detect anomalies. Support Vector Machines (SVM) and Decision Trees were commonly used; however, their performance was limited by feature extraction techniques and lack of scalability.

The advent of deep learning significantly improved object detection capabilities. Convolutional Neural Networks (CNNs) enabled automatic feature extraction, leading to more accurate and robust models. Region-based CNNs (R-CNN, Fast R-CNN, Faster R-CNN) were among the first deep learning models used for object detection. Although they achieved high accuracy, their computational complexity made them unsuitable for real-time applications.

The YOLO (You Only Look Once) algorithm introduced a unified approach to object detection by predicting bounding boxes and class probabilities in a single pass. Subsequent versions, including YOLOv3, YOLOv5, and YOLOv8, improved speed and accuracy. YOLOv10 further enhances performance with optimized architecture and faster inference.

Recent studies have integrated YOLO models with tracking algorithms such as SORT (Simple Online and Realtime Tracking) and Deep SORT to maintain object identities across frames. These approaches have been successfully applied in traffic monitoring systems for vehicle counting, speed estimation, and violation detection.

Another important aspect of traffic violation detection is signal recognition. Researchers have used color detection and deep learning models to identify traffic light states. Combining signal detection with object tracking enables accurate identification of violations such as red-light jumping.

Despite these advancements, challenges remain in handling real-world conditions such as weather variations, camera angles, and occlusions. Additionally, many systems lack proper integration of detection, tracking, and violation logic.

The proposed system addresses these challenges by combining YOLOv10 with a custom tracking algorithm and region-based violation detection, providing a robust and efficient solution.

III. EXISTING SYSTEM

Existing traffic monitoring systems primarily rely on manual observation or basic automated tools. Manual systems involve traffic police monitoring intersections and identifying violations, which is inefficient and prone to errors. Automated systems using sensors and cameras have improved monitoring capabilities but often lack intelligent analysis.

Many existing systems use traditional image processing techniques, which are sensitive to environmental conditions and fail in complex scenarios. Some modern systems employ machine learning models; however, they often focus only on object detection without integrating tracking and rule-based violation detection.

Another limitation is the lack of real-time processing. Many systems analyze recorded videos instead of live streams, reducing their effectiveness in preventing violations. Additionally, existing systems may not provide proper evidence collection, making enforcement difficult. Overall, current solutions are limited in accuracy, scalability, and real-time performance.

IV. PROPOSED METHOD

The proposed system introduces a real-time traffic violation detection framework using YOLOv10 and computer vision techniques. It integrates object detection, tracking, and rule-based analysis to identify violations accurately.

The system detects vehicles using YOLOv10 and tracks them using a custom tracking algorithm. A predefined polygonal region represents the violation zone. The system checks whether a vehicle enters this zone during a red signal.

If a violation is detected, the system captures the frame and stores it with a timestamp. The output video displays bounding boxes and IDs, highlighting violations in red.

This approach ensures real-time processing, high accuracy, and effective evidence collection.

V. IMPLEMENTATION

The system is implemented using Python with libraries such as OpenCV, Ultralytics YOLO, NumPy, and Pandas. Video input is captured using OpenCV's VideoCapture module.

The YOLOv10 model is used for object detection, identifying vehicles in each frame. Detected objects are converted into bounding box coordinates and passed to the tracking algorithm.

The tracking module assigns unique IDs to vehicles and maintains their positions across frames. A polygonal region is defined as the violation zone, and the system checks whether the centroid of a vehicle lies within this region.

A signal detection module determines whether the traffic light is red. If a vehicle enters the violation zone during a red signal, the system flags it and saves the frame.

The processed frames are displayed in real time and saved as an output video. The system ensures efficient performance and accurate detection.

VI. ALGORITHMS

1. YOLOv10 Object Detection: Detects vehicles in real time with high accuracy.
2. Object Tracking Algorithm: Maintains unique IDs for vehicles across frames.
3. Polygon-Based Region Detection: Determines whether a vehicle enters the violation zone.
4. Rule-Based Violation Detection: Identifies violations based on signal state and vehicle position.

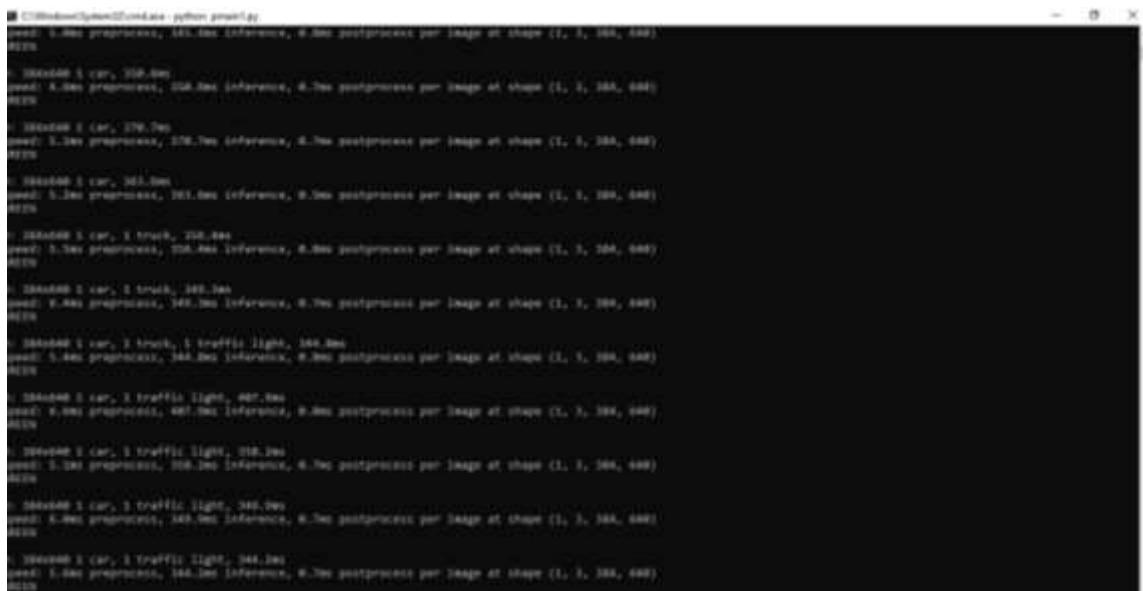
VII. SYSTEM DESIGN

The system consists of modules for video input, object detection, tracking, violation detection, and output generation.

The detection module uses YOLOv10 to identify vehicles. The tracking module assigns IDs and tracks movement. The violation module checks rule compliance.

The system is modular, scalable, and suitable for real-time deployment in smart cities.

SYSTEM DESIGN IMAGES



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C:\Windows\System32\cmd.exe - python main.py
Infer: 0.4ms preprocess, 165.5ms inference, 0.5ms postprocess per image at shape (1, 3, 384, 640)
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Infer: 0.3ms preprocess, 165.5ms inference, 0.5ms postprocess per image at shape (1, 3, 384, 640)
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VIII. CONCLUSION

This research presents a robust and efficient framework for real-time traffic rule violation detection using advanced computer vision and deep learning techniques. By leveraging the capabilities of the YOLOv10 object detection model, along with object tracking and region-based analysis, the system successfully identifies vehicles and detects violations such as red-light jumping with high accuracy and reliability.

One of the key strengths of the proposed system lies in its real-time processing capability. Unlike traditional traffic monitoring approaches that depend on manual observation or

offline analysis, this system operates continuously on live or recorded video streams. The integration of OpenCV with the YOLOv10 model ensures rapid detection and processing of frames, making the system suitable for deployment in high-traffic urban environments. Furthermore, the use of a tracking algorithm enables consistent identification of vehicles across multiple frames, reducing redundancy and improving the precision of violation detection.

Another significant contribution of this work is the implementation of a polygon-based region of interest combined with traffic signal state detection. This approach allows the system to accurately determine whether a vehicle has violated traffic rules by entering a restricted zone during a red signal. The ability to capture and store images of violating vehicles with timestamps provides valuable evidence for enforcement agencies, enhancing accountability and legal compliance.

The experimental results demonstrate that the system performs effectively under various conditions, including different lighting scenarios and traffic densities. The use of YOLOv10 ensures a good balance between detection speed and accuracy, while the modular design of the system allows for easy scalability and integration with additional features. Compared to existing systems, the proposed solution offers improved automation, reduced human intervention, and enhanced reliability.

Despite its advantages, the system has certain limitations. Factors such as extreme weather conditions, occlusions, and poor camera angles can affect detection accuracy. Additionally, the current implementation focuses primarily on red-light violations and does not cover other types of traffic violations such as overspeeding or lane discipline. These limitations highlight areas for future improvement.

Future work can focus on integrating Automatic Number Plate Recognition (ANPR) to identify violating vehicles and link them with owner databases for automated fine generation. The system can also be extended to detect multiple types of violations and incorporate advanced tracking algorithms such as Deep SORT for improved performance. Integration with IoT-enabled traffic signals and cloud-based storage systems can further enhance scalability and enable centralized monitoring.

In conclusion, the proposed traffic violation detection system represents a significant step toward intelligent transportation systems and smart city infrastructure. By combining deep learning, computer vision, and real-time analytics, the system provides an effective solution for improving road safety, reducing traffic violations, and supporting law enforcement agencies. With further enhancements and real-world deployment, this technology has the potential to transform traffic management and contribute to safer and more efficient urban mobility.



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