Multi-Violation Detection in Two-Wheeler Traffic Surveillance Using YOLOv11

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Abstract: Rapid urbanization and the increasing use of two-wheelers in urban transportation have led to a significant rise in traffic violations and road accidents. Violations such as riding without helmets and triple riding are major causes of severe injuries and fatalities, particularly in densely populated traffic environments. Traditional traffic monitoring systems mainly depend on manual surveillance and conventional CCTV monitoring, which are time-consuming, labor-intensive, and often incapable of providing accurate real-time enforcement. To address these limitations, this work proposes an AI-based real-time two-wheeler traffic violation detection system using advanced YOLOv8 and YOLOv11 object detection models.

The proposed framework utilizes deep learning and computer vision techniques to automatically detect motorcycles, riders, helmets, no-helmet cases, triple riding violations, and vehicle number plates from real-time traffic images and video streams. The system performs simultaneous multi-object detection within a unified pipeline and applies rule-based violation analysis for intelligent traffic monitoring. A comparative analysis between YOLOv8 and YOLOv11 is conducted to evaluate detection accuracy, robustness, and real-time performance under complex urban traffic conditions. Experimental results demonstrate that YOLOv11 achieves improved object localization, higher detection precision, and better generalization capability compared to YOLOv8. The proposed system enhances automated traffic law enforcement, reduces human intervention, and contributes to safer and smarter urban transportation systems.

Index terms - — *Deep Learning, Computer Vision, YOLOv8, YOLOv11, Real-Time Object Detection, Helmet Detection, Triple Riding Detection, Number Plate Recognition, Intelligent Traffic Surveillance, Traffic Violation Detection, Urban Road Safety, Artificial Intelligence.*

1. INTRODUCTION

Rapid urbanization and the growing dependence on two-wheelers for daily transportation have significantly increased traffic congestion and road safety challenges in modern cities. Two-wheelers are widely preferred because of their affordability, fuel efficiency, and ability to navigate through dense traffic conditions. However, the increasing number of motorcycles on roads has also led to a rise in traffic violations and accident-related fatalities. Among the most common violations, riding without helmets and triple riding are major causes of severe injuries and deaths in road accidents. Although traffic regulations and safety laws have been implemented strictly in many countries, effective monitoring and enforcement remain difficult due to the limitations of traditional surveillance systems. Manual monitoring by traffic police and conventional CCTV-based observation methods are time-consuming, labor-intensive, and highly prone to human error, making them inefficient for large-scale real-time traffic management.

Recent advancements in Artificial Intelligence (AI), Deep Learning, and Computer Vision have created new opportunities for developing intelligent transportation and automated traffic monitoring systems. Object detection algorithms belonging to the YOLO (You Only Look Once) family have demonstrated remarkable performance in detecting multiple objects accurately and efficiently within complex real-world environments. Modern YOLO architectures provide high-speed object localization and classification capabilities, enabling real-time analysis of traffic surveillance video streams. By leveraging these advancements, intelligent systems can automatically identify motorcycles, riders, helmets, no-helmet violations, and vehicle number plates simultaneously. Such automated systems improve monitoring accuracy, reduce dependency on human intervention, and support efficient traffic law enforcement in urban environments.

This work proposes an AI-based real-time two-wheeler traffic violation detection system using advanced YOLOv8 and YOLOv11 object detection models. The proposed framework integrates multi-object detection, violation analysis, and vehicle identification into a unified intelligent surveillance pipeline. The system is capable of detecting helmet violations, triple riding cases, and vehicle number plates from real-time traffic images and video streams with high accuracy and speed. A comparative analysis between YOLOv8 and YOLOv11 is also performed to evaluate their effectiveness in terms of detection precision, robustness, and real-time performance under challenging urban traffic conditions. The proposed system aims to support intelligent traffic surveillance, enhance road safety, and contribute toward the development of smart city transportation infrastructure.

2. LITERATURE SURVEY

a) Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks:

This paper presented Faster R-CNN, an enhanced object identification framework that integrates Region Proposal Networks (RPN) with Fast R-CNN to increase detection speed and accuracy. Computational bottlenecks resulted from the use of distinct region proposal algorithms in traditional object identification techniques. By sharing convolutional features across the region proposal and detection networks, Faster R-CNN overcame this constraint and allowed for almost free proposal creation. The system maintained real-time processing capacity while achieving state-of-the-art object detection performance on benchmark datasets including PASCAL VOC and MS COCO. The suggested approach became one of the fundamental architects for contemporary object detection systems and greatly increased the accuracy of object localization.

b) SSD: Single Shot MultiBox Detector:

This study presented SSD (Single Shot MultiBox Detector), a real-time item detection system that eliminates the need for separate area proposal phases by performing object localization and classification in a single deep neural network. SSD effectively detects objects of varied sizes and aspect ratios by generating predictions using several feature maps at different resolutions. The framework achieved competitive detection accuracy and fast processing speed while streamlining the object detection pipeline. SSD beat a number of conventional object identification techniques while retaining real-time speed, according to experimental results on benchmark datasets including PASCAL VOC and COCO. SSD is an effective and scalable option for intelligent computer vision applications, according to the study.

c) You Only Look Once: Unified, Real-Time Object Detection:

YOLO (You Only Look Once), a unified real-time object identification method that reframed object detection as a single regression issue, was presented in this work. YOLO used a single neural network to process the full image in order to concurrently forecast bounding boxes and class probabilities, in contrast to conventional approaches that applied classifiers on suggested image sections. The suggested design maintained good detection performance while achieving very fast processing speeds. Real-time applications can benefit from quick YOLO processing of photos at extremely high frame rates. According to the study, YOLO efficiently generalized across many visual domains and dramatically decreased incorrect background detections. YOLO became a significant advancement in intelligent surveillance systems and real-time computer vision.

d) YOLO9000: Better, Faster, Stronger:

YOLO9000, an improved real-time object identification system that can identify over 9000 item types, was presented in this study. By implementing multi-scale training methods, the study enhanced previous YOLO designs and made it possible for the same model to function well at various picture resolutions. Through a joint training approach, YOLO9000 integrated object detection and picture classification datasets, enabling the system to identify object classes even in the absence of explicit detection annotations. In comparison to SSD and Faster R-CNN models, experimental findings demonstrated increased processing speed and detection accuracy. For large-scale intelligent vision applications, the suggested architecture proved the efficacy of scalable and fast object identification.

e) YOLOv3: An Incremental Improvement:

In order to increase detection accuracy while preserving high real-time processing speed, this study introduced YOLOv3, an enhanced version of the YOLO object detection framework. To enhance object localization and classification performance, a number of architectural enhancements and optimization strategies were implemented. YOLOv3 improved the simultaneous identification of tiny and big objects by using deeper feature extraction networks and multi-scale prediction processes. According to experimental assessment, YOLOv3 outperformed competitor detection models like RetinaNet while achieving better mAP scores than earlier YOLO versions. According to the study, YOLOv3 is a very effective and precise object recognition framework that may be used for computer vision, traffic monitoring, and real-time intelligent surveillance.

3. METHODOLOGY

i) Proposed Work:

The proposed work introduces an intelligent AI-based traffic surveillance system designed to automatically detect two-wheeler traffic violations in real time using advanced deep learning and computer vision techniques. The system utilizes YOLOv8 and YOLOv11 object detection models to identify motorcycles, riders, helmets, no-helmet cases, and vehicle number plates from traffic images and live video streams. By integrating multi-object detection into a single unified framework, the proposed system can simultaneously monitor multiple traffic violations such as helmet violations and triple riding with high speed and accuracy. The framework is trained using a custom annotated dataset containing different traffic scenarios, lighting conditions, and rider variations to improve detection robustness in real-world urban environments.

The proposed system also incorporates a violation analysis mechanism that applies logical association rules to determine whether riders are wearing helmets and to identify multiple riders on a single motorcycle. In addition, the system detects and isolates vehicle number plates, enabling future integration with automated license plate recognition and digital traffic enforcement systems. A comparative evaluation between YOLOv8 and YOLOv11 is performed to analyze detection performance, processing speed, precision, and scalability. Experimental analysis demonstrates that YOLOv11 provides improved object localization and better generalization capability for complex traffic environments. The proposed framework reduces manual monitoring effort, supports intelligent transportation management, and contributes toward safer and smarter urban traffic surveillance systems.

ii) System Architecture:

The proposed system architecture is designed as an intelligent end-to-end traffic surveillance framework that performs automated detection of two-wheeler traffic violations using deep learning and computer vision techniques. The architecture begins with traffic surveillance video streams and captured road images obtained from CCTV cameras and intelligent monitoring devices. These input images are passed to the preprocessing stage, where operations such as image resizing, normalization, and data augmentation are performed to improve image quality and prepare the data for deep learning analysis. The processed images are then forwarded to the YOLOv8/YOLOv11 object detection module, which simultaneously detects motorcycles, riders, helmets, no-helmet cases, and vehicle number plates using bounding boxes, class labels, and confidence scores.

The detected objects are further analyzed by the violation analysis module, where logical association techniques are applied to identify traffic rule violations such as no-helmet riding and triple riding. The system also extracts vehicle number plates for vehicle-level identification and future enforcement activities. Finally, the framework generates automated traffic violation reports and real-time alerts containing details such as violation type, vehicle information, confidence score, and timestamp. This integrated architecture enables accurate real-time monitoring, minimizes human intervention, and provides a scalable solution for intelligent urban traffic surveillance and road safety enforcement.

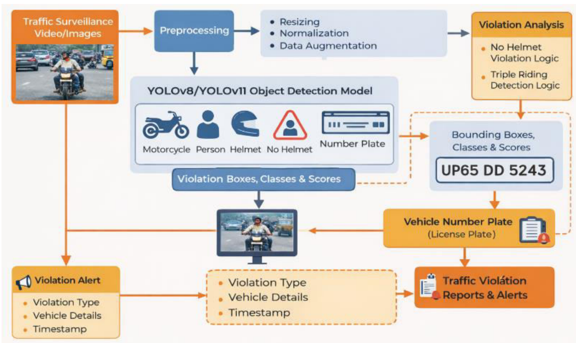

Fig1 proposed architecture

iii) Modules:

1. Data Acquisition Module

The Data Acquisition Module is responsible for collecting traffic surveillance images and video streams from CCTV cameras, roadside monitoring systems, and intelligent traffic devices. It continuously captures real-time traffic scenes under different environmental and road conditions. The collected images and video frames act as the primary input for the violation detection framework. Reliable data acquisition ensures proper visibility of motorcycles, riders, helmets, and number plates for accurate traffic analysis.

2. Preprocessing Module

The preprocessing module prepares raw traffic images and video frames for deep learning analysis. It performs operations such as image resizing, normalization, noise reduction, frame extraction, and image enhancement to improve input quality. Data augmentation techniques including rotation, flipping, scaling, and brightness adjustment are also applied during training to improve model robustness against varying weather conditions, lighting environments, and camera viewpoints.

3. Object Detection Module (YOLOv8 / YOLOv11)

This module forms the core of the proposed system and uses advanced YOLOv8 and YOLOv11 deep learning algorithms for real-time object detection. The module simultaneously detects motorcycles, riders, helmets, no-helmet cases, and vehicle number plates using bounding boxes and confidence scores. The YOLO-based architecture provides fast processing speed, accurate object localization, and efficient multi-object recognition suitable for intelligent traffic monitoring applications.

4. Violation Analysis Module

The Violation Analysis Module automatically identifies traffic rule violations using rule-based logical association techniques. Helmet violations are detected when riders are identified without helmets, while triple riding violations are recognized when more than two persons are associated with a single motorcycle. This module supports simultaneous detection of multiple violations from a single traffic frame, improving automated traffic law enforcement efficiency.

5. Number Plate Identification Module

This module detects and extracts vehicle number plates from traffic images for vehicle-level identification and monitoring. The extracted number plates can be used for generating traffic penalties, maintaining digital enforcement records, and integrating with OCR-based license plate recognition systems. The module enhances automated vehicle tracking and intelligent traffic management capabilities.

6. Alert and Reporting Module

The Alert and Reporting Module generates automated traffic violation notifications and structured digital reports. The generated reports include details such as violation type, vehicle information, confidence score, date, time, and timestamp. These reports can be stored in centralized databases or forwarded directly to traffic authorities for real-time enforcement and traffic management operations.

iv) Algorithms:

1. YOLOv8 Object Detection Algorithm

YOLOv8 is a real-time one-stage object detection algorithm used in the proposed system for detecting motorcycles, riders, helmets, no-helmet cases, and vehicle number plates from traffic surveillance images. The algorithm processes the entire image in a single forward pass and predicts bounding boxes, object classes, and confidence scores simultaneously. YOLOv8 uses an anchor-free detection mechanism and an optimized backbone network, which improves detection speed and localization accuracy. Its lightweight architecture enables efficient real-time traffic monitoring while maintaining high precision in complex urban environments. The model also supports better feature extraction and faster inference, making it suitable for intelligent transportation and surveillance applications.

2. YOLOv11 Object Detection Algorithm

YOLOv11 is an advanced version of the YOLO family designed to provide enhanced object detection accuracy and robustness. In the proposed framework, YOLOv11 is used to improve the detection of safety-critical objects such as helmets and vehicle number plates under challenging traffic conditions. The algorithm incorporates improved feature extraction techniques, better generalization capability, and optimized learning mechanisms for handling small and overlapping objects. YOLOv11 achieves higher mean Average Precision (mAP) while maintaining real-time processing performance. Due to its improved detection capability and scalability, YOLOv11 is highly effective for large-scale intelligent traffic surveillance and automated traffic violation detection systems.

4. EXPERIMENTAL RESULTS

The experimental evaluation of the proposed system was conducted using real-time traffic surveillance images and video datasets containing motorcycles, riders, helmets, no-helmet cases, triple riding scenarios, and vehicle number plates. The system was implemented using Python, OpenCV, and Ultralytics YOLO frameworks, and the performance of YOLOv8 and YOLOv11 models was comparatively analyzed under different urban traffic conditions. Experimental observations demonstrate that both models achieved efficient real-time object detection; however, YOLOv11 provided superior detection accuracy, better object localization, and improved robustness for detecting small and safety-critical objects such as helmets and number plates. The system successfully generated bounding boxes, confidence scores, and violation classifications for multiple traffic violations simultaneously.

The proposed framework effectively identified helmet violations and triple riding cases with minimal false detections while maintaining high processing speed suitable for intelligent traffic surveillance applications. The violation analysis module accurately associated riders with motorcycles and detected rule violations using logical decision mechanisms. The generated outputs included violation alerts, detected vehicle details, timestamps, and structured reporting information for automated traffic enforcement. Experimental analysis confirmed that the proposed AI-based framework significantly reduces manual monitoring effort and improves the efficiency, scalability, and reliability of urban traffic violation detection systems.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class k}$$

$$n = \text{the number of classes}$$

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

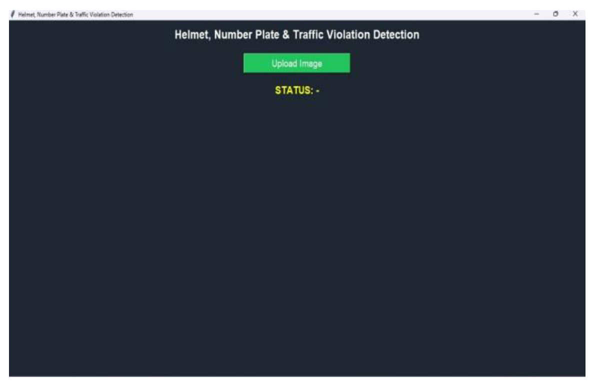

Fig2 upload image

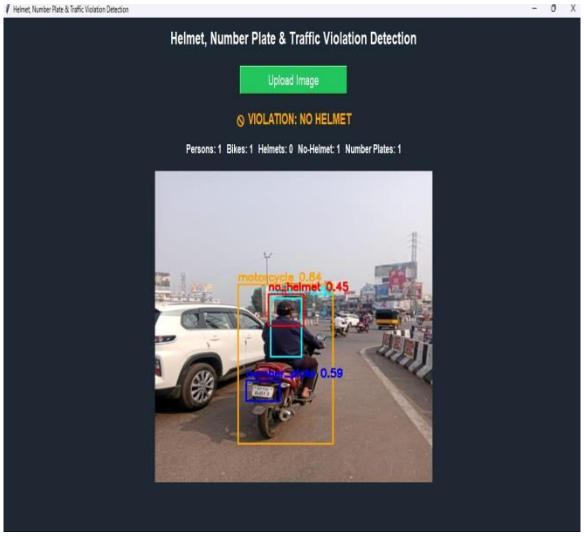

Fig3 results

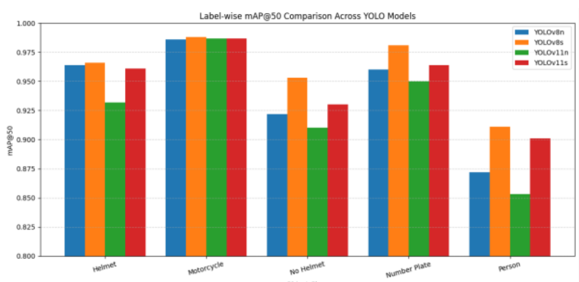

Fig4 predicted analysis

5. CONCLUSION

This work presented an AI-based real-time two-wheeler traffic violation detection system using advanced YOLOv8 and YOLOv11 object detection models for intelligent traffic surveillance applications. The proposed framework successfully detects motorcycles, riders, helmets, no-helmet violations, triple riding cases, and vehicle number plates within a unified deep learning pipeline. By integrating computer vision techniques with automated violation analysis, the system provides accurate and efficient real-time monitoring of urban traffic conditions. Experimental evaluation demonstrated that YOLOv11 achieved better detection accuracy, improved object localization, and stronger generalization capability compared to YOLOv8, particularly for small and safety-critical objects such as helmets and number plates.

The proposed system significantly reduces the dependency on manual traffic monitoring and enhances the effectiveness of automated traffic law enforcement. The framework supports simultaneous multi-violation detection with high processing speed and scalability, making it suitable for deployment in smart city transportation and intelligent surveillance environments. Overall, the developed system contributes toward improving road safety, minimizing traffic violations, and enabling smarter and more reliable urban traffic management solutions through the use of deep learning and real-time computer vision technologies.

6. FUTURE SCOPE

The future scope of the proposed system can be extended by integrating advanced Artificial Intelligence and smart transportation technologies to improve the accuracy, scalability, and automation of traffic monitoring systems. Future enhancements may include the integration of Optical Character Recognition (OCR) techniques for automatic vehicle number plate recognition and direct linkage with traffic enforcement databases for generating digital penalties and automated challan systems. The framework can also be expanded to detect additional traffic violations such as signal jumping, over-speeding, lane violations, mobile phone usage while riding, and dangerous driving behaviors. Furthermore, integrating cloud computing and IoT-based smart surveillance infrastructure can improve centralized monitoring and large-scale deployment across smart city environments.

The proposed framework can also be enhanced by incorporating more advanced deep learning architectures and edge AI technologies for faster inference and low-latency processing on embedded devices and smart cameras. Future research may focus on improving detection performance under challenging environmental conditions such as rain, fog, nighttime traffic, and heavy occlusion scenarios. In addition, the integration of real-time analytics dashboards, predictive traffic analysis, and AI-driven traffic management systems can further strengthen intelligent transportation infrastructure. These improvements will contribute toward safer roads, automated traffic governance, and the development of efficient smart city surveillance systems.

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