Smart Traffic Violation Detection System Using YOLOv8

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Abstract

Traffic violations are increasing due to rapid urbanization and an increase in the number of vehicles per capita creating accidents and congestion on the road. Most of the traditional methods for traffic violation detection are error-prone and manual involvement doesn't achieve effective results. The proposed system uses YOLOv8 for the real-time detection of riders, helmets and motorcycles and also OCR for automatic license plate recognition. Spatial correlation theory has been applied to detect most common issues like helmet and triple riding violations. The proposed system achieved a precision of 89.91% for helmet detection and 76.63% for triple riding detection demonstrates effectiveness in real-world traffic situations.

Keywords: Traffic Violation Detection, YOLOv8, ALPR, Computer Vision, Artificial Intelligence.

1. Introduction

As smart traffic monitoring and execution system develops important role in real-time computer vision that converts unstructured, random CCTV data into structured and verifies activities. Deep-learning-based violation detection models effectively perform in a variety of illuminated and environmental settings that supports the use of AI-driven approaches in real-time traffic monitoring [3]. Existing studies show that YOLO based systems can effectively detect red-light violations with high accuracy in real-world traffic scenarios [1]. YOLOv8 is a single-stage detector with better precision.

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Accurate detection of implementation in real-world challenges is achieved by latency detection of cars, riders, pedestrians, traffic signals and license plates in various metropolitan situations with unsafe situations. The system establishes an effective basis for downstream tracking and spatial rule evaluation to prevent violations, red light running and rider counts by identifying critical entities and violation alerts on a frame-by-frame.

Computer-vision-based traffic monitoring has been shown to effectively identify violations in crowded environment [2]. This process uses ANPR in two parts: plate localization and Tesseract OCR with plate-related preprocessing and limited decoding to connect detected violations with vehicle identification. Tesseract uses particular settings to analyze text based on plate segmentation using YOLOv8.

Finally, multi-frame voting decreases false positives and negatives caused by the common noise, blur and restriction seen in roadside cameras. A modular method combining YOLOv8 detection with Tesseract OCR provides machine-readable plate data for automatic tickets, incident reports and connects to back-end control systems at the optimal volume accuracy ratio. The combined architecture improves implementation ability and durability: YOLOv8 is an image collection for reliable limit boxes at real-time speeds and Tesseract is a low-cost, semi-structured identifier for modified, stabilized plate crops. As a result, many metropolitan areas have a closed-loop, data-driven evaluation system for a violation from ROI detection to OCR verification of vehicle identification for both an installation and maintenance approach.

1.1 Problem Formulation

The aim of this research is to create an accurate visually-based traffic violation detection system accurately detects helmet and triple riding violations in two-wheeler by developing the proper spatial connection between riders, helmets and two-wheelers. This work was performed in real time with minimum problems caused by blocking and to maintain reduced computation costs and adaptable by traffic monitoring systems.

From the above mentioned challenges, the proposed method in the presented research based on the use of the YOLOv8 algorithm combined with the application of spatial reasoning for the detection of riders, helmets and motorcycles in traffic images and video footage. Additionally, the use of the optical character recognition technique for the extraction of data from the plates of the vehicles identified in the images and videos for the detection of violated vehicles. Furthermore, the system will have the ability to calculate the number of riders for each motorcycle.

Deep learning models for traffic monitoring achieved significant results, reliable spatial connection between riders, helmets and motorbikes remains a challenge in real-life situations such as blocking, high traffic and different perspectives of the camera. Most previous models are affected by misleading correlations or involve complicated multi-step processing results inappropriate for real-time execution. This work focuses on resolving the problem by utilizing lightweight spatial reasoning and real-time YOLOv8 for accurate detection of helmets and triple riding violations.

2. Related Work

Recent advancements in computer vision and deep learning have significantly contributed to the development of automated traffic violation detection systems. Early studies focused on traffic signal and red-light violation detection using traditional image processing and early deep learning approaches demonstrating the feasibility of vision-based enforcement systems [1-4]. While these methods achieved detection accuracy, they were often sensitive to lighting variations, camera angles and environmental noise, limiting their robustness in real-world traffic scenarios [15].

YOLO-based object detection models have been widely applied for real-time traffic monitoring and violation detection with the adoption of deep learning. Several studies have demonstrated improved accuracy using YOLO architectures for detecting traffic violations and generating automated enforcement outputs [5-7]. The analytical reviews further highlight the effectiveness of machine learning-based approaches while identifying challenges such as occlusion and overlapping objects in dense traffic environments [8]. The recent works using YOLO models have extended detection capabilities to include automated challan generation and real-time deployment scenarios [9-11].

Several studies have specifically addressed two-wheeler traffic violations such as helmet non- compliance using convolutional neural networks and YOLO-based frameworks. The research [12] explored CNN-based detection for two-wheeler violations, while the research [13,14] proposed YOLOv5-based helmet detection systems with improved precision. However, these approaches based on heuristic or isolated detection strategies, leading to false positives when reliable spatial association between riders and helmets is not established. Additionally, manual traffic enforcement systems continue to be error-prone and unsuitable for large-scale continuous monitoring [17].

Recent multi-violation detection frameworks attempt to detect multiple offenses simultaneously, improving functionality but increasing computational complexity and limiting real-time deployability [18,19]. These limitations highlight the focused, efficient and scalable solution capable of accurately detecting two-wheeler traffic violations under real-world conditions. Table 1 shows the limitations and challenges in existing traffic violation detection systems.

Table 1. Limitations and Challenges in Existing Traffic Violation Detection Systems

Study / Approach	Technique Used	Limitations
Traditional computer vision methods	Edge detection, Hough Transform	Sensitive to lighting variations and camera angles; poor generalization
YOLOv3-based systems	Deep learning–based object detection	Reduced accuracy in dense traffic scenes
YOLOv5-based systems	Improved object Detection	False positives due to occlusion and overlapping riders
Rule-based helmet detection	Bounding box heuristics	Helmets detected off-rider may be misclassified
Multi-violation frameworks	Complex multi-stage Pipelines	High computational cost and limited real- time performance

3. Methodology

YOLO-based systems have shown better performance in real-time violation detection workflows and automated enforcement tasks [9]. This methodology addresses the general steps taken to develop the ML based traffic offense detection system, no helmet and triple riding violations using a pre-trained object detection model - YOLOv8 and license plate detection by using Tesseract OCR.

The proposed system utilizes a deep learning-based model to detect traffic violations in two-wheelers in images and videos. YOLOv8 object detection model has been used to detect bikers, helmets and two-wheelers to perform spatial associations to detect violations of helmet rules and triple riding by bikers. The general steps and framework occur in five stages: data collection, data preparation, training, violation detection and system evaluation and deployment. Figure 1 shows the flow diagram of traffic violation detection system.

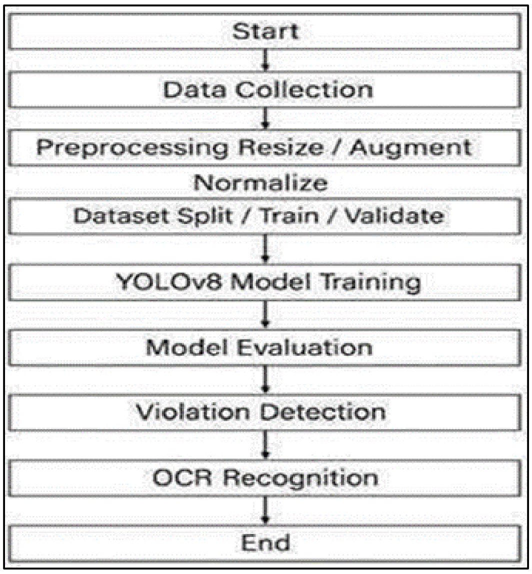

Figure 1. Flow Diagram of Traffic Violation Detection

3.1 Data Collection and Data Preparation

The dataset used for this research includes images, rider videos from a traffic camera system and an open-access dataset. The two traffic violations are studied:

- Helmet Violation – It detects riders who are not wearing helmets
- Triple Riding – It detects more than two persons riding on a motorcycle

Roboflow was used manually to modify each image, assigned bounding boxes for the following classes:

- Wearing a helmet or not
- Two individuals
- Three individuals

The modified dataset was then divided into three subsets:

- Training set (70%)
- Validation set (20%)

- Testing set (10%)

3.2 Data Preprocessing

The basic data preparation is important for improving the quality and consistency of the data collection before training the YOLOv8 model. The appropriate preprocessing allows for the model obtains all the minute details of detection and functions effectively under different real-life traffic circumstances that one may face the issues on every day. The following steps were performed in this work:

- **Image Resizing:** All images were resized to 640 × 640 pixels, the most optimal input size for training a YOLOv8 model.
- **Data Augmentation:** The techniques such as horizontal flipping, rotation, scaling, modifying brightness and including noise were used to improve dataset range and decrease overfitting.
- **Normalization:** The pixel values were normalized from 0 to 1 to provide correct training and increase speed.
- **Label Verification:** All labels were manually validated in RoboFlow to identify missing, duplicate or incorrect bounding boxes.
- **Dataset Organization:** The processed dataset was organized into folders for images and labels in each subset (train/val/test) to ensure integration with the YOLOv8 system.

3.3 Model Architecture

An advanced deep learning model Ultralytics developed the YOLOv8. YOLOv8 models are more accurate and efficient compared to their YOLO predecessors. The key components of YOLOv8 models are:

- **Backbone:** TheC2F module design is used for efficient feature extraction. It finds multi-scale spatial characteristics in input images. The feature maps are collected from various resolutions using a feature aggregation network. It improves object recognition for objects of varied sizes.

- **Head:** It has a decoupled detection head. It carries object classification and bounding-box regression
- **Inference:** It makes detection in a single pass. It also predicts bounding boxes and class probabilities. It supports real-time processing for traffic monitoring systems.

3.4 YOLOv8 Variant Selection

In this research, the YOLOv8s model variation was used to detect traffic violations. The decision of YOLOv8s was based on the reason that it provides a balanced combination of detection accuracy and computing complexity. As a result, YOLOv8s was chosen because it has a faster detection speed and reduced computing complexity than the other YOLO model variations but performed for rider, helmet and motorbike recognition in traffic.

3.5 Model Training

Training was performed on a GPU-enabled platform with the Ultralytics YOLOv8 system application. Table 2 illustrates the model training configuration and hyperparameters.

Table 2. Model training Configuration and Hyperparameters

Parameter	**Value**
Image Size	640 × 640
Batch Size	16
Epochs	150
Optimizer	SGD (Stochastic Gradient Descent)
Learning Rate	0.001
Weight Decay	0.0005

3.6 Violation Detection Logic

After the YOLOv8 model has performed object detection on images or video frames, the bounding box outputs are analyzed further to identify particular traffic violations. This research focuses at two major crimes: triple riding and helmet violations.

3.6.1 Helmet Violation Detection

This section identifies helmet violations by detecting both the rider and the helmet in the same frame. The YOLOv8 model classifies the objects like person, helmet and no helmet. The system detection works as follows:

- When a motorbike is detected, the module searches for a helmet in the specified area above the rider's head.
- A "Helmet Violation" is provided if the rider's head is not covered by a bounding box.
- If the Helmet falls under the limit, no violation is detected.

This spatial verification between the rider and the helmet confirms that the model does not inaccurately categorize helmets located further in the frame as being worn by the rider.

3.6.2 Triple Riding Detection

The triple riding detection goal is to count multiple people recognized on a single motorcycle. The YOLOv8 model uses the following reasons to differentiate each person and motorbike in a frame:

- Each motorbike provides a reference bounding box.
- The system counts the number of person in bounding boxes within the motorcycle's restricted region.
- The system indicates a "Triple Riding Violation" when it detects more than two people on a motorcycle.

This count-based technique performs effectively in traffic situations when numerous motorcycles are found.

3.6.3 License Plate Recognition – Tesseract OCR

The identified motorcycle's bounding box is used to identify the license plate. A fixed region of interest (ROI) is defined at the rear part of the motorbike bounding box, where the license plate is usually found. This ROI is retrieved and sent into the OCR module for text recognition.

When a violation is reported, Tesseract OCR immediately detects the vehicle. For example,

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- The license plate position is based on the motorcycle's identified bounding box.
- The image is converted to grayscale, filtered and minimized for improved character readability.
- Tesseract OCR scans image characters and collects plate numbers for violator's registration.

This enables the traffic authority to automatically identify violators and collect complete data.

3.7 Mathematical Formulation for Violation Detection Logic

A. Spatial Overlap Threshold for Helmet Violation Detection

Let

- B_p denote the bounding box of a detected rider (person),
- B_h denote the bounding box of a detected helmet

The spatial overlap between the rider and helmet is computed using the Intersection over Union (IoU) metric:

$$IoU(B_p, B_h) = \frac{|B_p \cap B_h|}{|B_p \cup B_h|} \quad (1)$$

A helmet is considered to be correctly worn if the overlap between Bp and Bh exceeds a predefined threshold τ_h:

$$IoU(Bp, Bh) \geq \tau h \quad (2)$$

The system removes a helmet violation if no helmet satisfies this condition for a detected rider.

B. Person–Motorcycle Association for Triple Riding Detection

Let

- B_m denote the bounding box of a detected motorcycle
- B_{P_i} denote the bounding box of the i detected person
- $C(Bp\ )$ denote the center point of Bp_i

A person is associated with a motorcycle if the center of the person's bounding box lies within the motorcycle's bounding box:

$$C(B_{p_i}) \in B_m \tag{3}$$

The total number of persons associated with a motorcycle is computed as:

$$N = \sum_{i=1}^{n} 1\,(C(B_{p_i}) \in B_m) \tag{4}$$

where $1(\cdot)$ is the indicator function.

If $N > 2$ the system identifies a triple riding violation.

3.8 System Implementation

A working model of traffic monitoring system was created by combining a live video footage with a trained YOLOv8 model. Figure 2 represents the model workflow. The system performs the following actions:

- It records videos from CCTVs.
- It uses YOLOv8 prediction for each frame.
- It uses limit boxes to show identifiable objects (e.g. riders, helmets).
- It creates alerts and record violations by taking images and mark the timings for reporting.

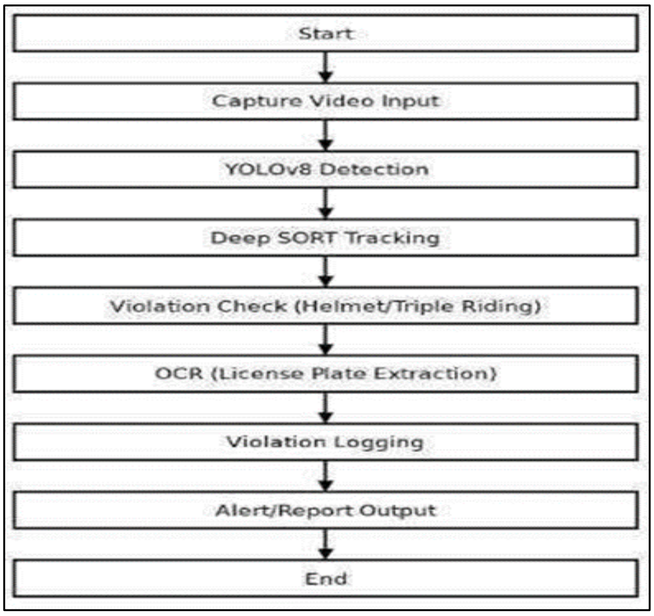

Figure 2. Model Workflow

4. Results

The results of the YOLOv8 model are consistent with previous research showing that improved YOLO systems significantly improve helmet violation detection accuracy [13]. The model's performance in real-world situations was examined using various kinds of factors including accuracy, precision, recall and mean average precision. The algorithm for detecting violations performed effectively in various traffic situations.

4.1 Helmet Violation Detection

This model improves accurate recognition, flexibility under various settings and head postures. It will accurately identify riders with helmets by performing spatial verification. The results are constant in different levels of traffic and illuminated conditions showing the capacity to accept limited visibility and differences in rider direction. The proposed method works in real-world circumstances for detecting helmet violations. Figure 3 represents the helmet violation detection.

Figure 3. Helmet Violation Detection

4.2 Triple Riding Detection

The system could detect more than two riders on the motorcycle. The detection performance of the system is better with low error in detection caused by the overlapping of vehicles and filtered images from the cameras. The spatial association logic could identify the riders on the same motorcycle even in high traffic situations. This test proves that the method designed for detecting triple riding. Figure 4 shows the triple riding detection.

Figure 4 Triple Riding Detection

4.3 License Plate Recognition

The license plate recognition system was utilized in another method to detect helmet, triple riding violations and identify the cars that violated these laws. The OCR module effectively recognized motorbike license plates from visual representations that were easily visible to the human eye under normal situations. The accuracy will be decreased when the motorbike images were blurred, smudged or taken in darkness. Figure 5 shows the license plate reading.

Figure 5. License Plate Reading

4.4 Evaluation

A restricted test dataset was used to evaluate the system using standard measures like precision, recall, F1-score and mAP@0.5. The evaluative metrics show the YOLOv8s model can identify violations with high precision, allowing it suitable for real-time traffic monitoring in this situation. The key performance results are explained in below table 3.

Table 3. Performance Metrics of Traffic Violation Detection Models

Model / Violation Type	Precision (%)	Recall (%)	F1 Score (%)	mAP@0.5 (%)
Helmet Detection Model	89.91	86.37	88.1	92.46
Triple Riding Detection Model	76.63	57.14	65.5	57.81

Two YOLOv8 models were developed and trained for 150 epochs includes the helmet detection model and the triple riding detection model. The helmet detection model achieved an accuracy of 89.91%, recall of 86.37%, F1-score of 88.1% and mAP@0.5 of 92.46% showing accurate and effective detection with few false positives or negatives in various situations where riders without helmets may be present.

The Triple Riding Detection Model reached an accuracy of 76.63%, recall of 57.14%, F1-score of 65.5% and mAP@0.5 of 57.81% illustrates sufficient accuracy with more complicated detection of multiple riders in random traffic situations. Feature extraction, bounding box regression and processing speed results are verified by YOLOv8.

The recall observed in triple-riding detection is decreased due to numerous barriers, overlapping riders and various seating positions in crowded traffic environments. These challenges lead to identify riders in a single frame. As a result, the current technique has an inbuilt limitation provides the way for additional temporal connection and multi-frame tracking mechanisms in future implementations to increase rider counting accuracy.

5. Conclusion

AI and ML technologies have played a significant role in enhancing the speed and accuracy of real- time traffic violation detection systems [17]. This project presents a smart traffic violation detection system using artificial intelligence. A deep learning model based on

YOLOv8 is used to locate and classify common traffic violations such as helmet and triple riding violations. Optical Character Recognition (OCR) is implemented to recognize license plate numbers from images of traffic violations. The proposed automated method allows detection, reporting and violation tracking with minimal human involvement. This technique uses data preparation, parameter modification and dataset augmentation to achieve optimal model performance.

Computer vision algorithms have been demonstrated for effective techniques detecting traffic violations in various types of lighting situations, weather circumstances and camera locations. The resulting system is adaptable, scalable and effective in continuous road and highway monitoring, reducing the requirement for manual observation and the risk of human error. The result shows that the proposed method accurately recognizes helmet and triple riding violations. The experimental results show that the proposed YOLOv8-based system can identify helmet and triple riding violations with high accuracy in real-time traffic situations. The combined spatial analysis and automated license plate identification improves the system's usability for traffic law enforcement. This study provides a specific and adaptable method for smart traffic monitoring systems by handling important challenges such as blocking, scalability and real-time processing.

In future, the system improved by accepting numerous camera inputs, modifying performance depends on weather and lighting conditions and using cloud computing for large-scale deployment. AI-based surveillance solutions also perform continuous violation detection and traffic density analysis allowing for scalable and adaptable traffic monitoring systems.

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