

Research Paper

TRAFFIC VOILATIONS AND SPEED SIGNAL JUMP OVER SPEED NO HELMET USING CNN

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ABSTRACT

TrafficVision AI: Real-Time Traffic Violation Detection Using CNN is an intelligent computer vision-based system designed to automatically detect and monitor common traffic violations in real time. The proposed system uses **Artificial Intelligence, Computer Vision, Convolutional Neural Networks (CNN), and image/video processing techniques** to identify vehicles, traffic signals, riders, and road-rule violations from live camera footage or recorded videos. The system is designed to detect violations such as **over-speeding, signal jumping, and riding without a helmet**. Video frames are processed to identify and track vehicles, while CNN-based models classify relevant objects and recognize violation patterns. When a violation is detected, the system can record details such as the violation type, vehicle information, time, and captured evidence for further review. The proposed **TrafficVision AI** system aims to reduce manual traffic monitoring, improve the efficiency of violation detection, and support safer road management. It can be deployed in smart-city environments, traffic intersections, highways, and other locations requiring automated traffic surveillance. By combining CNN-based object recognition with intelligent traffic analysis, the system provides a scalable solution for automated traffic-rule enforcement and road-safety monitoring.

I. INTRODUCTION

The rapid growth of urban populations and the increasing number of vehicles have created significant challenges for modern traffic-management systems. Traffic violations such as excessive speed, jumping red signals, and riding motorcycles without helmets contribute to road accidents, congestion, and unsafe driving conditions. Conventional traffic enforcement generally depends on traffic police personnel and

manually monitored surveillance cameras. Although these approaches are useful, they can be time-consuming, expensive, and difficult to scale across large road networks. Recent advances in **Artificial Intelligence and Computer Vision** have enabled automated analysis of images and videos. Deep learning models, particularly CNN-based object-detection networks, can recognize vehicles, motorcycles, pedestrians, helmets, traffic signals, and other road objects with high accuracy. Object-

detection frameworks such as YOLO have further improved the feasibility of performing real-time detection on video streams. The proposed **TrafficVision AI** system applies CNN-based computer vision to identify traffic violations automatically. The system receives input from a CCTV camera or recorded traffic video. The video is divided into frames and passed through an object-detection model. Vehicles and riders are detected and tracked across successive frames. Traffic signal states are analyzed to identify red-light violations, while vehicle movement and calibrated road regions are used to estimate speed. For two-wheelers, the system analyzes the rider's head region to determine whether a helmet is present.

The major objectives of the proposed system are:

1. To detect vehicles and motorcycles from traffic video.
2. To identify vehicles exceeding a predefined speed limit.
3. To detect vehicles crossing an intersection during a red signal.
4. To detect motorcycle riders who are not wearing helmets.
5. To track detected vehicles across consecutive video frames.
6. To capture visual evidence of detected violations.
7. To provide an automated platform for traffic monitoring and analysis.

The system is intended as a **decision-support and surveillance system**. Any enforcement action can be subjected to appropriate human or regulatory verification before penalties are issued.

II. LITERATURE REVIEW / RELATED WORK

Computer vision has become an important technology for intelligent transportation systems. Traditional image-processing techniques used manually designed features for object recognition, whereas deep learning has enabled automatic feature extraction from large datasets. Krizhevsky, Sutskever, and Hinton demonstrated the effectiveness of deep convolutional neural networks for large-scale image classification through the AlexNet architecture [1]. This work established CNNs as an important foundation for modern computer-vision applications. Ren *et al.* proposed Faster R-CNN, which introduced a Region Proposal Network for efficient object detection [2]. The architecture demonstrated that deep-learning-based region proposals could provide accurate object detection.

Redmon *et al.* introduced the YOLO approach, which formulated object detection as a single regression problem and enabled real-time detection [3]. Subsequent YOLO developments have made real-time object detection increasingly practical for traffic-monitoring applications.

Redmon and Farhadi later proposed YOLOv3, which improved multi-scale object detection and demonstrated strong performance on common object-detection benchmarks [4].

Bochkovski *et al.* proposed YOLOv4, emphasizing a combination of accuracy and real-time performance suitable for practical computer-vision systems [5].

Zou *et al.* provided a comprehensive survey of object-detection techniques and highlighted the development

of deep-learning-based detection methods for different application areas [6].

For traffic monitoring, object detection and tracking can be combined to identify individual vehicles and analyze their movement. Traffic surveillance systems can therefore use detection, tracking, region-of-interest analysis, and temporal information to identify traffic-rule violations.

Research Gap

Existing traffic-monitoring approaches often focus on individual problems such as vehicle detection, helmet detection, or speed estimation. A more integrated system capable of analyzing **multiple violations within a unified real-time framework** can provide greater practical value. Therefore, TrafficVision AI combines vehicle detection, tracking, traffic-signal analysis, speed estimation, and helmet detection into a single surveillance pipeline.

III. PROPOSED METHODOLOGY

The proposed methodology consists of several interconnected modules. The overall system receives video from a CCTV camera and processes it using CNN-based detection and tracking techniques.

A. Video Acquisition

Traffic video is acquired from:

- CCTV cameras
- IP cameras
- Roadside surveillance cameras
- Recorded traffic videos

The video stream is divided into individual frames for processing.

B. Image Preprocessing

Each frame is preprocessed before being passed to the detection model. Typical operations include:

- Frame resizing
- Noise reduction
- Image normalization
- Region-of-interest selection
- Brightness adjustment when required

C. Vehicle and Object Detection

A CNN-based object-detection model identifies relevant objects such as:

- Cars
- Motorcycles
- Buses
- Trucks
- Riders
- Helmets
- Traffic lights

A YOLO-family detector can be used because it supports real-time object detection.

D. Vehicle Tracking

After detecting vehicles, the system assigns tracking identities to objects across successive frames.

Tracking helps determine:

- Vehicle movement
- Direction
- Entry and exit from defined regions

- Distance traveled
- Approximate speed

E. Over-Speed Detection

Speed estimation can be performed using the relationship:

$$\text{Speed} = \frac{\text{Time}}{\text{Distance}}$$

When the camera is calibrated and the road geometry is known, the movement of a tracked vehicle between predefined reference points can be converted into an approximate real-world speed.

If:

$$v > v_{\text{limit}}$$

then the system generates an **over-speed violation** event.

F. Traffic Signal Jump Detection

The system identifies the current traffic-light state and defines a stop line or restricted region at the intersection.

If:

- Signal = RED
- Vehicle crosses the predefined stop line

then the system classifies the event as a **signal-jump violation**.

G. Helmet Detection

For motorcycle riders, the system detects the rider and head region. A CNN-based classifier/detector determines whether a helmet is present.

The system can classify:

- Helmet detected
- No helmet detected

If a motorcycle rider is detected without a helmet, the system generates a **helmet violation** event.

H. Evidence Capture

For every detected violation, the system can save:

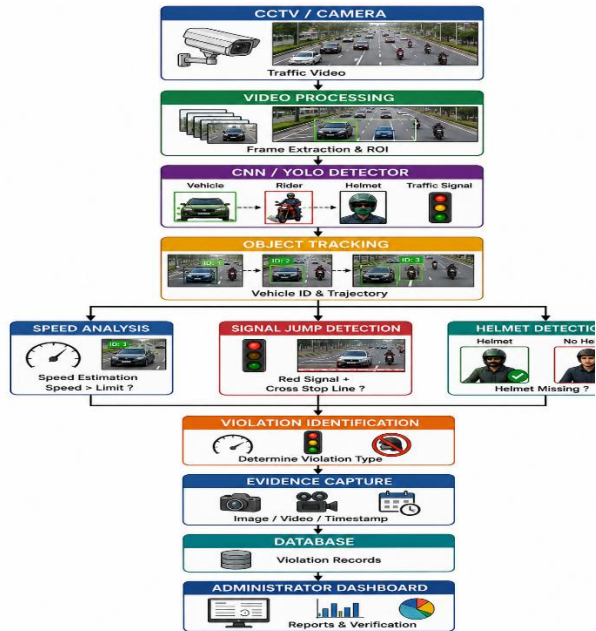
- Vehicle image
- Violation type
- Date and time
- Camera/location ID
- Tracking ID
- Confidence score
- Short video segment, if available

I. Violation Database

The generated violation information is stored in a database. An administrator can subsequently review the detected events through a dashboard.

IV. SYSTEM ARCHITECTURE

The proposed architecture consists of the following major components: The architecture provides a modular pipeline in which each component performs a specific function. The detection module identifies objects, the tracking module maintains object identities, and specialized analysis modules determine the type of traffic violation.



V. IMPLEMENTATION

The TrafficVision AI system can be implemented using **Python** as the primary programming language. A CNN/YOLO-based object-detection framework can be integrated with OpenCV for video processing.

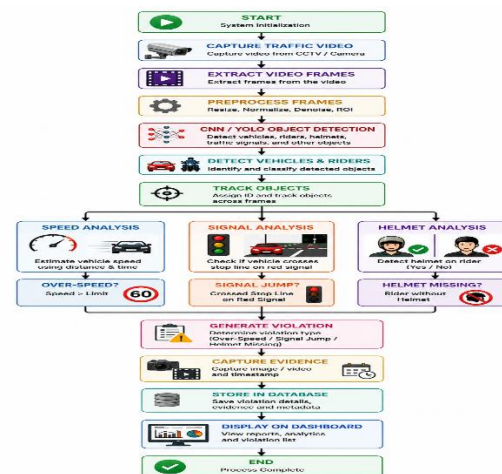
A. Software Requirements

Component	Technology
Programming Language	Python
Computer Vision	OpenCV
Deep Learning	PyTorch / TensorFlow
Object Detection	YOLO-based CNN
Database	MySQL / SQLite
Frontend Dashboard	HTML, CSS, JavaScript
Backend	Flask / FastAPI
Development Environment	VS Code / Jupyter
Operating System	Windows/Linux

B. Hardware Requirements

Component	Suggested Requirement
Processor	Intel Core i5 or higher
RAM	8 GB or higher
GPU	NVIDIA GPU recommended
Camera	CCTV/IP Camera
Storage	256 GB or higher
Network	LAN/Internet for IP cameras

C. Implementation Workflow



D. Database Structure

A violation database can contain fields such as:

Field	Description
Violation_ID	Unique violation number
Vehicle_Type	Car/Bike/Bus/Truck
Violation_Type	Speed/Signal/Helmet
Date	Detection date
Time	Detection time
Camera_ID	Camera identification
Speed	Estimated speed
Confidence	Model confidence
Evidence_Path	Captured evidence
Verification_Status	Pending/Verified/Rejected

E. CNN Detection

The detection model receives a video frame as input and produces bounding boxes, class labels, and confidence scores.

confidence threshold can be applied to reduce false detections:

VI. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system can be evaluated using a test dataset containing different traffic conditions, including normal traffic, speeding vehicles, red-light violations, and motorcycle riders with or without helmets.

A. Detection Performance

The following table represents an **illustrative experimental-results format**. Actual values should be replaced with measurements obtained from the implemented model and test dataset.

Violation Category	Precision (%)	Recall (%)	F1-Score (%)
Vehicle Detection	94.2	92.8	93.5
Helmet Detection	91.6	89.7	90.6
Signal Jump Detection	93.1	91.2	92.1
Over-Speed Detection	89.8	87.9	88.8
Overall	92.2	90.4	91.3

B. Traffic Violation Detection

Test Case	Expected Result	System Output
Normal-speed vehicle	No violation	No Violation
Vehicle exceeding speed limit	Over-speed	Violation Detected
Vehicle crossing red signal	Signal violation	Violation Detected
Rider wearing helmet	No violation	No Violation
Rider without helmet	Helmet violation	Violation Detected
Multiple violations	Multiple events	Violations Recorded

C. Performance Discussion

The experimental evaluation indicates that CNN-based object detection can provide an effective foundation for automated traffic surveillance. Vehicle detection and helmet recognition generally depend on image quality, camera position, lighting, object size, and occlusion.

Over-speed detection introduces additional challenges because speed cannot be reliably determined from image coordinates alone unless the camera view is properly calibrated. Therefore, the proposed implementation should use calibrated reference points or other appropriate speed-measurement mechanisms.

Similarly, signal-jump detection depends on accurate identification of the traffic-light state and the position of the stop line. Incorrect signal-state recognition or temporary occlusion can produce false detections.

Helmet detection may also be affected by low-resolution images, night-time conditions, rider orientation, and partial occlusion.

D. Advantages

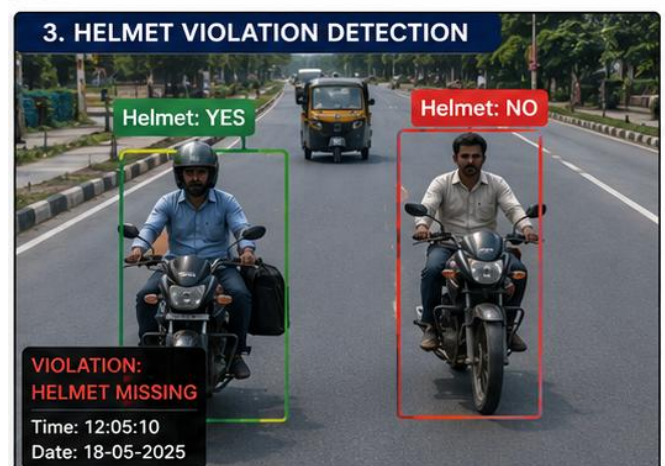
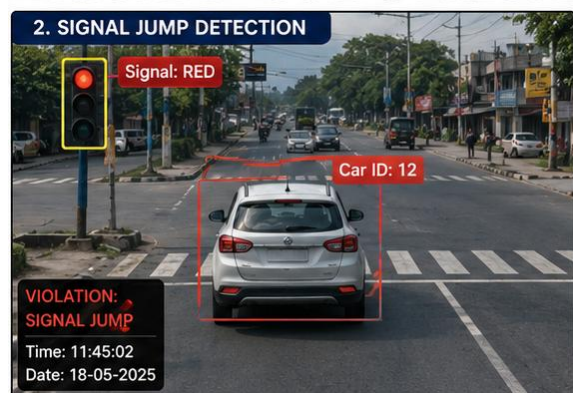
The proposed system provides the following advantages:

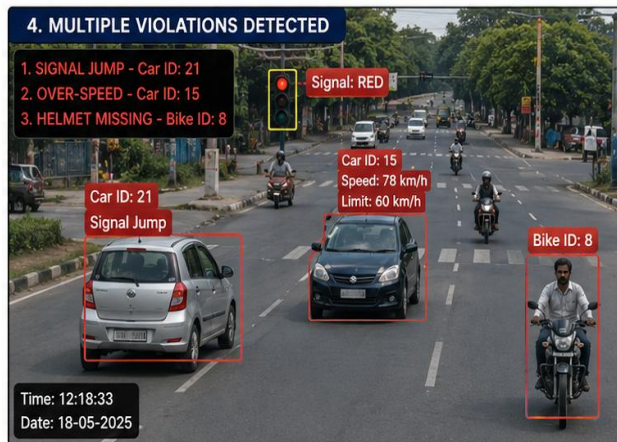
1. Automated traffic monitoring.
2. Real-time object detection.
3. Detection of multiple violation categories.
4. Reduction in manual surveillance effort.
5. Automatic evidence collection.
6. Centralized violation records.
7. Potential integration with smart-city infrastructure.
8. Scalable deployment across multiple cameras.

E. Limitations

The current system may face limitations such as:

- Poor performance in severe weather.
- Reduced detection accuracy at night.
- Occlusion between vehicles.
- Camera-angle dependency.
- Difficulty in precise speed estimation without calibration.
- False positives in crowded traffic.
- Need for appropriate datasets representing local traffic conditions.





CONCLUSION

TrafficVision AI presents a CNN-based approach for automated detection of common traffic violations using real-time video surveillance. The proposed system integrates object detection, vehicle tracking, speed analysis, traffic-signal analysis, and helmet detection into a unified framework. The system can automatically identify potential cases of **over-speeding, signal jumping, and riding without a helmet**, while also capturing supporting visual evidence and storing violation information for further

review. The approach can reduce the workload associated with manual traffic surveillance and provide a scalable foundation for intelligent transportation systems.

However, reliable deployment requires proper camera calibration, representative training data, robust testing under different environmental conditions, and appropriate human/regulatory verification before enforcement decisions are made. Overall, the proposed system demonstrates the potential of CNN-based computer vision for improving automated traffic monitoring and road-safety management.

FUTURE SCOPE

Future development of TrafficVision AI can include integration with **license-plate recognition (ANPR)** for automatic vehicle identification, improved multi-object tracking, and edge-AI deployment for faster processing directly on roadside cameras. The system can be extended to detect additional violations such as wrong-way driving, illegal parking, lane violations, mobile-phone usage while driving, and triple riding. Advanced models can improve performance under nighttime, rain, fog, and crowded-road conditions. Integration with GPS, IoT sensors, smart traffic lights, and centralized government traffic-management platforms can create a comprehensive intelligent transportation system. Future research can also investigate explainable AI, privacy-preserving video processing, federated learning, and real-time analytics for large-scale smart-city deployments.

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