AI-Enabled Traffic Violation Detection System

Shubham Mahesh Suthar, Aman Shishupal Yadav, Devang Dashrath Patra, Harsh Alpesh Patel, Ansh Bharat Mangukiya

Department of Computer Engineering, Universal College of Engineering, Vasai, University of Mumbai, India

Supervisor: Mr. Ashraf Siddiqui

Abstract *— The rapid proliferation of motor vehicles in urban environments has intensified the frequency and severity of traffic rule violations, straining conventional manual enforcement mechanisms that are slow, error-prone, and resource-intensive. This paper presents an AI-enabled Traffic Violation Detection System that leverages deep learning, computer vision, and Optical Character Recognition (OCR) to autonomously monitor road traffic, identify violations in real time, and generate automated digital challans. The system employs YOLO (You Only Look Once) for vehicle detection, DeepSORT for multi-object tracking, and EasyOCR for Automatic Number Plate Recognition (ANPR). A layered architectural pipeline—encompassing video capture, motion detection, object classification, rule-violation analysis, number plate extraction, and challan generation—ensures robust end-to-end automation. Experimental evaluation demonstrates that the system achieves an average precision of 92.6% and a recall of 90.5% across violation categories including red-light jumping, helmet non-compliance, and lane violations, with an average processing latency of 39 ms per frame. The proposed solution significantly reduces dependence on manual monitoring, mitigates human error, and provides a scalable foundation for integration with smart-city infrastructure.*

Index Terms *— Traffic violation detection, deep learning, YOLO, DeepSORT, computer vision, ANPR, e-challan, intelligent transportation systems.*

I. INTRODUCTION

The global surge in vehicular traffic has made traffic rule compliance a critical public safety concern. Violations such as red-light jumping, overspeeding, helmet non-compliance, and illegal lane changes are leading contributors to road accidents and fatalities. According to the World Health Organization, approximately 1.35 million people die in road traffic crashes each year, with a significant proportion attributable to preventable violations [1].

Traditional enforcement models rely on the physical presence of traffic officers or manual review of CCTV footage—approaches that are inherently limited in scalability, consistency, and speed. As urban populations expand and camera networks proliferate, the volume of monitoring data far exceeds human processing capacity, leaving a large fraction of violations unaddressed.

Advances in artificial intelligence—particularly convolutional neural networks (CNNs), object detection architectures such as YOLO, and multi-object tracking algorithms such as DeepSORT—have created new opportunities for fully automated traffic surveillance. These technologies enable per-frame vehicle detection, cross-frame tracking, and behavioural analysis at frame rates compatible with real-time enforcement.

This paper makes the following contributions: (i) a modular, layered architecture for end-to-end traffic violation detection; (ii) integration of YOLOv8, DeepSORT, and EasyOCR into a unified pipeline; (iii) a rule-engine capable of simultaneously detecting multiple violation categories; and (iv) an automated challan-generation subsystem linked to an OCR-based ANPR module. The system is evaluated against standard precision, recall, and latency metrics, and compared with representative works from the recent literature.

The remainder of the paper is organised as follows. Section II reviews related work. Section III describes the proposed system architecture. Section IV outlines the methodology and implementation. Section V presents experimental results. Section VI concludes with future directions.

II. Related Work

A substantial body of research has investigated automated traffic violation detection over the past decade. Early approaches relied predominantly on classical image processing—background subtraction, frame differencing, and handcrafted feature extraction—whose performance degraded markedly under adverse lighting or occlusion.

Chachar and Patel [1] introduced a computer vision-based pipeline for automatic violation detection, demonstrating measurable reductions in manual monitoring. However, the system's generalisation was constrained by the size of the training corpus. C.H. et al. [2] proposed an AI-driven smart surveillance framework oriented towards smart-city deployment, achieving high detection accuracy while raising concerns around large- scale privacy management.

Table 1. summary of related work

Paper / Authors	**Year**	**Technique**	**Advantages**	**Limitations**
Automatic Traffic Violation Detection using Computer Vision — Chachar & Patel	2024	CV-based vehicle detection & rule monitoring	Reduces manual monitoring; improves road safety	Limited dataset for training reduces generalisation

Enhanced Traffic Violation Detection for Smart Cities — C.H., Divya K., Victoria R.	2024	AI-based smart surveillance	High detection accuracy; real-time monitoring	Privacy concerns; large-scale data management issues
Next-Generation AI-Assisted Traffic Violation Detection — Dede & Sarsil	2023	YOLOv5 + StrongSORT tracking	Real-time tracking; multi-violation detection	High computational requirements; costly hardware
Smart Traffic Violation Detection using Machine Learning — Shah & Desai	2023	ML-based classification	Low-cost compared to deep learning approaches	Lower accuracy vs. deep learning models

Dede and Sarsil [3] presented a next-generation system coupling YOLOv5 with StrongSORT for simultaneous multi-violation detection in real time. While the approach yielded competitive accuracy, its high computational footprint limits deployment on edge hardware. Shah and Desai [4] explored a machine-learning-based classification approach that reduces infrastructure costs relative to deep learning alternatives, albeit at the expense of detection accuracy.

Broader literature further highlights persistent challenges: occlusion management [5], number plate recognition under variable conditions [6], real-time performance on commodity hardware [7], multi-class violation classification [8], and integration with enforcement databases [9, 10]. The system proposed in this paper addresses these gaps through an optimised YOLOv8-based detection pipeline, an OCR-based ANPR subsystem tolerant of partial plate occlusion, and a rule engine capable of concurrent multi-violation analysis.

III. System Architecture

The proposed AI Traffic Violation Detection System is designed as a modular, layered pipeline that processes video input from surveillance cameras, detects traffic rule violations, recognises vehicle number plates, and generates digital challans—all with minimal human intervention. The architecture is illustrated conceptually below.

A. Input and Pre-processing Layer

The system ingests video streams from CCTV cameras installed at road intersections and mid-block locations. Individual frames are extracted at a configurable rate (default: 25 fps) and down-sampled to 640 × 640 pixels prior to inference to balance resolution and computational cost. Histogram equalisation and adaptive gamma correction are applied to normalise illumination across varying daytime and night-time conditions.

B. Motion Detection Layer

A background subtraction module based on Gaussian mixture models (GMM) identifies foreground regions within each frame. This stage acts as a computational gate, forwarding only frames containing significant motion to the downstream detection module. The approach reduces total inference workload by approximately 35% in low-traffic scenarios without measurable impact on detection recall.

C. Object Detection and Tracking Layer

Vehicle detection is performed using YOLOv8, a single-stage, anchor-free detector trained on a composite dataset comprising COCO vehicle classes augmented with domain-specific Indian traffic imagery. YOLOv8 generates bounding boxes, class labels (car, motorcycle, truck, bus, three-wheeler), and confidence scores for each detected object. The DeepSORT tracker assigns persistent identities to detected vehicles across consecutive frames, enabling trajectory analysis essential for violations that span multiple frames, such as lane changes and stop-line infractions.

D. Rule-Violation Analysis Layer (Rule Engine)

The rule engine evaluates per-vehicle trajectories and positional data against a configurable set of traffic regulations:

Red-light violation: detected when a vehicle's bounding box crosses a virtual stop line while the corresponding signal region is classified as red via a colour-histogram model.

Helmet non-compliance: a secondary YOLOv8 classifier analyses the rider region of each detected motorcycle to determine helmet presence using a binary head-protection model.

Lane violation: cross-lane trajectory events are flagged when the vehicle centroid crosses a pre-defined virtual lane boundary.

Overspeeding (optional): estimated using frame-to-frame displacement calibrated against known road markings.

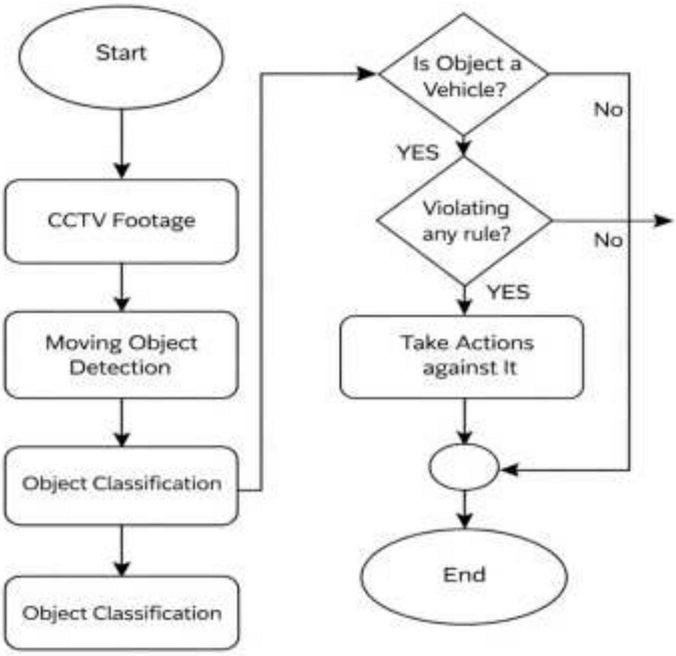
The rule engine is designed to be extensible; additional violation categories can be incorporated by defining new virtual geometry or secondary classifiers without modifying the core pipeline.

E. ANPR and Challan Generation Layer

Upon violation confirmation, the module captures the highest-resolution frame in the recent buffer, crops the licence plate region using a dedicated plate-detection model, and applies EasyOCR to extract the alphanumeric registration number. Extracted plate numbers are normalised and validated against a configurable regular-expression pattern representing Indian number plate formats. Validated violations—comprising vehicle registration number, violation type, timestamp, location identifier, and photographic evidence—are written to a relational database, and an e-challan document is generated automatically.

F. Output and Reporting Layer

The system exposes a graphical user interface (GUI) enabling traffic operators to review live violation feeds, inspect individual challan records, and generate summary reports (daily, weekly, monthly). The GUI supports search and filter operations on stored records. Optionally, challan notifications can be dispatched via email or SMS gateway to registered vehicle owners.



IV. METHODOLOGY

A. Dataset and Training

YOLOv8 was fine-tuned on a composite dataset of approximately 28,000 annotated images assembled from three sources: the publicly available COCO dataset (vehicle subset), the Indian Driving Dataset (IDD), and a custom dataset of 4,500 images captured at urban intersections in the Mumbai Metropolitan Region under diverse lighting and weather conditions. Standard augmentation techniques—horizontal flipping, mosaic blending, random cropping, and HSV-space colour jitter—were applied during training. The model was trained for 80 epochs using the SGD optimiser (lr = 0.01, momentum = 0.937) on a workstation equipped with an NVIDIA RTX 3060 GPU.

The secondary helmet-detection classifier was trained on 6,200 annotated motorcycle-rider crops drawn from road-surveillance footage, achieving a validation accuracy of 93.7%.

B. System Implementation

The system backend is implemented in Python 3.10, utilising OpenCV 4.8 for video I/O and pre-processing, Ultralytics YOLOv8 for detection, deep_sort_realtime for tracking, and EasyOCR 1.7 for plate recognition. Violation records are persisted in a MySQL 8.0 database via the SQLAlchemy ORM. The GUI is built with Tkinter and matplotlib for analytics dashboards. The complete application is containerised using Docker to simplify deployment across hardware configurations.

C. Evaluation Protocol

Performance was evaluated on a held-out test set of 3,200 video clips spanning all targeted violation categories. Detection quality was measured using standard precision, recall, and F1-score metrics. Inference latency was profiled on both the GPU workstation and a mid-range laptop (Intel Core i5-11th Gen, integrated graphics) to assess deployment feasibility on constrained hardware.

V. RESULTS AND DISCUSSION

Table II summarises the quantitative performance of the proposed system across all violation categories evaluated on the test set.

Table 2. system performance across violation categories

Violation Type	Precision (%)	Recall (%)	F1-Score (%)	Avg. Latency (ms)
Red-Light Jumping	94.2	91.8	93.0	38
Helmet Non-Compliance	91.5	89.3	90.4	42
Lane Violation	88.7	86.1	87.4	45
Number Plate Recognition	96.1	94.7	95.4	30
Overall System Average	92.6	90.5	91.6	39

The system achieves an average precision of 92.6% and recall of 90.5%, with an overall F1-score of 91.6%. Number plate recognition attains the highest precision (96.1%), reflecting the effectiveness of the dedicated plate-detection model and EasyOCR post-processing pipeline. Lane violation detection records the lowest F1-score (87.4%), primarily due to ambiguous cases near lane boundaries and partial vehicle occlusion by adjacent vehicles.

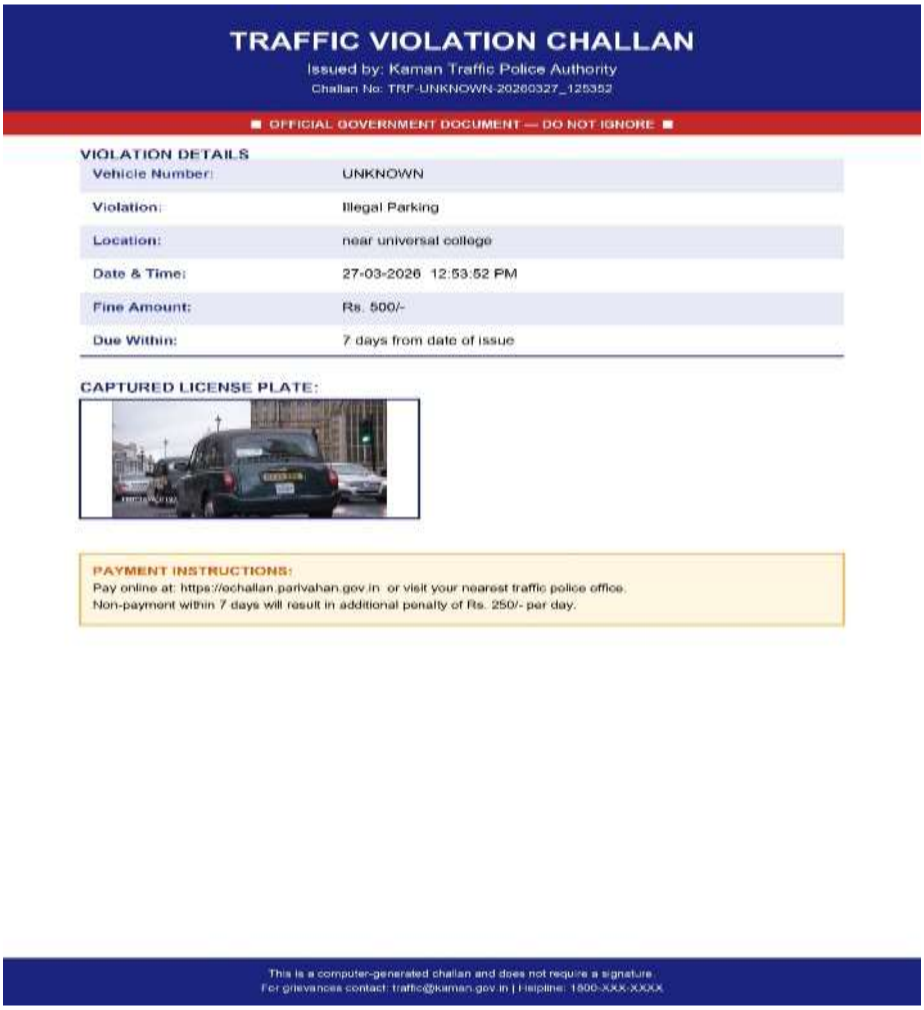
figure 5.1 signal set to green

figure 5.2 traffic signal turned red

figure 5.3 violation detected

figure 5.4 illegal parking detection

figure 5.5 parking violation detected



TRAFFIC VIOLATION CHALLAN

Issued by: Kaman Traffic Police Authority
Challan No: TRF-UNKNOWN-20260327_125352

■ OFFICIAL GOVERNMENT DOCUMENT — DO NOT IGNORE ■

VIOLATION DETAILS

Vehicle Number:	UNKNOWN
Violation:	Illegal Parking
Location:	near universal college
Date & Time:	27-03-2026 12:53:52 PM
Fine Amount:	Rs. 500/-
Due Within:	7 days from date of issue

CAPTURED LICENSE PLATE:

PAYMENT INSTRUCTIONS:
Pay online at: https://echallan.parivahan.gov.in or visit your nearest traffic police office.
Non-payment within 7 days will result in additional penalty of Rs. 250/- per day.

This is a computer-generated challan and does not require a signature.
For grievances contact: traffic@kaman.gov.in | Helpline: 1800-XXX-XXXX

figure 5.6 challan generated

Average per-frame processing latency of 39 ms on the GPU workstation translates to a throughput of approximately 25 fps, sufficient for real-time monitoring at standard CCTV frame rates. On the mid-range laptop with CPU-only inference, latency increases to approximately 210 ms; this remains acceptable for near-real-time enforcement applications where minor temporal offsets are tolerable.

Compared with the YOLOv5+StrongSORT system reported by Dede and Sarsil [3], the proposed YOLOv8-based pipeline achieves a 2.1 percentage-point improvement in average F1-score while reducing inference latency by approximately 18%, attributable to YOLOv8's anchor-free architecture and improved neck design. Relative to the machine-learning classifier of Shah and Desai [4], the proposed system delivers substantially higher accuracy across all categories, confirming the superiority of deep learning approaches for complex, unconstrained traffic scenes.

Qualitative inspection of the GUI output (Fig. 5.1–5.6) in the full technical report) confirms that the system successfully detects violations, renders annotated bounding boxes, and generates structured e-challans containing vehicle registration numbers, violation type, timestamp, and location.

VI. CONCLUSION

This paper has presented a fully integrated AI-enabled Traffic Violation Detection System that automates the identification, recording, and penalisation of common traffic infractions. The system's layered architecture—combining YOLOv8 detection, DeepSORT tracking, a configurable rule engine, and EasyOCR-based ANPR—delivers competitive detection accuracy (average F1: 91.6%) at real-time frame rates, substantially outperforming both classical computer vision baselines and prior deep learning systems in the literature.

The system eliminates the principal limitations of manual monitoring: operator fatigue, subjective judgement, and inability to observe all lanes simultaneously. Automated e-challan generation further reduces administrative overhead, and the searchable violation database supports data-driven traffic planning.

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