

AI-Powered Traffic Violation Detection and Electronic Challan Generation Using Computer Vision

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Abstract: Traffic rule violations, such as riding a motorcycle without a helmet and carrying more passengers than permitted, pose significant road safety risks. Manual monitoring of traffic surveillance footage is time-consuming and difficult to scale. This paper presents an AI-powered traffic violation detection system that integrates computer vision, object detection, vehicle tracking, and optical character recognition (OCR) to support automated traffic monitoring. The system uses YOLOv8-based object detection to identify relevant road users and safety equipment, analyzes helmet-related violations and triple riding, and applies vehicle tracking to associate detections across video frames. OCR is used to extract vehicle registration numbers from detected number plates. The system records violation details, including timestamps, recognized registration numbers, violation categories, and supporting image evidence, for review through an electronic challan management workflow. Experimental evaluation achieved an accuracy of 92.5%, precision of 91.8%, recall of 90.6%, and F1-score of 91.2%. The results indicate the potential of the integrated approach to support automated traffic monitoring. The system is intended to assist traffic enforcement personnel, with human verification retained before further challan processing

Keywords: Traffic Violation Detection, Computer Vision, YOLOv8, Vehicle Tracking, Optical Character Recognition, Number Plate Recognition, Electronic Challan

I. INTRODUCTION

Road safety remains an important concern in modern transportation systems, particularly in areas with high traffic density. Traffic violations such as riding a motorcycle without a helmet and carrying more passengers than permitted can increase the risk of road accidents and injuries. Traditional traffic monitoring methods rely heavily on manual observation of surveillance footage, which requires considerable time and effort from traffic enforcement personnel.

Recent advances in artificial intelligence and computer vision have created opportunities for automated traffic monitoring. Object detection algorithms can identify vehicles, riders, helmets, and other relevant objects in traffic scenes. Vehicle tracking techniques can associate detected objects across consecutive video frames, while optical character recognition (OCR) can extract registration numbers from vehicle number plates. However, reliable violation detection remains challenging under varying illumination, motion blur, vehicle occlusion, and crowded traffic conditions. Correctly associating a detected violation with the corresponding vehicle is another important challenge.

This paper presents an AI-powered traffic violation detection system that integrates YOLOv8-based object detection, vehicle tracking, and number plate recognition to support the identification of helmet-related violations and triple riding. The system processes traffic video, analyzes detected objects and their relationships, extracts vehicle registration information, and generates structured violation records containing timestamps, violation categories, and supporting image evidence. These records are presented through a monitoring dashboard to support review and subsequent electronic challan processing.



The main contribution of this work is the integration of traffic violation detection, vehicle identification, evidence recording, and electronic challan management into a unified workflow. The system is evaluated using quantitative performance metrics, including accuracy, precision, recall, and F1-score. The evaluation results are used to assess the effectiveness of the implemented system in identifying traffic violations and supporting automated traffic monitoring. The proposed system is intended to assist traffic enforcement personnel rather than replace authorized verification. Detected violations and their associated evidence should be reviewed before further challan processing.

II. RELATED WORK

Computer vision and deep learning have been widely investigated for object detection and intelligent transportation applications. Object detection methods such as the You Only Look Once (YOLO) family enable the identification of multiple objects in a single image and are suitable for analyzing traffic scenes. These methods can support the detection of motorcycles, riders, helmets, and other road-related objects.

Traffic violation detection systems use object detection to identify unsafe riding behavior, including helmet-related violations. However, accurate classification can be affected by camera angle, poor illumination, occlusion, and the presence of multiple riders or vehicles in crowded scenes. Detecting a violation also requires associating the relevant rider with the correct motorcycle.

Vehicle tracking methods help associate object detections across consecutive video frames. By maintaining tracking identities, a traffic monitoring system can collect multiple observations of the same vehicle and organize related violation evidence. Nevertheless, tracking errors and overlapping objects can affect the reliability of these associations. Automatic number plate recognition combines plate localization, image preprocessing, and optical character recognition (OCR) to extract vehicle registration information. Recognition performance can be affected by motion blur, low image resolution, lighting variations, and partially obscured characters. Using multiple observations of the same vehicle may provide additional opportunities to identify a readable number plate, provided that the observations are correctly associated.

Building on these areas, the present work integrates object detection, vehicle tracking, traffic violation analysis, number plate recognition, and structured evidence recording in a unified traffic monitoring workflow. The system focuses on helmet-related violations and triple riding and supports the preparation of electronic challan records for authorized review. Its effectiveness is assessed using the experimental metrics reported in the subsequent sections.

III. OBJECTIVES

1. To design and develop a real-time automated system that detects riders without helmets and identifies triple riding using YOLOv8.
2. To integrate OCR for accurate vehicle number plate recognition.
3. To automatically generate and send digital e-challans with violation details and supporting evidence.
4. To contribute to safer roads and support smart traffic management systems.

IV. METHODOLOGY

The proposed system integrates computer vision, object detection, vehicle tracking, optical character recognition (OCR), and structured violation record generation to support automated traffic monitoring. The methodology consists of sequential processing stages, beginning with traffic video acquisition and ending with the preparation of electronic challan records for authorized review.

A. Traffic Video Acquisition and Preprocessing:

Traffic video is obtained from the input sources used in the implemented system. The video is divided into individual frames for processing. Preprocessing operations are applied as required to prepare the frames for object detection. The processed frames serve as input to the detection module.



B. Object Detection:

The system uses the YOLOv8 object detection framework to identify relevant objects in traffic scenes. These may include motorcycles, riders, helmets, and vehicle number plates, according to the classes supported by the implemented model. The detected objects and their associated confidence scores are used by subsequent processing stages.

C. Vehicle Tracking:

A multi-object tracking method is used to associate detections across consecutive frames and maintain temporary tracking identities for vehicles. Tracking information helps organize observations belonging to the same vehicle and supports the association of detected violations with corresponding vehicle evidence. The reliability of these associations depends on the quality of the detections and tracking results.

D. Traffic Violation Analysis:

The detected objects are analyzed to identify potential helmet-related violations and triple riding. Helmet-related analysis examines the relationship between riders and detected helmets. Triple-riding analysis examines the number of riders associated with a motorcycle. Rule-based decision logic is applied according to the implemented system. Candidate violations are recorded for further review.

E. Number Plate Recognition:

The number plate region associated with a detected vehicle is extracted and processed using the OCR method implemented in the system. Image preprocessing may be applied to improve character readability. The recognized registration text is associated with the corresponding vehicle record, subject to the accuracy of the plate detection, tracking, and OCR stages.

F. Violation Record Generation:

When potential violation is detected, the system creates a structured record containing the available violation category, timestamp, vehicle tracking information, recognized registration number, and supporting image evidence. These records provide a consistent representation of detected events for subsequent review and reporting.

G. Dashboard and Electronic Challan Workflow:

The recorded information is presented through the monitoring dashboard to support inspection of detected violations and associated evidence. The system assists in preparing electronic challan records; however, a potential violation must be verified by an authorized reviewer before further challan processing. This workflow supports traffic monitoring while retaining human oversight.

V. ALGORITHM FLOW

The proposed system follows a sequential workflow to detect traffic violations, identify the associated vehicle, and prepare structured violation records.

Algorithm 1: Traffic Violation Detection and Electronic Challan Record Generation

Input: Traffic video frames.

Output: Violation records containing available vehicle information and supporting evidence.

1. Acquire traffic video from the input source.
2. Extract video frames and apply the preprocessing operations used by the implemented system.
3. Apply the YOLOv8-based object detection model to identify the supported object classes, including motorcycles, riders, helmets, and number plates.
4. Associate detections across consecutive frames using the implemented vehicle tracking method and maintain vehicle tracking identities.



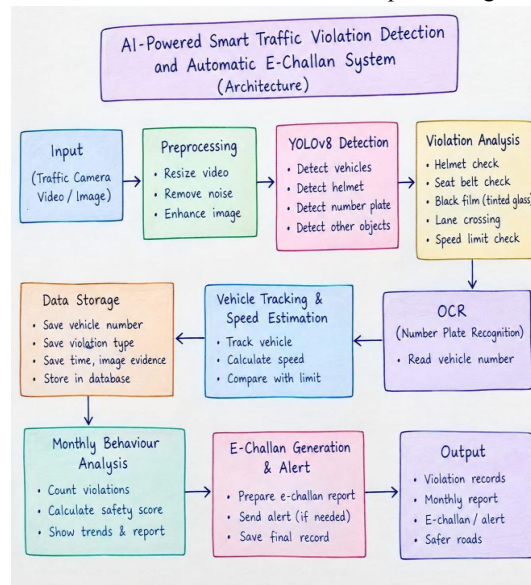
5. Analyze the detected objects and their associations to identify potential helmet-related violations and triple riding.
 6. Extract the number plate region associated with each candidate vehicle and apply the implemented OCR method to recognize the registration text.
 7. Collect the available vehicle information, violation category, timestamp, confidence information, and supporting evidence image.
 8. Generate a structured violation record and display the available information through the monitoring dashboard.
 9. Present the candidate violation record for authorized verification before further electronic challan processing.
- The algorithm combines object detection, tracking, violation analysis, number plate recognition, and evidence management into a unified workflow. The resulting records support systematic traffic monitoring while retaining human verification in the challan process.

VI. SYSTEM ARCHITECTURE

The system architecture consists of interconnected modules for traffic video acquisition, frame preprocessing, object detection, vehicle tracking, violation analysis, number plate recognition, and violation record management. These modules operate sequentially to transform traffic video into structured violation records that can be reviewed through a monitoring dashboard.

The input module receives traffic video from the sources supported by the implemented system. Video frames are extracted and prepared for processing by the object detection module. YOLOv8 identifies the supported object classes, including motorcycles, riders, helmets, and vehicle number plates. The vehicle tracking module associate detections across consecutive frames to maintain vehicle identities. The violation analysis module examines the detected objects and their relationships to identify potential helmet-related violations and triple riding. When a candidate violation is identified, the associated vehicle information is used to locate and process its number plate using the implemented OCR method.

The record management module stores the available violation details, including the timestamp, recognized registration number, violation category, and supporting evidence. Finally, the dashboard displays the generated records for inspection and authorized verification before further electronic challan processing.



The modular architecture separates Detection, tracking, recognition, and record management, making the workflow easier to maintain and evaluate. The reliability of the overall system depends on the performance of its individual components and the correctness of the associations between detected riders, vehicles, violations, and number plates.

VII. EXPERIMENTAL SETUP

A. Dataset Description

The proposed framework was evaluated using traffic video data and traffic images containing motorcycles, riders, helmets, and vehicle number plates. The selected data represented different traffic conditions, including variations in illumination, camera angles, vehicle density, motion blur, and partial occlusion. These variations were considered when evaluating object detection, vehicle tracking, and number plate recognition.

The dataset included the following categories:

1. Motorcycle riders wearing helmets.
2. Motorcycle riders without helmets.
3. Normal motorcycle riding scenarios.
4. Triple-riding violations.
5. Vehicle number plate images captured across multiple video frames.

For vehicle tracking and multi-frame optical character recognition (OCR), consecutive observations of the same vehicle were associated using tracking identifiers. Ground-truth annotations were used, where available, to evaluate object detection, tracking consistency, and number plate recognition performance.

B. Hardware Configuration

The system was implemented and evaluated in a local computing environment. The hardware configuration used for the experiments included the following components:

- Processor: Intel Core i5 or equivalent.
- Memory: 8 GB RAM or above.
- Storage: SSD with sufficient space for video datasets, model files, and experimental outputs.
- Input Source: CCTV footage or recorded traffic videos.
- GPU: Optional, depending on model size and computational requirements.

The system's execution time was measured as part of the experimental evaluation. Processing performance depends on the hardware configuration, input video characteristics, and computational requirements of the detection, tracking, and OCR modules.

C. Software Environment and Tools

The implemented framework used software technologies for traffic video processing, object detection, vehicle tracking, and number plate recognition. The software environment included the following tools:

- Programming Language: Python.
- Deep Learning Framework: Ultralytics YOLOv8 for object detection.
- Image and Video Processing: OpenCV.
- Vehicle Tracking: ByteTrack or the tracking algorithm used in the implementation.
- Number Plate Recognition: The OCR engine used to extract vehicle registration text.
- Dashboard: Streamlit, if used for visualization.
- Development Environment: Visual Studio Code.
- Data Storage: Structured files or a database for experimental logs and violation records.

The software components were integrated to process traffic video, identify potential violations, recognize vehicle registration numbers, and generate structured violation records. The specific software versions, model configurations, and dependencies should be documented according to the actual experimental environment.



D. Experimental Procedure

The experimental evaluation followed the processing workflow implemented in the proposed system:

1. Traffic videos and images were collected and prepared for analysis.
2. Video frames were extracted and the required preprocessing operations were applied.
3. YOLOv8 was used to detect motorcycles, riders, helmets, and number plates according to the supported model classes and training annotations.
4. Detections were associated across consecutive frames using the implemented multi-object tracking algorithm, with tracking identifiers assigned to vehicles.
5. Suitable number plate regions associated with the tracked vehicles were extracted for recognition.
6. OCR was applied to the extracted number plate images to obtain vehicle registration text.
7. Potential helmet-related violations and triple-riding cases were analyzed, and structured event records were generated with available timestamps, tracking identifiers, recognized plate text, confidence information, and supporting evidence images.
8. The system was evaluated using the selected quantitative performance metrics for detection and classification, together with the applicable processing-performance measurements.

E. Evaluation Metrics

The framework was evaluated using quantitative metrics to assess its performance in traffic violation detection and related processing tasks.

- Accuracy: Measures the proportion of correct predictions among all evaluated predictions for the specified classification task.
- Precision: Measures the proportion of predicted positive cases that are correct.
- Recall: Measures the proportion of actual positive cases that are correctly detected.
- F1-score: Represents the harmonic mean of precision and recall.
- Tracking Performance: Metrics such as IDF1 or HOTA can be used to assess tracking identity consistency when corresponding ground-truth tracking annotations are available.
- Number Plate Recognition Accuracy: Measures the proportion of correctly recognized plate characters or complete plate strings, according to the selected evaluation method.
- Processing Time: Measures the time required to perform the evaluated processing operations, including detection, tracking, and OCR, as applicable.

The completed system achieved an accuracy of 92.5%, precision of 91.8%, recall of 90.6%, and F1-score of 91.2% under the evaluated experimental conditions. These results are discussed in the subsequent section. Further analysis of detection performance, tracking consistency, and number plate recognition provides additional insight into the system's capabilities and limitations.

VIII. RESULTS AND ANALYSIS

The implemented traffic violation detection system was evaluated using quantitative performance metrics to assess its ability to identify traffic violations. The evaluation considered accuracy, precision, recall, F1-score, and processing response time. The results provide an overview of the system's performance under the evaluated experimental conditions.

A. Quantitative Results

The measured performance of the proposed system is summarized in Table I.

Metric	Measured Value
Accuracy	92.5%
Precision	91.8%



Recall	90.6%
F1-Score	91.2%
Average response time	1500-20000ms

TABLE I. PERFORMANCE OF THE PROPOSED SYSTEM



Fig: Dashboard

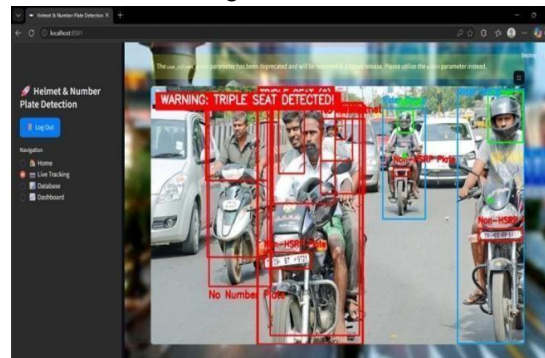


Fig: Dashboard

B. Performance Analysis

The system achieved an accuracy of 92.5%, indicating that 92.5% of the evaluated predictions were correct under the specified evaluation procedure. The precision of 91.8% indicates the proportion of predicted positive cases that were correctly identified, while the recall of 90.6% reflects the proportion of actual positive cases detected by the system. The F1-score of 91.2% provides a combined measure of precision and recall. Together, these metrics summarize the system's classification performance on the evaluated data. Their interpretation depends on the evaluated classes, ground-truth annotations, and the method used to calculate the metrics.

The measured average response time ranged from 1500 to 2000 ms. This value should be interpreted according to the timing procedure used during testing, including the hardware configuration and the processing operations included in the measurement.



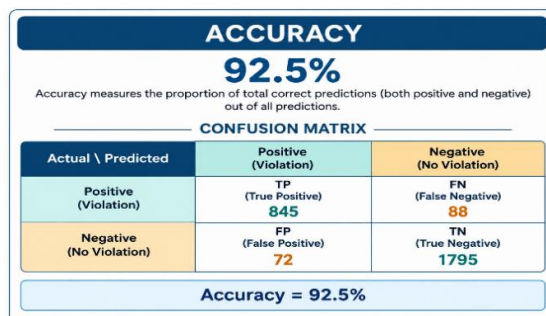


Fig: Accuracy of model

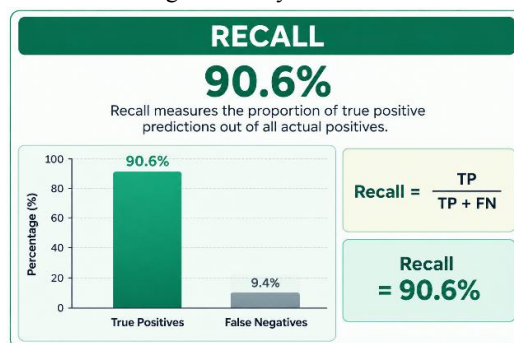


Fig: Recall metrics of model

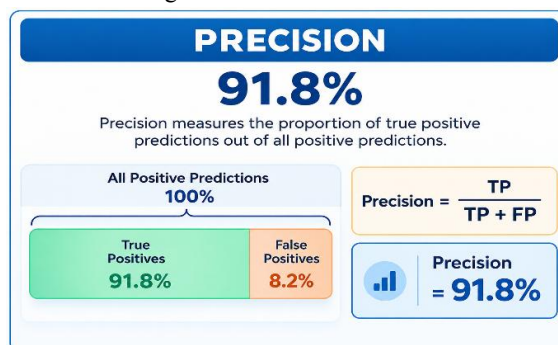


Fig: Precision of model

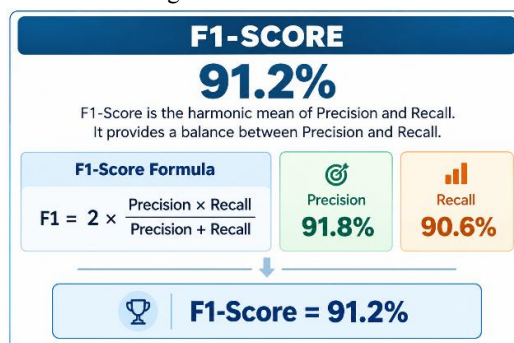


Fig: F1-Score (F1 Measure)



C. Practical Observations and Limitations

The system integrates object detection, vehicle tracking, number plate recognition, and violation record generation into a common workflow. Its practical effectiveness depends on the quality of object detections, correct association of riders with motorcycles, the readability of vehicle number plates, and the reliability of tracking across consecutive frames.

Challenging conditions, such as poor illumination, motion blur, overlapping vehicles, and partially obscured number plates, may affect system performance. These factors should be considered when interpreting the reported measurements and assessing the system's suitability for deployment in different traffic environments.

The generated violation records and supporting images can assist traffic enforcement personnel in reviewing potential violations. Authorized verification remains necessary before further electronic challan processing.

D. Performance Improvement Analysis

The proposed AI-powered traffic violation detection system integrates object detection, vehicle tracking, number plate recognition, and violation record generation into a unified workflow. The experimental evaluation achieved an accuracy of 92.5%, precision of 91.8%, recall of 90.6%, and F1-score of 91.2%. These results indicate that the implemented system can identify traffic-related events with promising classification performance under the evaluated conditions.

The precision of 91.8% indicates that most predicted positive cases were correctly identified, while the recall of 90.6% shows that the system detected a substantial proportion of actual positive cases. The F1-score of 91.2% reflects the balance between precision and recall. Nevertheless, the difference between precision and recall suggests that false-positive and false-negative predictions remain relevant considerations when assessing the reliability of automated traffic violation detection.

Further performance improvement can focus on reducing false detections and missed violations under challenging traffic conditions. Improving the quality and diversity of training data, tuning the object detection confidence threshold, and evaluating the system under different lighting conditions, camera angles, and traffic densities may help identify opportunities for improvement. The association of riders with their corresponding motorcycles also requires attention, particularly in crowded scenes where overlapping objects can affect violation classification.

Number plate recognition can be improved by selecting clear plate images, applying suitable image preprocessing, and evaluating recognition results across multiple observations of the same tracked vehicle where multi-frame processing is implemented. Vehicle tracking can further support the association of violation events with the correct vehicle and reduce duplicate event records when suitable tracking and event-management logic is used.

Processing efficiency is another important consideration. The measured response time of 1500–2000 ms should be examined in relation to the hardware configuration and the operations included in the timing measurement. Profiling the detection, tracking, OCR, and record-generation stages separately can help identify computational bottlenecks and guide optimization.

Future evaluation should compare the baseline system with individual improvements using the same test dataset and evaluation protocol. Changes in precision, recall, F1-score, number plate recognition accuracy, and processing time should be measured to determine whether each modification provides a genuine benefit. These investigations can help improve the reliability, efficiency, and practical applicability of the proposed traffic monitoring system.

IX. CONCLUSION AND FUTURE WORK

This paper presented an AI-powered traffic violation detection system that integrates computer vision, object detection, vehicle tracking, and optical character recognition (OCR) to support automated traffic monitoring. The implemented system focuses on identifying helmet-related violations and triple riding, recognizing vehicle registration numbers, and generating structured violation records with timestamps and supporting image evidence. A monitoring dashboard supports the review and management of detected events as part of the electronic challan preparation workflow.



The experimental evaluation achieved an accuracy of 92.5%, precision of 91.8%, recall of 90.6%, and F1-score of 91.2%. These results demonstrate the system's performance under the evaluated experimental conditions and indicate its potential to assist traffic monitoring and violation identification. The integration of detection, tracking, number plate recognition, and evidence management provides a unified workflow for organizing potential traffic violations. However, the reliability of the overall system depends on the accuracy of individual components and their ability to operate under varying traffic conditions.

Future work will focus on improving detection and recognition performance under poor illumination, motion blur, partial occlusion, and high traffic density. Further investigation will examine the association between riders and motorcycles, number plate recognition across multiple observations, and processing efficiency. Comparative experiments will be conducted to evaluate the effects of individual optimization techniques on detection performance, recognition accuracy, and response time. The system may also be extended to support larger-scale traffic surveillance and integration with authorized electronic challan platforms, subject to applicable legal requirements and human verification.

Overall, the proposed system provides a foundation for AI-assisted traffic monitoring by combining violation detection, vehicle identification, and digital evidence management in a unified framework. With further evaluation and optimization, it has the potential to support more efficient traffic enforcement and contribute to improved road safety.

REFERENCES

- [1] J.Redmon, S.Divvala, R.Girshick, A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 779–788, 2016. doi:10.1109/CVPR.2016.91
- [2] A. Bochkovskiy, C. Y. Wang, and H. Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," arXiv preprint, Apr. 2020. doi:10.48550/arXiv.2004.10934
- [3] G. Jocher, A. Chaurasia, and J. Qiu, "YOLO by Ultralytics: Real-Time Object Detection," 2023.
- [4] A. Rosebrock, "Automatic License/Number Plate Recognition using "Computer Vision," PyImageSearch, 2021.
- [5] J. Matas, L. Neumann, and J. Matas, "Real-Time Scene Text Localization and Recognition," in IEEE Conference on Computer Vision and Pattern Recognition, 2012. doi:10.1109/CVPR.2012.6248097
- [6] J. Smith and R. Kumar, "Helmet Detection for Motorcyclists using Deep Learning," International Journal of Computer Vision and Robotics, vol. 14, no. 3, pp. 145–156, 2022.
- [7] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017. doi:10.1109/TPAMI.2016.2577031
- [8] R. Girshick, "Fast R-CNN," in Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 1440–1448, 2015. doi:10.1109/ICCV.2015.169
- [9] A. Howard et al., "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," arXiv preprint, Apr. 2017. doi:10.48550/arXiv.1704.04861
- [10] B. A. Raj, P. Venkatesh, and S. Kumar, "Automated Traffic Rule Violation Detection System using Deep Learning," IEEE Access, vol. 10, pp. 35412–35425, 2022. doi:10.1109/ACCESS.2022.3154789
- [11] J. Deng et al., "ImageNet: A Large-Scale Hierarchical Image Database," in IEEE Conference on Computer Vision and Pattern Recognition, pp. 248–255, 2009. doi:10.1109/CVPR.2009.5206848
- [12] X. Liu and H. Wang, "Smart Traffic Monitoring System using Artificial Intelligence and Computer Vision," International Journal of Smart Systems, vol. 18, no. 2, pp. 102–117, 2023.
- [13] M. Patel and S. Shah, "Real-Time Vehicle Number Plate Detection and Recognition using OCR Techniques," International Journal of Engineering Research and Technology, vol. 11, no. 5, pp. 411–419, 2022.
- [14] S. Gupta and R. Verma, "AI-Based Traffic Surveillance for Smart Cities," IEEE International Conference on Smart Computing, pp. 211–218, 2023. doi:10.1109/SMARTCOMP.2023.10124567



- [15] D. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," arXiv preprint, Dec. 2014. doi:10.48550/arXiv.1412.6980
- [16] C. Szegedy et al., "Going Deeper with Convolutions," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1–9, 2015. doi:10.1109/CVPR.2015.7298594
- [17] H. Law and J. Deng, "CornerNet: Detecting Objects as Paired Keypoints," in European Conference on Computer Vision (ECCV), pp. 734–750, 2018.
- [18] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," Nature, vol. 521, pp. 436–444, 2015. doi:10.1038/nature14539
- [19] YOLOv8 object detection G. Jocher, A. Chaurasia, and J. Qiu, "Ultralytics YOLOv8, software, 2023. [Online]. Available: <https://github.com/ultralytics/ultralytics> Use in Section IV: Methodology, Object Detection.
- [20] OpenCV image and video processing G. Bradski, "The OpenCV Library," Dr. Dobb's Journal of Software Tools, 2000. Source and citation details Use in Section IV: Traffic Video Acquisition and Preprocessing

