

# Road-Eye:- A Real Time Traffic Monitoring System Using AI

Salman Usmani<sup>1</sup>, Abdullah Tauseef<sup>2</sup>,

<sup>1</sup>Student, Dept. of CSE, Integral University, Lucknow, Uttar Pradesh, India

<sup>2</sup>Student, Dept. of CSE, Integral University, Lucknow, Uttar Pradesh, India

**Under the Guidance of:** Mariyam Fatima, Assistant Professor, Dept. of CSE, Integral University, Lucknow, Uttar Pradesh, India

\*\*\*

**Abstract** - The rapid growth of urban populations has placed immense pressure on city traffic infrastructure, making real-time, intelligent monitoring a necessity rather than an option. Conventional signal control mechanisms, which operate on predetermined timing schedules, are inherently incapable of responding to the fluctuating demands of modern traffic. This paper introduces Road Eye, a decentralized, AI-powered traffic monitoring and adaptive signal control system that combines computer vision, edge computing, and Internet of Things (IoT) sensor networks into a cohesive operational framework. The architecture deploys deep learning object detection and multi-object tracking algorithms directly on edge devices positioned at intersections, enabling local video analysis without transmitting raw footage to central servers. Processed traffic metrics are relayed to a backend analytics module for dynamic signal phase optimization. System evaluation was conducted using SUMO-based traffic simulation across a representative urban intersection scenario. Experimental outcomes confirm a 38% reduction in average vehicle waiting time, a 40% decrease in queue length, and a fourfold improvement in signal response latency when compared to traditional fixed-time controllers. Road Eye offers a scalable, computationally efficient, and privacy-preserving solution for intelligent transportation infrastructure deployment in smart cities.

**Key Words:** Intelligent Transportation Systems, Edge Computing, Computer Vision, Deep Learning, Adaptive Signal Control, Smart City Infrastructure, Real-Time Vehicle Detection.

## 1. INTRODUCTION

Over the past two decades, unplanned urban expansion and a sharp rise in private vehicle ownership have collectively transformed city roads into sites of persistent gridlock. The economic consequences of traffic congestion are well documented: the INRIX Global Traffic Scorecard (2023) estimated that urban congestion costs the United States alone approximately \$87 billion annually in lost productivity, a figure that is mirrored, though less precisely

measured, across developing nations. Beyond economics, stop-and-go traffic significantly elevates tailpipe emissions, contributing to urban air quality deterioration and carbon footprint enlargement.

Against this backdrop, the limitations of legacy traffic management infrastructure have become increasingly difficult to ignore. Fixed-cycle traffic signal controllers, first deployed in the early twentieth century, operate on a rigid schedule that was engineered for average, predicted traffic volumes rather than real-time demand. These systems cannot differentiate between a congested arterial road and one operating well below capacity, and as a result they introduce unnecessary delay even when the physical conditions no longer warrant it.

Although centralized Intelligent Transportation Systems (ITS) have attempted to remedy this through cloud-based data aggregation, they introduce their own bottleneck: the latency incurred during data transmission to remote servers can exceed the decision window required for effective signal adjustment. Recent progress in edge computing and embedded AI has opened a viable path toward decentralizing traffic intelligence. By situating computational resources at the intersection level rather than in a distant data center, processing delays can be reduced by an order of magnitude, enabling truly responsive signal control.

When combined with computer vision pipelines built around state-of-the-art object detection architectures such as YOLO and multi-object tracking frameworks like DeepSORT, edge-deployed AI nodes can extract rich, actionable traffic metrics from live camera feeds without ever storing identifiable imagery.

## 2. Problem Statement

Despite decades of investment in urban traffic infrastructure, most cities continue to rely on control paradigms that were designed when vehicle volumes were a fraction of today's figures. The specific shortcomings of current systems can be organized around five interrelated failure modes:

Static signal scheduling: Fixed-time controllers cannot modulate green phase duration in response to stochastic

demand variations, leading to systematic over-provision at uncongested approaches and under-provision at saturated ones.

**Cloud processing latency:** Centralized ITS architectures transmit video streams or sensor readings to remote

servers before analysis can begin. Round-trip communication delays routinely exceed four to eight seconds, well beyond the response window of effective adaptive control.

**Scalability constraints:** Expanding centralized systems to incorporate additional intersections demands proportional increases in bandwidth, storage, and server capacity, creating non-linear cost escalation.

**Privacy and bandwidth concerns:** Continuous transmission of raw video from public intersections raises legal and ethical concerns regarding surveillance, particularly in jurisdictions with strict data protection legislation.

### 3. OBJECTIVES OF THE STUDY

To design and validate a complete AI-based real-time traffic monitoring architecture suitable for deployment at urban intersections.

To integrate edge computing nodes into the system architecture in order to minimize processing latency and reduce dependence on cloud infrastructure.

To evaluate system performance through SUMO-based simulation and benchmark results against conventional fixed-time traffic control.

To ensure privacy-conscious data handling by restricting raw video transmission and retaining only anonymized traffic metrics.

## 4. LITERATURE REVIEW

### 4.1 Deep Learning for Vehicle Detection

The application of convolutional neural networks to vehicle detection in traffic video has matured rapidly since the introduction of region-based CNN architectures. Among single-stage detectors, YOLO (You Only Look Once) has established itself as a dominant framework owing to its ability to perform real-time inference without sacrificing

meaningful accuracy. Redmon and Farhadi's (2018) foundational work demonstrated that a unified detection network could process images at 45 frames per second while sustaining competitive mean Average Precision (mAP) scores. Subsequent iterations, including YOLOv5, YOLOv7, and the more recent YOLOv8 series, have pushed precision-recall trade-offs further through architectural innovations such as cross-stage partial networks and decoupled detection heads.

### 4.2 Multi-Object Tracking in Traffic Surveillance

Detecting individual vehicles frame-by-frame addresses only part of the traffic monitoring problem. Understanding flow dynamics requires persistent vehicle identification across sequential frames, a task addressed by multi-object tracking (MOT) algorithms. DeepSORT, proposed by Wojke et al. (2017), extends the SORT algorithm by integrating appearance descriptor embeddings with Kalman filter-based motion prediction, enabling robust re-identification even after brief occlusions.

## 5. METHODOLOGY

The design of Road Eye follows a layered, real-time intelligent processing pipeline that prioritizes low latency, computational efficiency, and closed-loop control. The pipeline comprises five functional stages:

#### Data Acquisition:

High-resolution IP cameras and supplementary IoT sensors are installed at each monitored intersection to record vehicle speed, loop detector occupancy, and pedestrian crossing activity.

#### Edge-Based AI Processing:

The edge device applies a pre-trained YOLOv8 model to detect and classify vehicles and pedestrians. Detected objects are then passed to a DeepSORT tracker.

**Data Aggregation:** Extracted metrics are transmitted over a secure MQTT connection to a centralized analytics server. No raw video frames are transmitted.

**Traffic Analysis:** The analytics server fuses data, computes network-level congestion indices, and generates short-horizon traffic forecasts.

## 6. AI MODEL IMPLEMENTATION

The object detection component employs YOLOv8, selected for its balance between inference speed and detection

accuracy on resource-constrained edge hardware. The model was fine-tuned on a combined dataset comprising UA-

DETRAC and a supplementary set of annotated intersection images. The model detects passenger cars, buses, motorcycles, trucks, and pedestrians.

Table -1: YOLOv8 Detection Performance — Intersection Test Set

Metric	Value	Benchmark (YOLOv5)
Precision	92.3%	88.7%
Recall	89.1%	85.4%
mAP@0.5	90.6%	87.2%
Inference Speed	28 ms/frame	34 ms/frame

## 7. DATA, SIMULATION, AND EXPERIMENTAL RESULTS

System evaluation was conducted using SUMO (Simulation of Urban Mobility). A synthetic four-lane signalized intersection was modelled with two traffic demand scenarios: a peak-hour scenario generating 1,800 vehicles per hour, and an off-peak scenario at 600 vehicles per hour. The Road Eye adaptive controller was compared against a fixed-time baseline plan with cycle lengths optimized using Webster's formula.

Table -2: Comparative System Performance — SUMO Simulation Results

Performance Metric	Fixed-Time Controller	Road Eye (Adaptive)
Avg. Waiting Time	85.2 sec	52.7 sec (138%)
Avg. Queue Length	30 vehicles	18 vehicles (140%)
Signal Response Delay	8.1 sec	1.9 sec (177%)
Throughput Rate	42 veh/cycle	61 veh/cycle (145%)

## 8. LIMITATIONS

While the results presented here are encouraging, several practical limitations constrain the current iteration of Road. Eye and should be addressed before large-scale

deployment is considered: Capital infrastructure cost, sensitivity to camera placement and calibration, adverse weather performance, model drift and retraining overhead, and its current single-intersection scope.

## 9. CONCLUSIONS

This paper has presented Road Eye, a prototype AI-driven traffic monitoring and adaptive signal control system designed to address the fundamental inadequacies of fixed-time signal control in contemporary urban environments.

The architecture integrates YOLOv8-based object detection, DeepSORT multi-object tracking, IoT sensor fusion, and a demand-responsive optimization module within a three-tier edge-to-server deployment model. The choice of edge

computing as the primary inference platform is a deliberate architectural decision that resolves the latency constraints of

cloud-dependent alternatives and simultaneously avoids the privacy risks associated with raw video transmission. These results position Road Eye as a technically viable and practically meaningful contribution to the field of Intelligent Transportation Systems.

## 10. ACKNOWLEDGEMENT

We extend our deepest gratitude to Ms. Mariyam Fatima, Department of Computer Science and Engineering, Integral University, for her valuable guidance, supervision, and continuous support throughout the development and evaluation of this research.

## 11. REFERENCES

1. Asad, U., & Martin, Y. (2024). Latency optimization in edge-enabled urban traffic management: A comparative evaluation. *Journal of Intelligent Transportation Systems*, 18(4), 245–259.
2. Chen, X., Liu, Q., & Zhao, P. (2024). Comparative performance of single-stage object detectors in low-resource edge deployments for traffic surveillance. *IEEE Transactions on Intelligent Transportation Systems*, 25(3), 1124–1138.
3. Djahel, S., Salehie, M., & Lal, T. (2023). Environmental and economic costs of urban traffic congestion: A multi-city analysis. *Transportation Research Part D: Transport and Environment*, 119, 103–118.

4. INRIX. (2023). INRIX 2023 global traffic scorecard. INRIX Research.
5. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., & Berg, A. C. (2016). SSD: Single shot multibox detector. *Computer Vision – ECCV 2016*.
6. Liu, Z., Gao, Y., & Tian, K. (2023). Communication latency constraints in cloud-dependent intelligent traffic systems: Measurement and mitigation strategies. *Vehicular Communications*, 42, 100–117.
7. Lopez, P. A., et al. (2018). Microscopic traffic simulation using SUMO. In *Proceedings of the 21st International Conference on Intelligent Transportation Systems*.
8. Nguyen, T. H., & Park, J. W. (2024). Edge AI deployment strategies for real-time intersection monitoring: An empirical study. *IEEE Access*, 12, 34112–34128.
9. Redmon, J., & Farhadi, A. (2018). YOLOv3: An incremental improvement. *arXiv preprint arXiv:1804.02767*.
10. Schaffland, A., Nelson, J., & Schöning, J. (2024). Digital twin-enabled reinforcement learning for adaptive signal control in urban traffic networks. *Transportation Simulation Journal*, 9(1), 55–72.
11. Wang, B., Zheng, H., & Qian, K. (2024). AI-driven intelligent traffic signal optimization: A reinforcement learning perspective. *Smart Cities Review*, 12(2), 102–118.
12. Wang, C.-Y., Bochkovskiy, A., & Liao, H.-Y. M. (2023). YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. *CVPR 2023*.
13. Wojke, N., Bewley, A., & Paulus, D. (2017). Simple online and realtime tracking with a deep association metric. *ICIP 2017*.