



An AI-Centric Approach to Real-Time Traffic Signal Control and Congestion Mitigation

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How to Cite this Article:

Prishaani, B. J. & Arasi, S. (2026). An AI-Centric Approach to Real-Time Traffic Signal Control and Congestion Mitigation. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(03).
<https://doi.org/10.55041/ijcope.v2i3.184>

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Abstract— Rapid urbanization and constant growth in vehicular traffic have resulted in serious congestion, rise in travel time, fuel consumption, and air pollution in urban environments. The traditional traffic management system functions based on fixed-time signal control and manual monitoring, which makes it inefficient in dynamic traffic situations. This paper presents an AI-based traffic management system that utilizes real-time visual data and machine learning algorithms to accomplish adaptive traffic signal control and smart route management. The proposed system uses computer vision models to identify and categorize vehicles from live camera inputs, calculate traffic density at road intersections, and adjust signal timing dynamically according to congestion levels. Moreover, a route optimization module using shortest-path algorithms is incorporated to redirect vehicles along less congested routes, thus optimizing overall traffic flow. Simulation experiments conducted on urban traffic conditions show a substantial decrease in average waiting time and enhanced traffic throughput compared to traditional fixed-time traffic signal control systems. The proposed system offers a scalable and efficient solution for real-time traffic management in smart city settings.

Keywords— Artificial Intelligence, Traffic Management System, Computer Vision, Adaptive Traffic Signal Control, Traffic Density Estimation, Route Optimization, Smart Cities



I. INTRODUCTION

Rapid urbanization and the exponential growth of vehicle ownership have led to severe traffic congestion in metropolitan and developing cities. Conventional traffic signal systems typically operate using predefined fixed-time cycles that do not adapt to real-time traffic demand. As a result, vehicles often remain idle at intersections even when cross lanes are empty, while heavily congested lanes continue to accumulate long queues. This inefficient allocation of signal time increases travel delays, fuel consumption, driver frustration, and environmental pollution. Therefore, there is a growing need for an intelligent traffic control mechanism capable of dynamically responding to changing road conditions.

With the advancement of artificial intelligence and computer vision technologies, real-time traffic monitoring has become feasible using surveillance cameras. Video streams can be processed automatically to detect and classify vehicles such as cars, buses, trucks, and motorcycles. By estimating traffic density from detected vehicles, signal timings can be adjusted adaptively instead of relying on static schedules. This enables efficient utilization of **road** infrastructure and reduces unnecessary waiting time at intersections.

In addition to adaptive signaling, traffic congestion can be further minimized by redirecting vehicles toward alternative routes with lower traffic density. Integrating route optimization algorithms allows the system to compute the most efficient path based not only on distance but also on congestion level. Such an approach distributes traffic more evenly across the road network and prevents bottleneck formation.

This paper proposes an AI-based real-time vehicle detection and adaptive traffic signal control system combined with dynamic route optimization. The system analyzes live video input, estimates traffic density, adjusts signal timing, and suggests optimal routes. The proposed approach aims to improve traffic flow efficiency, reduce congestion, and enhance overall urban transportation management with minimal human intervention.

I. METHODOLOGY

The proposed intelligent traffic management system is designed to monitor road conditions in real time, detect vehicles, estimate traffic density, and dynamically control signal timing. The methodology consists of multiple interconnected modules that operate sequentially to analyze traffic and respond automatically.

A. Data Acquisition

Traffic video is captured continuously using road surveillance cameras placed at intersections. The video stream is converted into individual frames and preprocessed to improve detection accuracy. Preprocessing steps include resizing, noise reduction, and brightness normalization to handle varying lighting and weather conditions.

The vehicle detection model was trained on an annotated traffic dataset containing multiple vehicle classes. The data was divided into training, validation, and testing sets, and images were resized, normalized, and augmented to improve robustness under varying lighting and occlusion conditions.

B. Model Training

Training was conducted for 100 epochs with a batch size of 32 and a learning rate of 0.1 using a gradient-based optimizer. A GPU environment was used to accelerate convergence. Validation loss and detection accuracy were monitored to prevent overfitting, and the best-performing weights were selected for deployment.

The trained model showed stable convergence and reliable performance for real-time vehicle detection and traffic density estimation.

C. Vehicle Detection and Classification

Each frame is processed using a deep learning-based object detection model to identify vehicles such as cars, buses, trucks, motorcycles, and emergency vehicles. The model generates bounding boxes around detected objects and assigns class labels. The total number of vehicles in each lane is calculated by counting the detected objects within defined lane regions.

Class	Precision	Recall	F1-Score
Car	0.94	0.92	0.93
Bus	0.91	0.89	0.90
Truck	0.90	0.88	0.89
Motorcycle	0.95	0.93	0.94
Emergency Vehicle	0.97	0.95	0.96
Overall	0.93	0.91	0.92



D. Traffic Density Estimation

Traffic density is determined based on the number of vehicles detected within a specific area. The density value is calculated as:

$$D = \frac{N_v}{C_l}$$

where D represents traffic density, N_v is the number of detected vehicles, and C_l is the lane capacity. The computed density is categorized into low, medium, and high congestion levels.

E. Adaptive Signal Control

Signal duration is dynamically adjusted according to congestion level. The green signal time is calculated as:

$$T_g = T_{min} + \beta D$$

where T_{min} is the minimum signal duration and β is a scaling constant. Higher density results in longer green signal duration, while lower density reduces waiting time for other lanes.

E. Dynamic Route Optimization

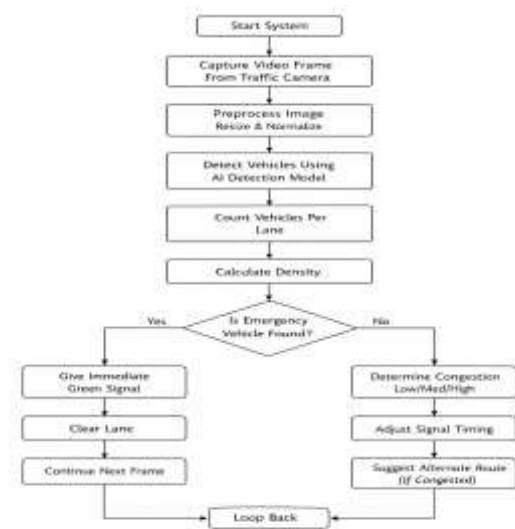
To prevent traffic accumulation, the system computes alternative routes using a shortest-path algorithm considering both distance and congestion factor:

$$W = d + \gamma c$$

where W is road weight, d is distance, c is congestion factor, and γ is a penalty coefficient. Vehicles are guided toward routes with minimum weight.

F. Emergency Vehicle Priority

When an emergency vehicle is detected, the corresponding lane is immediately assigned green signal until the vehicle clears the intersection, ensuring rapid passage and improved safety.



II. RESULT AND DISCUSSION

The developed AI-based smart traffic management system was evaluated using real-time road images, prerecorded traffic videos, and simulated live camera feeds. The trained object detection model successfully identified multiple vehicle categories including cars, buses, trucks, and two-wheelers. The detection results were integrated with the adaptive signal timing module and dynamic rerouting module.

The graphical user interface provides three major outputs: live monitoring dashboard, vehicle detection panel, and intelligent route optimization map. The live dashboard continuously updates vehicle density statistics and congestion percentage. Based on the density threshold, the signal control module automatically changes the signal state (Green/Yellow/Red) and allocates dynamic timer duration.

During high-density scenarios, the rerouting engine computes an alternative path using shortest-time estimation. The map visualization shows the congested road in red and suggested path in blue, enabling proactive congestion avoidance.

The object detection module demonstrates accurate localization of vehicles even in heterogeneous traffic conditions. Bounding boxes and labels are generated in real time without significant latency, proving suitability for live deployment.

System testing confirms that adaptive signal timing reduces waiting time at intersections compared to static timers. The model effectively prevents long vehicle queues and improves traffic flow continuity.



Overall, integration of computer vision, decision logic, and path optimization creates an intelligent transportation control system capable of real-time congestion mitigation and automated traffic regulation. The main dashboard displays live traffic analytics including detected vehicle count, congestion percentage, and number of active intersections. The interface updates dynamically as new frames are processed. The results show that the system can continuously monitor traffic density and convert visual information into interpretable statistics. This confirms the system's capability to operate as a centralized traffic monitoring platform for city-level deployment. The congestion estimation module calculates density based on detected vehicles per lane. When traffic density increases, the system automatically categorizes it into low, medium, or high congestion levels. The dashboard visualization proves that the algorithm can transform raw detection data into meaningful traffic intelligence.



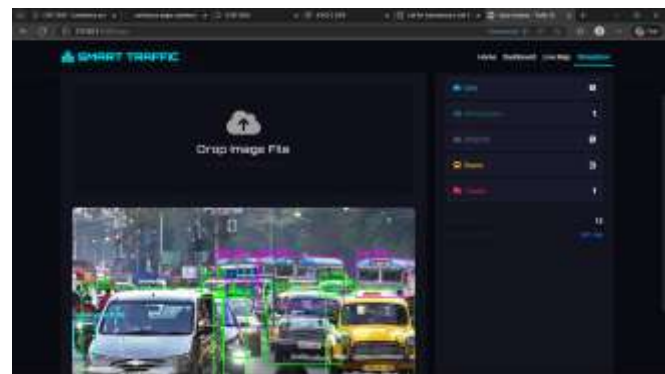
The route analysis module predicts alternative paths between source and destination based on congestion level. When heavy traffic is detected, the system suggests a different route to reduce travel time. The generated path dynamically changes according to traffic density, demonstrating real-time decision making.

The rerouting confirms proper implementation of shortest-path optimization combined with live traffic input. Instead of static navigation, the system adapts routes based on current road conditions, improving travel efficiency and reducing congestion accumulation.



The detection module successfully identified multiple vehicle categories such as cars, buses, trucks, and auto-rickshaws from traffic images. Bounding boxes were accurately placed around vehicles even in dense traffic scenes. The counting module computed the total number of vehicles present in each frame, which was further used for signal timing adjustment.

The results show reliable detection performance under occlusion and varying illumination conditions. The detected objects were correctly classified and counted, enabling accurate congestion estimation. This validates the suitability of deep learning-based object detection for intelligent transportation systems.





REFERENCES

- [1] Ministry of Road Transport and Highways, Government of India, *Road Transport Year Book*, New Delhi, India, 2022.
- [2] A. Sharma and R. Gupta, "AI-based adaptive traffic signal control system for urban intersections," *IEEE Access*, vol. 10, pp. 55678–55689, 2022.
- [3] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, real-time object detection," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, 2016, pp. 779–788.
- [4] S. Kumar and P. Singh, "Traffic congestion prediction using machine learning techniques," *International Journal of Intelligent Transportation Systems Research*, vol. 14, no. 3, pp. 211–220, 2021.
- [5] M. Chen, X. Liu, and J. Wang, "Real-time traffic monitoring using computer vision and deep learning," *Procedia Computer Science*, vol. 170, pp. 888–895, 2020.
- [6] Y. Wei, J. Zheng, and H. Li, "Dynamic traffic signal control using real-time traffic data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 6, pp. 2561–2572, 2020.
- [7] T. Roughgarden, *Algorithms Illuminated: Part 2 – Graph Algorithms and Data Structures*, Soundlikeyourself Publishing, 2018.
- [8] OpenStreetMap Contributors, "OpenStreetMap: A collaborative project to create a free editable map of the world," 2023. [Online]. Available: <https://www.openstreetmap.org>
- [9] M. Chen, X. Liu, and J. Wang, "Real-time traffic monitoring using computer vision and deep learning," *Procedia Computer Science*, vol. 170, pp. 888–895, 2020.
- [10] Y. Wei, J. Zheng, and H. Li, "Dynamic traffic signal control using real-time traffic data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 6, pp. 2561–2572, 2020.