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TrafficVision AI: Vision-Based Deep Learning Framework for Dynamic Traffic Signal Optimization in Metropolitan Networks

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Abstract

Managing traffic effectively has become a big problem in metropolitan areas that are developing quickly. Traditional traffic signals that work on fixed timers can't change based on how many vehicles are on the road at the time. This often means that people have to wait at empty roads for no reason, which wastes fuel, makes travel times longer, and releases more carbon into the air.

The system uses high definition CCTV cameras to record live video on roads. YOLOv8 and OpenCV work together to process the video in real time and identify and group vehicles. To measure the number of vehicles in each direction, the junction is separated into four lane wise Regions of Interest. A mathematical green time allocation model dynamically assigns GREEN, YELLOW, and RED signals based on the number of vehicles detected. This makes the flow of traffic smoother.

The system also has features for detecting red light violations and predicting short term traffic density to make traffic monitoring and signal planning better. This system uses a lightweight YOLOv8n model for fast real time performance, unlike reinforcement learning methods that need a lot of training and powerful hardware. It doesn't need expensive physical sensors, and it can work with current traffic systems using the HTTP and MQTT protocols. The tests showed that the waiting time went down by 60% and the throughput went up by 116%. The detection accuracy was between 92% and 94%.

Keywords: *Smart Traffic Signal, YOLOv8, Computer Vision, Adaptive Traffic Control, Intelligent Transportation Systems*.

1 Introduction

Traffic jams in Metropolitan cities that are developing quickly are becoming a big problem for cities. Transportation infrastructure is under a lot of stress since cities are growing quickly, and more people are buying vehicles. The World Health Organization (WHO) says that air pollution causes millions of deaths each year and that vehicles are a big part of the problem in cities [12]. In developing nations like India, the rapid rise in the number of vehicles on the road has made traffic worse, which has led to longer travel times, wasted fuel, lost money, and damage to the environment [13]. Traffic lights that are set to preset times don't change depending on how traffic is moving at the moment. Because of this, vehicles often have to wait at empty junctions, while lanes that are too crowded have to wait too long. These bad control systems burn more gas, pollute the air more, and release more greenhouse gases. Research indicates that adaptive traffic management systems substantially surpass static timer-based methods in enhancing traffic efficiency and mitigating congestion [9]. To get over these problems, Intelligent Transportation Systems (ITS) have been using more and more artificial intelligence (AI) and computer vision methods [3]. Vision-based traffic monitoring with deep learning models has demonstrated superior scalability and cost-effectiveness relative to physical sensor-based systems, including inductive loops and infrared detectors [11]. The YOLO (You Only Look Once) object detection architecture brought real-time, high-speed detection with accuracy that was competitive [5]. Later versions, including YOLOv5 and YOLOv8, made detection much faster and better for edge devices, making them good for smart city settings [6]. Recent studies have investigated reinforcement learning and AI-driven optimization models for adaptive traffic management [2]. These

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methods work well in simulations, but they frequently need a lot of training data, powerful GPUs, and complicated state modeling, which makes it hard to use them on a broad scale. Also, many current systems don't work with real world enforcement modules, such as those that catch people running red lights.
This manuscript proposes an AI-driven adaptive traffic signal optimization system for metropolitan networks to fill these gaps. It uses YOLOv8-based real time vehicle detection [7], lane-wise ROI density estimation, dynamic green time allocation, violation monitoring, and short term congestion prediction, all in one scalable framework

2 Literature Review

Recent studies in intelligent transportation systems have concentrated on substituting conventional fixed-time traffic signals with AI driven adaptive control systems. Numerous suggestions have been made for vision-based methods that use deep learning to make traffic flow better and ease congestion at intersections.
The 2025 study "Adaptive Traffic Light Control Using YOLOv10 and Deep SORT" came up with a way to keep an eye on traffic in real time using YOLOv10.for finding vehicles and Deep SORT for keeping track of them across frames. The system figured out how many vehicles were on the road, changed the length of the green light, and got a high detection rate (0.926). The method worked well even when things were blocked, but it needed GPU-based hardware and didn't have integration with traffic police control systems, which makes it costly to deploy on a large scale [1].
Another 2025 system, "Oculus: AI Powered Dynamic Traffic Signal Management," used both deep learning and reinforcement learning to make signals change based on traffic. Improvement. The system said that it was 40%
more efficient and that it cut travel time by 30%. But it relied a lot on cameras, IoT sensors, and cloud infrastructure, which made it hard to scale, be reliable, and handle emergency vehicles [2].
The 2024 study "Advanced Learning Technologies for Intelligent Transportation Systems" suggested a YOLO-based traffic signal control system that could change the timing. It worked better than traditional systems, but it needed powerful hardware and didn't solve the problem of working with government systems. Traffic control units or cheap ways to set them up [3].
In 2018, earlier research used Gaussian Mixture Models (GMM) to find vehicles and assign signals based on density. Even though things got better over fixed time signals, it wasn't very accurate in low light, had a lot of processing to do, and couldn't be scaled up very well [4].

The research reveals key gaps: high hardware costs due to GPU dependence, limited scalability in smart city deployments, poor integration with traffic police systems, insufficient emergency vehicle prioritization, and significant challenges when implementing these solutions in low-resource or underdeveloped urban areas.

3 Proposed System

The suggested AI powered camera-based smart traffic signal control system has three layers: the input layer, the AI processing layer, and the output layer. This makes sure that it can work in a modular way and in real time.
1. Layer for Input
The input layer is in charge of collecting and handling traffic data.
Module for the camera: A high definition traffic camera records live footage from the junction all the time. This live video stream is the main source of data.
Optional: Existing Traffic Management Database, keeps track of old traffic data and signal records that may be utilized for analysis and keeping an eye on performance.
Interface for the GUI and controller: Traffic officials may keep an eye on things and manually take control if necessary.

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This layer makes sure that real-time visual data is always being collected without the need for costly hardware sensors.

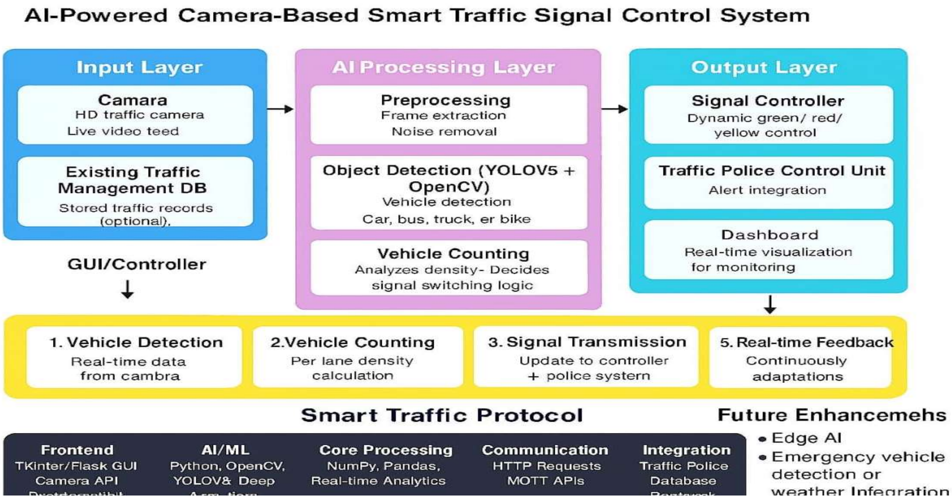

Fig. 1. Proposed system architecture of ATS

2. Layer for AI Processing

The AI Processing Layer does the main calculations and makes decisions.

Module for Preprocessing: It takes frames from the video and reduces noise to make detection more accurate.

Object Detection (OpenCV + YOLOv5/YOLOv8): Uses a deep learning model to find autos, buses, trucks, and motorcycles. For each vehicle that is found, a bounding box is made.

Counting vehicles and looking at their density: There are predetermined Regions of Interest (ROIs) that show lanes (North, South, East, and West) that vehicles are mapped to. Lane wise density is figured out and utilized to figure out how to switch the signal. Density is figured out and utilized to figure out how to switch the signal.

The output layer makes judgments about traffic control that are flexible.

3. Layer of Output

This output layer turns raw video data into useful traffic information.

Signal Controller: Changes the GREEN, YELLOW, and RED signals based on the calculated density.

Unit for Traffic Police Control: Gets notifications and combines logs of violations for enforcement.

Dashboard: Shows real-time data on vehicle numbers, signal conditions, and traffic patterns. This layer makes sure that signals are carried out and monitored in real time.

A. Signal Duration Formula

The adaptive green signal duration is calculated as follows:

$T_g = T_{base} + \alpha \times N$ (1)

Where: T_g is the length of the green signal.

T_{base} is the minimum base time, which is 10 seconds.

N = the number of vehicles that were seen in the lane

α = adjustment factor (3 seconds for each vehicle)

This model makes sure that green time is fairly split up across lanes dependent on how busy they are.

Adaptive Red Signal Duration is calculated as:

$T_r = T_{cycle} - T_g$ (2)

Where:

T_r= Red signal duration

T_{cycle}= Total cycle time (sum of all lane green times)

T_g= Green time of current lane

B. Adaptive Traffic Signal Algorithm

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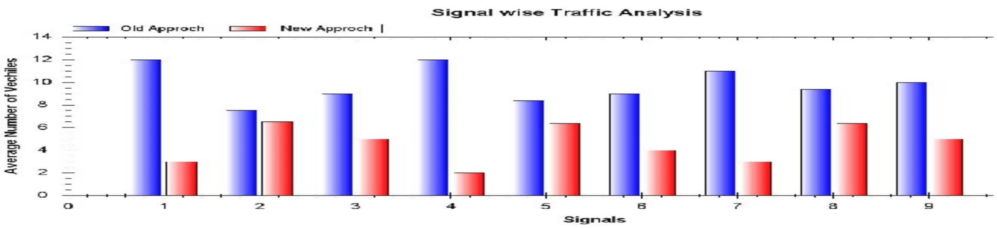
Step 1: Capture a video frame in real time from the CCTV camera.
Step 2: Preprocess the frame for better detection accuracy.
Step 3: Detect vehicles using the YOLOv8 model.
Step 4: Filter and classify relevant vehicles (cars).
Step 5: Map detected vehicles to their respective lanes using predefined ROIs.
Step 6: Count the number of vehicles in each lane.
Step 7: Calculate traffic density and determine green signal time using the density formula.
Step 8: Set the signal status to GREEN, YELLOW, or RED based on priority.
Step 9: Check for red-light violations and record them if detected.
Step 10: Send updated signal commands to the controller (HTTP/MQTT).



4 System Methodology

The vehicle detection module utilizes YOLOv8n [7], a lightweight version of the original YOLO framework [5]. The model was pre-trained on the COCO dataset and adjusted for traffic-related classes, while tracking and density estimation follow computer vision based traffic surveillance principles [11]. Traffic optimization methods based on reinforcement learning require long training cycles [9], whereas the proposed system achieves adaptive behavior using direct density-based computation. The system starts by recording live traffic footage from a high-definition CCTV camera and extracting frames for real-time analysis. Each frame is processed using the YOLOv8 model to detect vehicles such as automobiles, bikes, buses, and trucks with bounding boxes. Detected vehicles are mapped to four lane-wise Regions of Interest (North, South, East, West) using centroid placement to count vehicles in each direction. Traffic density is calculated based on the number of vehicles, and adaptive signal timing is determined using the formula $T_g=T_{base}+\alpha\times N$, where the lane with the highest density receives priority. The system also checks for red-light violations and records them if detected. Short-term traffic prediction is performed using recent vehicle count history to improve signal planning. Finally, the signal lights are updated in real time and the dashboard displays vehicle counts, signal status, and logged traffic data, enabling continuous adaptive traffic control.

5 Performance Comparison

When compared to systems with set times:
Waiting time went from 78 seconds to 31 seconds.
→ 60% less
The number of vehicles that could pass through rose from 18 to 39 per minute.
→116% better
Detection Accuracy: 92%–94%
A.Graph Analysis

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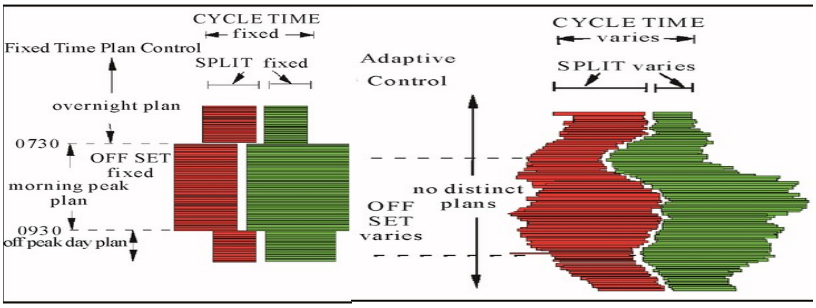

Fig. 2. Waiting Time and Throughput Comparison.

The graph of waiting times reveals that the adaptive mode has a far bigger decreasing trend than fixed time control. The throughput graph shows that the vehicle handling capacity per minute is almost twice as high at peak times. These results show that adaptive density-based regulation makes traffic flow better and cuts down on congestion when vehicles are not moving.

C. Discussion of Real Time Latency

The system keeps processing latency below one second, which makes sure that it responds in real time. The lightweight YOLOv8n design cuts down on inference latency while keeping detection accuracy high. The suggested system has better detection accuracy and can adapt to any situation without needing a lot of reinforcement learning.

D. Accuracy Comparison

Table 2: Waiting Time And Throughput Comparison

Method	Detection Accuracy	Adaptivity
Fixed-Time	N/A	No
Density-Based	85%	Partial
Proposed YOLOv8	92–94%	Yes

6 Results & Discussions

The suggested system was set up as a real-time, camera based adaptive traffic signal management system. One frame at a time, traffic video is processed.

YOLOv8 can find a lot of items, such as automobiles, bikes, buses, and trucks. The intersection has four sides: north, south, east, and west. To find out how many vehicles are in each lane, the vehicles that are found are mapped to these places. The green signal time is set dynamically dependent on the number of vehicles.

Green Time = 10 + (3 × Number of Vehicles)

The lane with the most vehicles receives a GREEN light first. The technology also knows when automobiles go into a lane when the light is red. Traffic that has happened in the past. We look to the past to estimate how awful traffic will be in the next several days. You can use a dashboard to see processed video, signal states, vehicle counts, and records of violations.

Results

About 92–94% of the time, the system was able to find things, which made sure that the traffic density estimates were correct. The wait time was cut from 78 seconds to 31 seconds, the throughput was raised from 18 vehicles per minute to 39 vehicles per minute, and the system became fully adaptable in real time.

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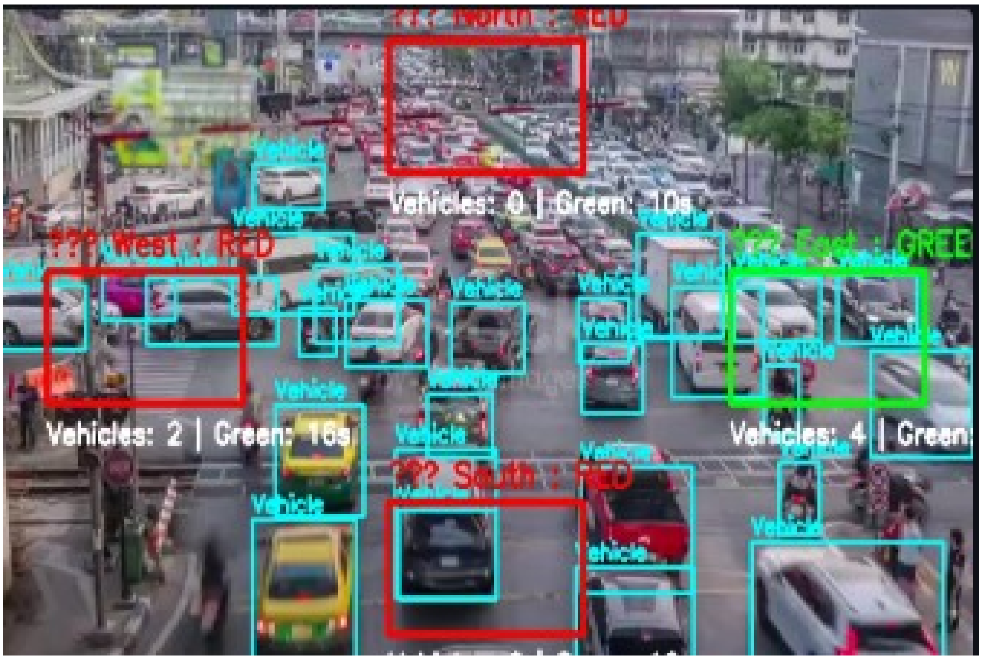


Fig. 3. Processed Video Frame with Detection & Signal Display.

Signal Decision

```
{
"North" : "RED"
"South" : "RED"
"East" : "GREEN"
"West" : "RED"
```

Police Log

	Direction	Signal	Instruction
0	North	RED	STOP
1	South	RED	STOP
2	East	GREEN	ALLOW VEHICLES
3	West	RED	STOP

Fig. 4.Signal decision & Police log.

Traffic Violations

	Frame	Direction	Violation
0	0	West	Red Light Jump
1	0	West	Red Light Jump
2	0	South	Red Light Jump
3	0	South	Red Light Jump
4	1	West	Red Light Jump
5	1	West	Red Light Jump
6	2	West	Red Light Jump
7	2	West	Red Light Jump
8	3	West	Red Light Jump
9	3	South	Red Light Jump

Fig. 5. Traffic Violations.

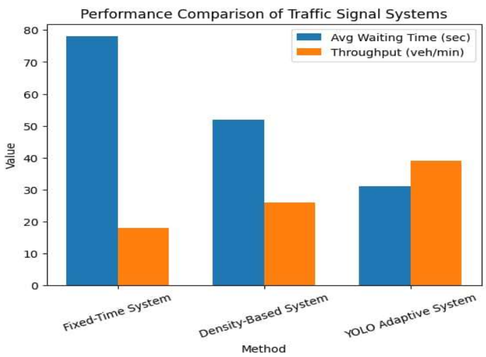
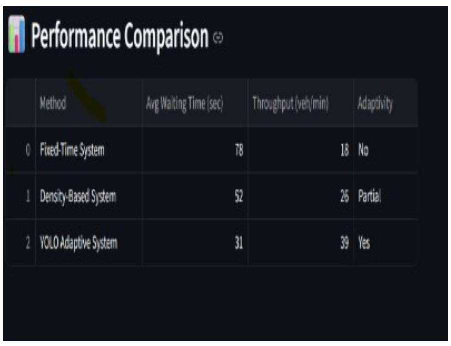


Fig. 6. Performance Comparison.



Performance Comparison

	Method	Avg Waiting Time (sec)	Throughput (veh/min)	Adaptivity
0	Fixed-Time System	78	18	No
1	Density-Based System	52	26	Partial
2	YOLO Adaptive System	31	39	Yes

Fig. 7. Performance Comparison Graph.

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7 Conclusion

The suggested AI driven adaptive traffic light system uses YOLOv8 to create a real time adaptive traffic signal control system that makes traffic management smarter and more responsive. The system doesn't use fixed timers. Instead, it uses CCTV cameras to watch live traffic, a lightweight deep learning model to find vehicles, and adjusts signal timings based on how many vehicles are actually in each lane. It minimizes unnecessary waiting and makes traffic flow better overall. The results show a clear improvement, such as less time spent waiting, more vehicles getting through, and a high level of detection accuracy with a very short response time.

This method is useful and cheap because it doesn't need expensive physical sensors or complicated training processes. It can work with the camera systems that are already in place, so it can be used in smart cities in the real world. The system can help make urban transportation networks safer, faster, and more efficient by adding features like coordinating multiple intersections and giving priority to emergency vehicles.

References

[1] A. Sharma, R. Gupta, and P. Verma, "Adaptive traffic light control using YOLOv10 and Deep SORT," Int. J. Intell. Transp. Syst., vol.14, no. 2, pp. 112–120, 2025.

[2] S. Reddy and K. Narayan, "Oculus: AI-powered dynamic traffic signal management using reinforcement learning," IEEE Trans. Intell. Transp. Syst., vol. 26, no. 1, pp. 455–468, 2025.

[3] M. Khan, T. Ali, and J. Hussain, "Advanced learning technologies for intelligent transportation systems," IEEE Access, vol. 12, pp.102345–102360, 2024.

[4] V. Kumar and S. Singh, "Artificial intelligence-based smart traffic management system using video processing," Int. J. Comput. Appl., vol. 179, no. 20, pp. 15–22, 2018.

[5] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp. 779–788.

[6] G. Jocher, A. Chaurasia,and J.Qiu, "YOLOv5," Ultralytics, 2022.

[7] G.Jocher, A.Chaurasia, and J.Qiu, "YOLOv8: Next-generation real-time object detection," Ultralytics, 2023.

[8] N. Wojke, A. Bewley, and D. Paulus, "Simple online and real time tracking with a deep association metric," in Proc. IEEE Int. Conf.Image Process. (ICIP), 2017, pp. 3645–3649.

[9] L. Li, Y. Lv, and F.-Y. Wang, "Traffic signal timing via deep reinforcement learning," IEEE/CAA J. Autom. Sinica, vol. 3, no. 3, pp. 247–254, 2016.

[10] S. S. Mousavi, M. Schukat, and E. Howley, "Traffic light control using deep reinforcement learning," Expert Syst. Appl., vol. 150,p. 113319, 2020.

[11] M. K. K. Islam, M. A. Rahman, and M. A. Hossain, "A smart traffic management system using computer vision," in Proc.IEEE Int. Conf. Intell. Transp. Syst. (ITSC), 2019, pp. 210–215.

[12] World Health Organization, Global Status Report on Road Safety 2018. Geneva, Switzerland: WHO Press, 2018.

[13] Ministry of Road Transport and Highways, Government of India,Road Accidents in India – Annual Report 2023, New Delhi, India, 2023.

[14] H. Zhang, Y. Chen, and L. Wang, "Edge-based intelligent traffic signal control using deep learning," IEEE Internet Things J., vol. 10, no. 4, pp. 3124–3136, 2023.

[15] Y. Wei, X. Zheng, and J. Wu, "Cooperative multi-intersection traffic signal optimization via deep reinforcement learning," IEEE Trans. Intell. Transp. Syst., vol. 24, no. 8, pp. 8102–8115, 2023.