

**AI-DRIVEN ADAPTIVE TRAFFIC MANAGEMENT SYSTEM***Rasika Kamble**UG Student, Department of Electronics and Telecommunication Engineering
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vaishnavi.utpat@sknscoe.ac.in***Abstract:**

Increasing traffic demand has made efficient signal management a significant challenge, particularly at busy urban intersections. Conventional traffic signals generally rely on predetermined timing plans and therefore cannot adjust their operation according to the changing number of vehicles on different approaches. This can result in unnecessary waiting, uneven utilization of green time, longer queues, and increased fuel consumption. To address this issue, this work proposes an AI-driven adaptive traffic management system capable of modifying signal timing according to the observed traffic condition.

The proposed system uses a camera to acquire live traffic footage, while OpenCV performs video processing and defines separate regions for the four approaches of the intersection. YOLOv8 is employed to detect vehicles and obtain individual vehicle counts for each direction. These counts are converted into traffic-density information and supplied to an adaptive timing algorithm that determines the appropriate green duration. The resulting control commands are transmitted wirelessly to ESP32 controllers, which operate the corresponding red, yellow, and green signal LEDs. By combining computer vision, deep-learning-based vehicle detection, adaptive decision-making, and embedded control, the proposed approach provides a flexible alternative to fixed-time traffic operation. The system is intended to improve green-time utilization, reduce unnecessary vehicle waiting, and support the development of intelligent traffic infrastructure.

Keyword: Artificial Intelligence (AI), YOLOv8, OpenCV, ESP32, Computer Vision.



1. INTRODUCTION:

Traffic conditions at urban intersections can change considerably within a short period because the number and type of vehicles approaching each road are not constant. However, many conventional signal systems continue to operate using predefined timing sequences. Such an approach does not account for the actual traffic demand of individual approaches and may allocate the same or similar green duration even when one direction has substantially more vehicles than another. Consequently, traffic queues can increase, drivers may experience longer delays, and available road capacity may not be utilized efficiently. These limitations create a need for traffic-control mechanisms that can observe current road conditions and modify signal operation accordingly.

Recent progress in artificial intelligence, deep learning, and computer vision has provided new possibilities for automated traffic observation. Video-based systems can obtain information about road conditions without requiring a separate sensing device for every traffic lane. Object-detection models belonging to the YOLO family are particularly useful for real-time applications because they can locate multiple objects within a video frame. In the proposed system, YOLOv8 is used to identify vehicles from traffic-camera footage, while OpenCV provides the image-processing functions required for handling the video stream and defining the observation regions. Vehicles such as cars, motorcycles, buses, and trucks can therefore be detected and associated with their respective traffic approaches.

The information obtained from vehicle detection can be used to estimate the demand of individual roads at an intersection. Instead of assigning an identical fixed green period to every approach, an adaptive controller can give greater priority to an approach carrying a larger traffic load while maintaining appropriate timing for other approaches. This makes the signal-control process more responsive to the current traffic situation. In the proposed architecture, Python performs the central processing and decision-making, while ESP32 microcontrollers receive the resulting timing commands and control the traffic-light LEDs.

A vision-based traffic-management approach can also reduce dependence on multiple road-installed sensing devices. A strategically positioned camera can observe vehicles across several regions of an intersection, making the system easier to modify or expand. The approach can therefore provide a practical platform for experimenting with adaptive traffic control based on real-time vehicle information.

Further improvements can be incorporated into the proposed framework, including emergency-vehicle priority, pedestrian recognition, IoT connectivity, remote monitoring, and traffic-demand prediction. Such capabilities can extend the system from basic density-based signal control toward a more comprehensive intelligent transportation platform. Accordingly, this work focuses on the integration of camera-based monitoring, YOLO-based vehicle detection, traffic-density estimation, and adaptive signal control for a four-way intersection.



2. LITERATURE SURVEY:

1. M. Lamrabet, M. A. Chentoufi, and R. Ellaia (2026) proposed an emergency-aware adaptive traffic signal control system using YOLO-based emergency vehicle detection and SUMO simulation. The study focused on providing signal priority based on detected emergency conditions and demonstrated improvements in traffic signal efficiency and congestion management.
2. A. S. Alhazmi, A. Hamza, and A. Moubayed (2026) conducted a comparative study of different YOLO models for adaptive traffic signal control. The models were evaluated based on detection accuracy, inference speed, and computational efficiency. The study reported that YOLOv8 provided a good balance between these parameters for real-time traffic applications.
3. X. Han, Z. Qu, and S. Xia (2026) developed a Teacher–Student Adversarial YOLO model for traffic object detection under adverse environmental conditions. Their approach used domain adaptation techniques to improve vehicle detection performance in challenging conditions such as fog, rain, and low-light environments.
4. W. Song, J. Min, and J. Zhang (2026) proposed an adaptive multi-convolutional kernel fusion-based YOLO network for traffic object detection. The model used cross-scale feature fusion to improve the identification of small and distant vehicles while maintaining real-time detection capability.
5. N. L. Byenkya, N. Rose, and O. Nixon (2026) introduced a YOLOv11-based object detection system with continuous learning for dynamic road environments. The model was updated using newly collected road data, which improved its adaptability and robustness under changing traffic conditions.
6. L. Lyu, S. I. Guler, and V. V. Gayah (2026) proposed an adaptive action selection strategy based on reinforcement learning for intelligent traffic signal control. The system dynamically selected signal actions according to traffic conditions and achieved reductions in vehicle delay and queue length.
7. L. Li, Y. Zhao, Z. Zhou, and H. K. Lo (2026) developed an end-to-end traffic signal control approach based on fixed-location detector occupancy patterns. Deep learning techniques were used to optimize signal control under uncertain traffic demand, resulting in improved intersection performance.
8. H. Wang et al. (2026) presented an adaptive traffic signal control method based on Multi-Agent Soft Actor-Critic reinforcement learning. The approach enabled cooperation among multiple intersections and improved traffic throughput while reducing congestion.
9. M. Raza, M. Kazmi, H. M. Kidwai, H. R. Khan, S. A. Qazi, K. Arshad, and K. Assaleh (2025) developed a real-time adaptive traffic light control system using YOLO-based vehicle detection and Passenger Car Equivalent (PCE)-aware density estimation. Their approach dynamically adjusted traffic signal timings and helped reduce average traffic delay.



10. O. A. Ayegbusi, A. O. Akinwumi, O. L. Ogbeide, A. O. Akingbesote, J. R. Obafemi, O. D. Akinrolabu, and O. Rotiba (2025) proposed a deep learning-based traffic signal control system using the YOLO algorithm for vehicle detection. The detected traffic conditions were used to support adaptive signal operation, resulting in improved traffic flow and reduced vehicle waiting time.
11. S. Shirulkar, R. Makode, and R. Khandelwal (2025) presented an adaptive traffic signal management system based on real-time vehicle detection and tracking. Computer vision techniques were used to estimate traffic density, and the signal timing was adjusted accordingly. The system improved intersection efficiency compared with conventional fixed-time signal systems.
12. M. Ravichandran, K. Laxmikant, and A. Muthu (2024) developed a smart traffic control system using YOLOv8 for real-time lane-wise vehicle detection. OpenCV was used along with the detection model to estimate traffic density and dynamically manage traffic signal timing.
13. S. Papanashi, M. Chadaga, R. Kshithi, S. S. Huddar, K. Sreelakshmi, and P. Ramakanth Kumar (2024) proposed an adaptive traffic signal timing approach using YOLOv10 and computer vision. The system analyzed traffic footage to estimate vehicle density and dynamically optimized the duration of traffic signals, improving traffic movement and reducing congestion.
14. R. Mahadshetti, J. Kim, and T.-W. Um (2024) developed Sign-YOLO, an attention-based YOLOv7 model for traffic sign detection. The proposed approach improved detection accuracy under varying weather, lighting, and occlusion conditions.
15. C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao (2023) introduced YOLOv7, an advanced real-time object detection model incorporating trainable bag-of-freebies techniques. The model achieved high detection accuracy while maintaining fast inference performance.
16. G. Jocher, A. Chaurasia, and J. Qiu (2023) presented the Ultralytics YOLO framework, which introduced efficient object detection capabilities including anchor-free detection and improved training strategies. The framework provided improved detection accuracy and faster inference, making it suitable for real-time applications.
17. K. F. L. Chu, A. Y. S. Lam, and V. O. K. Li (2022) proposed an end-to-end off-policy deep reinforcement learning approach for traffic signal control. Their method optimized traffic signal decisions dynamically and demonstrated improved signal performance with reduced traffic delay.
18. A. Haydari and Y. Yilmaz (2022) conducted a survey on deep reinforcement learning applications in intelligent transportation systems. The study identified reinforcement learning as a promising approach for traffic signal control, traffic prediction, and autonomous transportation applications.
19. S. Li, W. Deng, and Z. Liu (2020) proposed a deep adaptive traffic signal controller based on reinforcement learning. The system used spatial-temporal traffic state information and long-

term planning to optimize signal control. The results showed reduced vehicle delay and improved traffic efficiency compared with conventional fixed-time traffic signal systems.

3. PROPOSED METHODOLOGY:

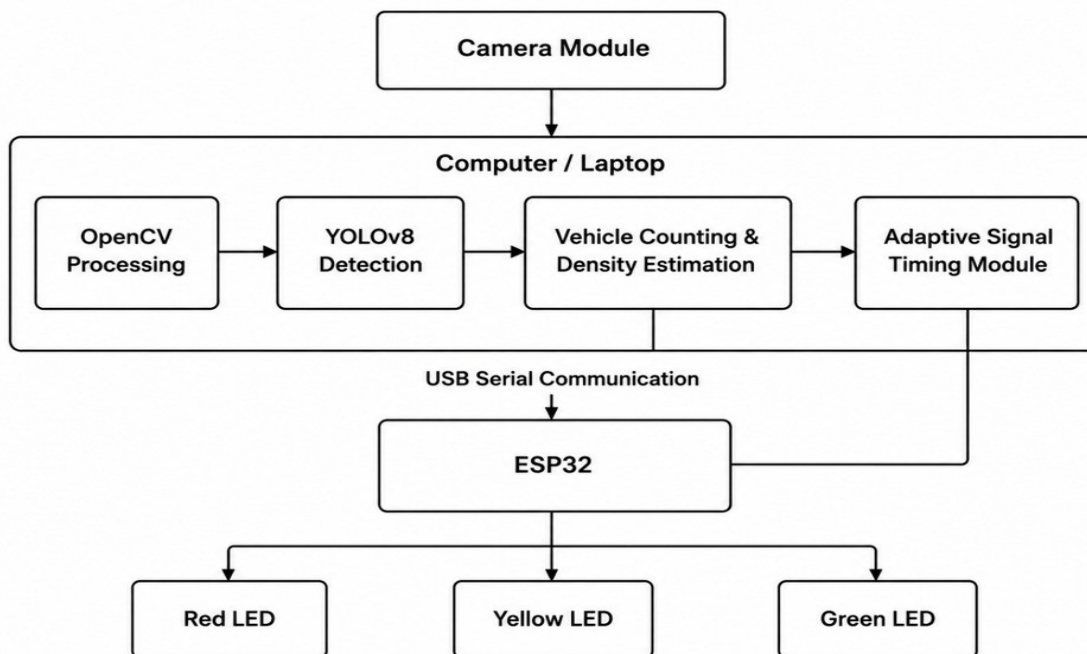


Figure 1 Block Diagram of AI-Driven Adaptive Traffic Management System

Proposed Methodology

The proposed system is designed for a four-way intersection with four traffic approaches: North, South, East, and West. Its purpose is to replace a completely predetermined signal sequence with a control strategy that considers the current traffic demand observed at the intersection. The overall architecture consists of a camera-based monitoring unit, image-processing and vehicle-detection modules, a traffic-density estimation stage, an adaptive signal-timing algorithm, wireless communication, and ESP32-based signal controllers.

1. Camera Module

The camera module acts as the input source of the system. It continuously captures the live video of the traffic intersection. The captured video provides real-time information about the vehicles present in different directions. This video stream is sent to the computer or laptop for further processing.

2. OpenCV Processing

The live video received from the camera is processed using OpenCV. OpenCV captures the video



stream and divides it into individual frames. These frames are processed before being passed to the detection model. OpenCV also helps in displaying the video output and handling the Regions of Interest (ROI) used for vehicle counting.

3. YOLOv8 Vehicle Detection

The processed video frames are given as input to the YOLOv8 object detection model. YOLOv8 identifies the vehicles present in the traffic scene and generates bounding boxes around them. The system detects selected vehicle classes such as cars, buses, trucks, and motorcycles.

4. Vehicle Counting and Density Estimation

After vehicle detection, the system counts the vehicles present in the predefined traffic regions or lanes. The number of detected vehicles is used to estimate the traffic density. A higher number of vehicles indicates higher traffic density, while fewer vehicles indicate lower traffic density. This information is used as the main input for adaptive traffic signal control.

5. Adaptive Signal Timing Module

The estimated traffic density is analyzed by the adaptive signal timing module. Based on the vehicle count, the system decides which traffic direction should receive priority. The direction with higher traffic density is allocated a longer green signal duration, while the direction with fewer vehicles receives a shorter green duration. This helps in reducing unnecessary waiting time compared with fixed-time traffic signals.

The signal operation follows a safe sequence:

Green → Yellow → Red → Next Direction Green

6. USB Serial Communication

Once the signal timing decision is generated by the computer, the control command is transmitted to the ESP32 microcontroller using USB serial communication. The computer sends commands representing the required traffic signal state and timing.

7. ESP32 Controller

The ESP32 acts as the hardware control unit of the system. It receives the signal control commands from the computer and processes them according to the programmed logic. Based on the received command, the ESP32 controls the corresponding output pins connected to the traffic signal LEDs.

8. Traffic Signal LEDs

The traffic signal is represented using Red, Yellow, and Green LEDs.

- Red LED: Indicates that vehicles must stop.
- Yellow LED: Indicates a transition or caution period.
- Green LED: Indicates that vehicles are allowed to move.



The ESP32 activates these LEDs according to the adaptive signal timing generated by the AI-based traffic analysis system.

9. Continuous Feedback Process

The entire system operates continuously in a loop. The camera repeatedly captures the traffic condition, YOLOv8 detects vehicles, the system calculates traffic density, and the adaptive module determines the appropriate signal timing. The updated command is then sent to the ESP32, which changes the traffic signal accordingly.

Conclusion:

This work presents a vision-based adaptive traffic-management framework for a four-way intersection in which signal operation is determined using the observed traffic demand. Rather than relying entirely on predefined signal durations, the system obtains traffic information from camera footage and processes it using OpenCV and YOLOv8. Vehicles are identified within direction-specific regions, and the resulting counts are used to estimate the relative traffic load of the North, South, East, and West approaches.

The estimated demand is supplied to an adaptive timing mechanism that selects suitable green durations while maintaining required transition intervals. The selected timings are communicated through Wi-Fi to two ESP32 controllers, which operate the traffic-light LEDs for the four approaches. This distributed arrangement provides a practical way to connect AI-based traffic analysis with physical signal control.

The proposed architecture demonstrates the potential of combining computer vision, deep learning, wireless communication, and embedded controllers for responsive traffic management. Future development can focus on emergency-vehicle priority, pedestrian recognition, vehicle-type-based control, traffic prediction using historical data, and cloud-based supervision. These additions could improve the system's ability to handle more complex traffic conditions and support its transition toward larger intelligent transportation applications.

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