IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

AI- Based Smart Traffic Management System

Prof. Swati Kale[1], Mr. Rushikesh Pagar[2], Mr. Pandurang Shirgire[3],

Mr. Rohit Romade[4], Mr. Aniket Patil[5]

Assistant Prof. Computer Engineering Department, Adsul's Technical Campus, Ahilyanagar, India[1]

Students, Electrical Engineering Department, Adsul's Technical Campus, Ahilyanagar, India[2,3]

Student, AIDS Engineering Department, Adsul's Technical Campus, Ahilyanagar, India[4]

Student, Computer Engineering Department, Adsul's Technical Campus, Ahilyanagar, India[5]

Abstract: *Traffic Increased traffic flow in growing cities causes congestion, higher fuel consumption, and frequent traffic jams. Traditional traffic management systems rely heavily on traffic police and fixed traffic light controls, which lack real-time adaptability. This study addresses the need for an efficient, intelligent traffic management solution to reduce congestion and optimize vehicle flow. Objective: The main objective of this study is to develop an Artificial Intelligence (AI)-based traffic management system using YOLO algorithms to detect vehicle density and dynamically adjust traffic signals. Methods: The system utilizes phone cameras to capture video of traffic lanes, and YOLO algorithms are employed for real-time object detection and density evaluation. Data collected from the cameras are processed using Python to determine the vehicle count in each lane. Based on this analysis, Arduino microcontrollers are programmed to prioritize traffic signals for lanes with higher vehicle density. The proof-of-concept implementation includes a prototype setup with two phone cameras, Arduino, and LEDs. Results: The system successfully detected vehicle density and adjusted traffic signals dynamically, demonstrating improved optimization of vehicle flow compared to traditional fixed-time signal systems. Real-time parallel processing ensured continuous monitoring and responsiveness to changing traffic conditions. Conclusions: The implementation of this AI-based traffic management system demonstrates significant potential to enhance traffic flow and reduce congestion. Future improvements could include scaling the system to larger networks and integrating additional sensors for better performance under varied environmental conditions*

Keywords: Traffic flow Optimization Open CV Artificial Intelligence Waiting time parallel processing Traffic Management System

I. INTRODUCTION

The rapid increase in vehicle numbers has significantly contributed to road congestion, which presents major challenges to both human safety and the environment. In cities like Kathmandu, where the vehicle population exceeds the available road capacity, traffic congestion has become a persistent issue. Despite resource constraints, the Metropolitan Traffic Police have effectively managed traffic flow, focusing on improving safety, reducing accidents, and implementing cost-efficient traffic management strategies. However, traditional traffic control systems, which rely on fixed signal timings based on historical data, struggle to adapt to dynamic traffic conditions, particularly during peak hours or after accidents. Artificial Intelligence (AI) provides a promising solution to these limitations. AI-based systems, utilizing YOLO (You Only Look Once) algorithms for real-time vehicle detection, offer the ability to dynamically adjust traffic signal timings based on real-time vehicle density [1]. Unlike conventional systems that rely on fixed-time or fuzzy control, AI-based traffic management systems process real-time data to optimize waiting times and reduce traffic congestion [2]. By adapting to fluctuating traffic volumes, AI-driven systems offer enhanced

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

efficiency in managing urban traffic. Traffic congestion not only leads to wasted time and resources but also contributes to increased emissions, significantly harming the environment. YOLO-based algorithms, with their ability to detect, classify, and count vehicles in real-time, optimize traffic flow by adjusting signal durations to prioritize lanes with higher vehicle density [3]. Moreover, AI-driven systems can prioritize emergency vehicles like ambulances and fire trucks, ensuring their swift passage through intersections and improving response times during critical situations [4] . Traditional traffic control systems, such as fixed-time signals, loop-based systems, and deep reinforcement learning (DRL) models, are limited in comparison to AI vision-based solutions. DRL-based systems enhanced by YOLO integration allow for real-time optimization that outperforms conventional methods [5]. This research explores the potential of AI to optimize traffic light control in congested urban environments, providing an adaptable, real-time solution to modern traffic challenges [6].

Objective of Project:

1. Vehicle Detection and Counting: Implement a deep learning-based approach using YOLO (You Only Look Once) to accurately detect and count the number of vehicles in images captured from surveillance cameras.
2. Traffic Congestion Classification: Classify traffic conditions into three levels—low, medium, and high congestion—based on predefined vehicle count thresholds to enable effective traffic flow monitoring.
3. Emergency Vehicle Detection: Identify and prioritize emergency vehicles (such as ambulances and fire trucks) in real-time to improve emergency response times and reduce delays in critical situations.
4. Automated Traffic Status Monitoring: Develop a user- friendly dashboard that allows traffic authorities to upload images, preview detections, and receive real- time updates on vehicle density and congestion levels.
5. Model Optimization and Selection: Provide options for selecting different YOLO models (YOLOv8s, YOLOv8n, YOLOv8x) to balance detection accuracy and computational efficiency based on specific use cases.
6. Scalability and Cost-Effectiveness: Design a fully software-based solution that can be deployed with minimal infrastructure modifications, making it a cost- effective and scalable approach for smart city applications.

II. LITERATURE SURVEY

• In 2018, ntelligent traffic management systems are crucial for achieving smart city objectives, which aim to improve the efficiency of urban traffic networks. Numerous approaches have been proposed to optimize traffic flow, leveraging a wide array of technologies and methodologies. Haider [7] introduced a machine learningbased system that dynamically adjusts traffic signal timing based on real-time traffic data, reducing congestion and enhancing overall traffic efficiency. This system utilizes historical traffic patterns to optimize signal control, ensuring smoother traffic flow.

• Liu et al. [8] explored the application of multi-agent Q-learning for intelligent traffic light control. Their approach, which relies on distributed agents, allows each agent to learn optimal signal timings based on real-time traffic conditions. This system can adapt to fluctuations in traffic volume, providing a notable improvement over traditional fixed-time traffic light system.

• Wang et al. [2] expanded on this concept by integrating a spatio-temporal multi-agent reinforcement learning (RL) approach to traffic light management. This method employs a graph-based model to represent the relationships between multiple intersections, enabling more effective coordination, particularly during peak traffic hours. The model's adaptability to varying traffic conditions makes it a promising solution for optimizing traffic flow in large urban areas. Further advancements in RL-based traffic control were made by Zhang [9], who combined RL with partial vehicle detection. This approach focuses on real-time decision-making, adjusting signal timings based on vehicle counts and traffic flow, allowing for more dynamic signal control.

• Kumar [10] further enhanced this model by introducing fuzzy inference systems into RL, enabling adaptive control in situations where precise traffic modeling is challenging. Deep reinforcement learning (DRL) has gained significant attention in recent years for traffic control.

• Pan [11] demonstrated that DRL-based systems could dynamically adjust signal timings in response to real-time data, improving overall traffic efficiency and reducing waiting times at intersections. These systems adjust to fluctuating traffic patterns, offering an advanced alternative to traditional traffic management methods. [12] proposed a smart traffic signal control system designed for smart cities, where real-time data processing facilitates adaptive traffic management. This system, which uses sensor-based data to guide decision-making, enhances traffic flow and reduces congestion in urban environments.

• Similarly, zhao [13] introduced a two-stage fuzzy control scheme to optimize signal timing at intersections, effectively balancing traffic loads and minimizing delays across multiple lanes. The role of AI and computer vision in modern traffic management has become increasingly important. YOLO (You Only Look Once), an object detection algorithm, has been widely studied for vehicle detection and counting.

• According to Nvidia's documentation [14], YOLO provides real-time object detection with high accuracy, making it well-suited for traffic management systems. [15]further validated YOLO's ability to handle large datasets efficiently, showcasing its potential as a robust tool for real-time vehicle counting and classification. Additionally, integrating AI systems with emergency vehicle prioritization has been explored by Sharma and Bansal [16], who proposed intelligent traffic light systems that utilize deep learning for traffic environment analysis. These systems not only optimize traffic flow but also enhance emergency response times by prioritizing the passage of vehicles such as ambulances and fire trucks.

• Lee et al.[17] proposed a smart traffic light controller using embedded systems, demonstrating the cost-effectiveness and feasibility of implementing intelligent traffic systems with low-cost hardware solutions. Their work highlights that intelligent traffic management can be achieved with embedded systems while maintaining system reliability and scalability. The use of intelligent agents in traffic control was further explored by Roozemond [18], who discussed the proactive role of agents in managing urban intersections in real-time. His work emphasized the importance of intelligent agents in managing traffic flow, a strategy that could enhance the flexibility and scalability of AI-based traffic systems. Kosonen [19] examined multi-agent fuzzy control, using real-time simulations to adjust signal timings based on fuzzy logic models. This approach improves decision-making in complex urban traffic networks, where precise modeling is difficult. Sutton and Barto [20] introduced reinforcement learning techniques, laying the groundwork for many advanced RL-based systems, including those used in traffic management. Further developments in AI-based object detection for traffic management were made by Open Data Science [21], who provided an overview of YOLO's capabilities in object detection and classification. This work strengthened YOLO's role as a leading technology for real-time vehicle detection in intelligent transportation systems.

• Liu and Qin [22] emphasized the potential of intelligent traffic light systems to provide scalable solutions that not only manage traffic but also improve emergency vehicle prioritization through realtime decision-making and AI integration. Zhang et al. [23] supported this by demonstrating smart traffic systems using real-time monitoring and intelligent control. Chavan [24] proposed a Cognitive Road Traffic Management System (CTMS) based on the Internet of Things (IoT), exploring the integration of IoT technologies with AI for smarter traffic management. This approach demonstrated the potential of combining AI with IoT to enhance urban traffic efficiency.

III. EXISTING SYSTEM

In Current traffic management systems primarily rely on real-time data from sensors and cameras to regulate traffic flow. Traditional approaches include vehicle detection using image processing techniques, such as Gaussian mixture models and foreground detection, to estimate traffic density. Some systems use fixed-time traffic signals or sensor-based adaptive control, where traffic lights adjust based on vehicle count and congestion levels. While these methods have improved traffic flow, they still face challenges such as,

Inaccurate detection in extreme weather conditions, limited scalability, and high infrastructure costs. In the context of AI-based traffic management, existing systems highlight the need for more intelligent and adaptable solutions. By integrating deep learning and predictive analytics, traffic signals can dynamically adjust in real-time based on historical

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 8, May 2026

Impact Factor: 8.2

data and live traffic conditions. Advanced AI techniques can enhance vehicle classification, optimize traffic light timings, and improve congestion prediction. This approach aims to create a self-learning system capable of handling diverse traffic scenarios more efficiently than traditional rule-based or sensor-driven methods. Inference for the Project Analyzing the existing systems suggests that incorporating advanced AI techniques—such as deep learning for more accurate vehicle recognition and predictive analytics for dynamic signal timing—can significantly enhance traffic flow management. An integrated approach that combines multi-modal sensor data with sophisticated video analytics can further reduce congestion, improve safety, and offer a robust solution adaptable to changing traffic patterns.

IV. METHODOLOGY

The rapid growth in vehicle numbers has led to increased traffic congestion, particularly in urban areas, which significantly delays travel times and contributes to environmental pollution. In this study, two traffic lanes, each experiencing varying levels of vehicle density, are monitored to assess real-time traffic flow and adjust traffic light control accordingly. This approach is based on intelligent traffic management systems outlined in previous research, which employ real-time data processing and adaptive control strategies.

A. Data Collection with IP Webcam Software

To collect real-time traffic data, we employ IP webcam software that connects to the network and transmits video footage over Wi-Fi, enabling remote monitoring of traffic conditions in both lanes. The camera captures video footage, compresses the data using the MJPEG format, and converts it into a digital signal. The resolution and frame rate of the camera are adjusted to ensure optimal video quality for accurate vehicle detection and counting, as demonstrated by several studies. This technique ensures high-quality video capture, critical for real-time object detection systems like YOLO.

B. Vehicle Detection Using YOLO Algorithm

The captured video data is processed using the YOLO (You Only Look Once) algorithm, a widely used real-time object detection method. YOLO is known for its ability to detect and classify objects (in this case, vehicles) within a single frame, providing high efficiency and real-time vehicle counting. YOLO's framework divides an image into a grid and predicts bounding boxes for detected objects, thus enabling dynamic traffic management. The efficiency of YOLO in processing frames quickly makes it ideal for real-time traffic light control applications, as demonstrated by previous research in the field. YOLO's application in traffic management systems has been studied in multiple contexts, including urban traffic flow optimization, vehicle classification, and real-time monitoring. This real-time processing allows for immediate adjustments to the traffic light cycle based on vehicle density, optimizing traffic flow and reducing congestion.

C. Integration with Arduino for Traffic Control

Once the vehicle count is determined, the data is transmitted to an Arduino microcontroller, which controls the traffic lights. The Arduino adjusts signal timing based on the vehicle density data received from the YOLO algorithm. This integration of YOLO with Arduino allows for dynamic adjustments to the traffic signal cycle, ensuring that the lane with higher vehicle density receives more green light time. The Arduino microcontroller is well-suited for real-time applications like this, as it can process and act on input data efficiently. This approach is based on the principles of adaptive traffic control systems, which continuously adjust signal timing in response to real-time data. Previous studies have shown the effectiveness of Arduino in managing traffic signals for smart cities and optimizing vehicle flow.

D. System Implementation and Evaluation

The combination of YOLO and Arduino creates an adaptable, real-time traffic management system. By processing data in parallel and adjusting the signals promptly, the system can improve traffic flow, reduce congestion, and minimize

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

environmental impact. Similar intelligent traffic control solutions have been implemented in various smart city projects, demonstrating their effectiveness in reducing wait times and optimizing traffic flow. This methodology offers a scalable and efficient solution for urban traffic management, enabling real-time responses to fluctuating traffic conditions.

E. . Algorithm and Flowchart

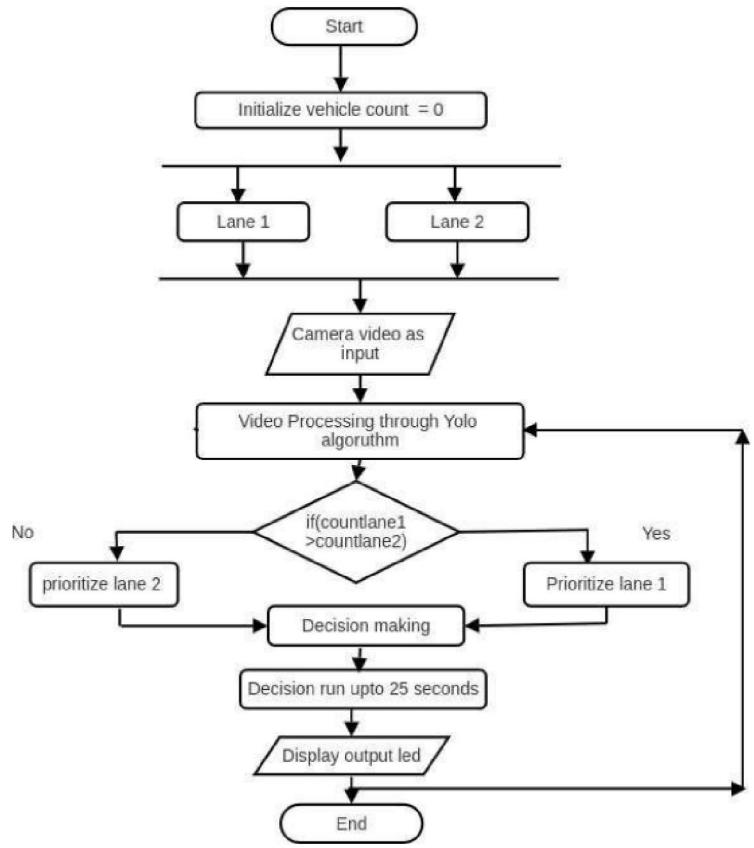

Fig. 1.Workflow Diagram

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 8, May 2026

Impact Factor: 8.2

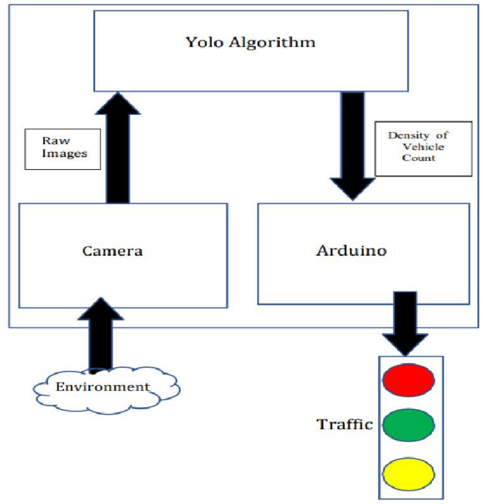

Fig. 2.Block Diagram

The proposed system employs the YOLO (You Only Look Once) algorithm to manage traffic flow at an intersection by dynamically adjusting traffic light signals based on real-time vehicle density. The process begins with the capture of live video data through a phone camera, which is then transmitted via an IP address over the same network to the system for processing.

The methodology for implementing a Smart AI-based Traffic Management System with real-time monitoring and adaptive traffic light control is structured in several stages:

1. Data Collection and Preprocessing Traffic Data Sources: Live feeds from CCTV cameras, IoT sensors, GPS systems, and satellite imagery are utilized for real-time data collection. Data Preprocessing: The raw traffic data undergoes image enhancement, noise reduction, and object detection preprocessing using OpenCV and deep learning techniques.

2. Object Detection and Classification Deep Learning Model: YOLOv8 (You Only Look Once) is used for detecting and classifying vehicles, pedestrians, and emergency vehicles.

Bounding Box and Labeling: Each detected vehicle is assigned a category (e.g., car, bus, ambulance), and its movement is tracked.

3. Real-Time Traffic Monitoring and Congestion Analysis Traffic Density Calculation: The system estimates traffic congestion by counting the number of vehicles at intersections and calculating the queue length and waiting time. Pattern Analysis: Historical traffic patterns and realtime data are used to predict peak hours, bottlenecks, and potential congestion zones.

4. Adaptive Traffic Signal Control Dynamic Signal Timings: Traffic lights are adjusted dynamically using reinforcement learning algorithms based on real-time traffic conditions. Priority Handling: Emergency Vehicle Detection: The system prioritizes ambulances and fire trucks by changing traffic signals accordingly. Public Transport Optimization: Public buses are given priority during high congestion periods.

5. System Optimization & Performance Enhancements GPU Acceleration: CUDA and OpenVINO frameworks enhance deep learning model execution speed. Multithreading: Parallel processing is implemented to maintain real-time performance while detecting multiple objects. Edge Computing: AI models are deployed on edge devices near traffic intersections to reduce latency.

6. Visualization & User Interface Graphical Dashboard: A real-time interface using PyQt5 provides visual monitoring of traffic conditions. Historical Data Reports: Traffic reports are stored in JSON/CSV format for long-term analysis.

7. Evaluation Metrics & Expected Outcomes Traffic Throughput Improvement: The number of vehicles passing through intersections increases. Reduction in Queue Length: Vehicles spend less time at signals. Lower Fuel

DOI: 10.48175/568

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 8, May 2026
Impact Factor: 8.2

Consumption: Reduced idling leads to lower CO_2 emissions. Faster Emergency Response Time: Ambulances and fire trucks navigate traffic efficiently.

V. ALGORITHMS

The Signal Switching Algorithm adjusts the go signal duration depending on the traffic density data provided via the vehicle detection module, while updating red light timings for other directions. The algorithm operates in a cyclical manner, switching signals according to each timer. It receives input from the sensing module, which provides vehicle data in JSON structure, with each detected vehicle labeled as a key, accompanied by confidence levels and coordinates as values.

The algorithm parses this data to determine the total count of each vehicle type, which is then used to calculate the optimal green light duration. Red signal times are adjusted for other directions accordingly. This algorithm is intended to be scalable, allowing for application across any quantity of signals at an junction. The Algorithm was developed with the following key factors in mind:

1. Processing Time: The duration needed for the algorithm to compute traffic density and determine the interval of the go signal, which informs the optimal moment for image capture.
2. Lane Count: The lane count at the junction.
3. Vehicle Counts by Class: The overall vehicle count in each category (cars, trucks, motorcycles, etc.).
4. Traffic Density: Calculated according to the above factors.
5. Start-Up Delay: The lag encountered by each vehicle during start-up, together with the increasing, non-linear delay affecting vehicles further back in the queue.
6. Average Speed per Vehicle Class: The average time taken for each vehicle class to clear the intersection once the go signal is activated.
7. Green Light Duration Limits: Minimum and maximum time thresholds for the green phase to prevent prolonged waits and traffic congestion.

VI. IMPLEMENTATION

A. Importing Required Libraries

The project begins by importing necessary libraries such as PyQt5, YOLO, PIL, numpy, and random. These libraries facilitate GUI creation, object detection, image processing, and traffic signal adaptation.

B. Loading and Processing Traffic Images

The system allows users to upload traffic images from four different lanes. These images are processed using YOLOv8 to detect vehicles, including cars, buses, trucks, and motorcycles. Additionally, a separate custom-trained YOLO model detects ambulances to prioritize emergency vehicles.

C. Preprocessing Traffic Data

The captured images undergo preprocessing, including format verification and resizing. The YOLO models analyze the images to count the number of vehicles in each lane. If an ambulance is detected, that lane is given the highest priority.

D. Extracting Traffic Density Features

The system extracts key traffic features such as vehicle count and ambulance presence. This information is used to determine optimal traffic light timings. The priority-based scheduling ensures efficient traffic flow.

E. Traffic Signal Adaptation with AI

Based on vehicle density, the system calculates signal durations dynamically. The green light duration is adjusted using predefined rules based on vehicle count. If an ambulance is detected, the system immediately grants priority to that lane.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 8, May 2026 Impact Factor: 8.2

F. GUI and Real-Time Monitoring

The system features an interactive GUI using PyQt5. It displays lane images, detected vehicle counts, and signal statuses in real time. A countdown timer ensures users are informed of the remaining signal duration for each lane. G.

G. Traffic Light Control Algorithm

The model processes the detected vehicle data and determines the optimal sequence for signal changes. The cycle follows:

• Green signal for the lane with the highest priority.
• Transition to yellow before switching to the next lane.
• Red signal for other lanes until their turn arrives.

H. Real-Time Adaptation of Traffic Timings

The system continuously updates traffic signals based on live input. As vehicle density changes, new images are analyzed, and signal durations are recalculated. This ensures efficient traffic flow and minimizes congestion.

VII. CONCLUSION

The development of this intelligent traffic system demonstrates a promising solution for managing traffic congestion through dynamic vehicle count-based adjustments to traffic signals. Unlike traditional fixed-time scheduling systems, which operate on predefined time cycles, this adaptive system offers real-time responses to traffic conditions, improving the flow of vehicles. It is especially advantageous in regions where road expansion is impractical.

REFERENCES

[1]. Y. Liu, L. Liu, and W. P. Chen, "Intelligent traffic light control using distributed multi-agent Q learning," IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC, vol. 2018-March, pp. 1–8, Jul. 2017, doi: 10.1109/ITSC.2017.8317730.

[2] D. Zhao, Y. Dai, and Z. Zhang, "Computational intelligence in urban traffic signal control: A survey," IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, vol. 42, no. 4, pp. 485– 494, Jul. 2012, doi: 10.1109/TSMCC.2011.2161577.

[3] V. Miz and V. Hahanov, "Smart traffic light in terms of the cognitive road traffic management system (CTMS) based on the Internet of Things," Proceedings of IEEE East-West Design and Test Symposium, EWDTS 2014, Jan. 2014, doi: 10.1109/EWDTS.2014.7027102.

[4] Z. Liu, "A Survey of Intelligence Methods in Urban Traffic Signal Control," IJCSNS International Journal of Computer Science and Network Security, vol. 7, no. 7, 2007.

[5] M. Bani Younes and A. Boukerche, "Intelligent Traffic Light Controlling Algorithms Using Vehicular Networks," IEEE Trans Veh Technol, vol. 65, no. 8, pp. 5887–5899, Aug. 2016, doi: 10.1109/TVT.2015.2472367.

[6] R. Zhang, A. Ishikawa, W. Wang, B. Striner, and O. K. Tonguz, "Using Reinforcement Learning with Partial Vehicle Detection for Intelligent Traffic Signal Control," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 1, pp. 404–415, Jul. 2018, doi: 10.1109/TITS.2019.2958859.

[7] M. B. Natafgi, M. Osman, A. S. Haidar, and L. Hamandi, "Smart Traffic Light System Using Machine Learning," 2018 IEEE International Multidisciplinary Conference on Engineering Technology, IMCET 2018, Jul. 2018, doi: 10.1109/IMCET.2018.8603041.

[8] Y. Liu, L. Liu, and W. P. Chen, "Intelligent traffic light control using distributed multi-agent Q learning," IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC, vol. 2018-March, pp. 1–8, Jul. 2017, doi: 10.1109/ITSC.2017.8317730.

[9] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 2016-December, pp. 779–788, Jun. 2015, doi: 10.1109/CVPR.2016.91.

[10] M. Sharma, A. Bansal, V. Kashyap, P. Goyal, and T. H. Sheikh, "Intelligent traffic light control system based on traffic environment using deep learning," IOP Conf Ser Mater Sci Eng, vol. 1022, no. 1, Jan. 2021, doi: 10.1088/1757-899X/1022/1/012122.

[11] T. Pan, "Traffic Light Control with Reinforcement Learning", Accessed: Jan. 09, 2025. [Online]. Available: https://github.com/OscarTaoyuPan/TrafficLightControl_QS.

[12] ultralytics, "COCO Dataset: All You Need to Know to Get Started." Accessed: Jan. 09, 2025. [Online]. Available: https://www.v7labs.com/blog/coco-dataset-guide

[13] D. Zhao, Y. Dai, and Z. Zhang, "Computational intelligence in urban traffic signal control: A survey," IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, vol. 42, no. 4, pp. 485– 494, Jul. 2012, doi: 10.1109/TSMCC.2011.2161577.