© DEC 2025 | IRE Journals | Volume 9 Issue 6 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I6-1712839

A Smart AI Based Solution Traffic Management with Real-Time Monitoring and Adaptation of Traffic Light Timings

SAMIKSHA DEBE[1], TANMAY PATIL[2], SANIYA GAWANDE[3], SHIVAM PANZADE[4], PRAJWAL PATIL[5]
[1, 2, 3, 4, 5]SB Jain Institute of Technology

Abstract- Traffic congestion in urban areas has become a critical challenge due to the increasing number of vehicles and inefficient signal management. Traditional traffic control systems lack adaptability, leading to delays and higher fuel consumption. This paper explores AI-driven traffic management using deep learning models like YOLOv8 for real-time vehicle detection and adaptive signal control. By integrating computer vision and machine learning, these systems optimize traffic flow, improve emergency response, and reduce environmental impact. While AI-based solutions offer significant advantages, challenges such as implementation complexity and scalability persist. This review highlights key advancements and future directions in intelligent traffic management.

Keywords - Smart Traffic Management, Artificial Intelligence (AI), YOLO Object Detection, Deep Learning, Reinforcement Learning

I. INTRODUCTION

Population growth and urbanization have created an exponential rise in vehicular traffic, leaving roads severely congested, travel times increased, fuel consumption higher, and air pollution worse. Existing traffic management systems tend to be based on static signal timing plans that cannot dynamically respond to changing traffic conditions, particularly during peak periods, emergencies, or unexpected road incidents (Chen et al., 2020). This inefficiency underlines the absolute necessity for smart, real-time solutions for enhancing traffic flow and mitigating urban transport challenges.

New developments in artificial intelligence (AI), especially computer vision and machine learning, present a potential solution to overcome these challenges. AI-based traffic control systems leverage real-time information from sensors, cameras, and vehicle movement to optimize and learn from traffic signals (Gao et al., 2021). These systems can not only identify traffic volume but also filter emergency vehicles like ambulances, reducing response times and even saving lives.
This study suggests an intelligent AI-driven traffic management system that utilizes real-time vehicle detection with the YOLO (You Only Look Once) object detection model and adaptive signal timing with live traffic data.

Through the application of computer vision and optimization algorithms like Genetic Algorithms (GA), the system modifies signal lengths at intersections dynamically to optimize vehicle wait times and maximize traffic flow. Additionally, the suggested system has a special mechanism to identify and give priority to ambulances in real-time so that they get a green signal at relevant intersections.

II. OBJECTIVE

The key objectives of this study are:

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.

III. LITERATURE SURVEY

Due to the rising number of vehicles, traffic jams have become increasingly common both nationally and worldwide, leading to substantial losses in man hours at key intersections. This persistent congestion underscores the necessity for more effective traffic management. In this study, we propose an intelligent traffic control system that leverages real-time video processing to accurately assess traffic density. Additionally, by incorporating Gaussian Mixture Models (GMM), our approach enhances the precision of vehicle detection and density estimation, even under challenging environmental conditions. This work demonstrates significant progress over traditional manual traffic control methods by offering a more adaptive and automated solution to reduce congestion.(Choudhary et al., 2018)

The rapid surge in vehicle numbers, urban expansion, and increased transportation needs are putting immense pressure on existing road networks. To mitigate urban congestion and lower carbon emissions, an Adaptive Traffic Signal Control (ATSC) system is necessary. Such a system adjusts signal timings in real time to accommodate both long-term trends and short-term fluctuations in traffic volume. This paper reviews current research on ATSC, examining methods used for both single and multiple intersections. Approaches include techniques based on Fuzzy Logic, Metaheuristic algorithms, Dynamic Programming, Reinforcement Learning, Deep Reinforcement Learning, and various hybrid models. The findings underscore that these advanced ATSC systems significantly enhance traffic management and contribute to a more sustainable urban transportation infrastructure.(Agrahari et al., 2024)

Traffic light control plays a critical role in easing congestion within urban mobility systems. This paper introduces a real- time traffic signal control method that employs deep Q- learning. Our approach features a reward function that factors in key metrics such as queue length, delay, travel time, and throughput, enabling the model to determine optimal phase changes based on current traffic conditions. The training of the deep Q network is conducted in two stages: an offline phase using pre-generated data with fixed schedules, followed by an online phase that incorporates live traffic data. A “phase gate” component is integrated into the network to streamline learning across different signal phases, and a “memory palace” mechanism is implemented to mitigate sample imbalance during training. We validate our method using both synthetic and actual traffic data from an intersection in Hangzhou, China. The results reveal notable improvements over traditional fixed-signal plans, with reductions in vehicle waiting time ranging from 57.1% to 100%, decreases in queue lengths between 40.9% and 100%, and a reduction in overall travel time from 16.8% to 68.0%.(Pan, 2023)

In today’s rapidly urbanizing environment, managing increasing vehicular congestion is critical. This study presents an Adaptive Dynamic Traffic Light Management System (DILMS) that harnesses AI, ML, and image processing technologies. The system uses real-time camera feeds to monitor traffic across multiple lanes, employing image analysis techniques for vehicle detection and counting. These counts are sent to a central processor, which calculates waiting times for each lane and then adjusts traffic signals accordingly. This approach not only minimizes waiting times and enhances traffic flow but also helps lower CO_2 emissions, making it a state-of-the-art solution for modern traffic management.(Gaur et al., 2024) Transportation systems heavily rely on the efficient flow of vehicles, yet many underdeveloped regions still depend on manual traffic light systems, which often result in wasted time, energy, and fuel due to their inability to make real- time decisions. In response, this study introduces an algorithm that automatically adjusts traffic signal durations based on live vehicle density data acquired from CCTV cameras near intersections. By leveraging Faster R-CNN for vehicle detection, the system dynamically synchronizes signal timings according to real-time conditions. A local dataset, collected in collaboration with Punjab Safe City and local police, was used to validate the approach. The proposed method achieved a class accuracy of 96.6% and a vehicle detection accuracy of 95.7%, while maintaining average precision, recall, F1 score, and detection accuracy of 0.94, 0.98, 0.96, and 0.95 respectively, thereby outperforming current state-of-the-art methodologies.("Vision Based Intelligent Traffic Light Management System Using Faster R-CNN," 2024) Traffic congestion in urban areas leads to longer travel times, increased fuel consumption, and heightened environmental pollution. This paper presents a novel Traffic Signal Management and Control System (TSMCS) that harnesses advanced sensor technologies and data-driven methods to optimize traffic flow and improve road safety. The system combines ultrasonic and LiDAR sensors for precise vehicle counting, adaptive algorithms for dynamic signal control, and cloud-based processing for real-time traffic forecasting. A significant feature of the system is its ability to prioritize emergency vehicles, thereby enhancing public safety. Case studies from Mumbai and Bangalore underscore the critical need for such innovative traffic management solutions. The contributions of this work include the application of multi-agent reinforcement learning, practical real-world evaluations,g and a framework for smart city integration, all of which contribute to improved traffic conditions and faster emergency responses. (Paul et al., 2023)

IV. EXISTING SYSTEMS

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 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.

V. METHODOLOGY

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 real-time 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 Consumption: Reduced idling leads to lower CO_2 emissions.

Faster Emergency Response Time: Ambulances and fire trucks navigate traffic efficiently.

VI. MODULE DESCRIPTION

1. Image and Video Processing Module Description:

This module is responsible for acquiring real-time visual data from traffic cameras or uploaded images. It processes input frames, ensuring they are in a compatible format for AI-based detection models. It also applies pre-processing techniques such as resizing, filtering, and enhancement for better accuracy in object detection.

Key Functions:
Capturing live video feeds from traffic cameras. Accepting manually uploaded images for traffic analysis.

Pre-processing images (resizing, noise reduction, and format conversion).

2. Object Detection and Classification Module Description:

Utilizing advanced deep learning models like YOLO (You Only Look Once), this module detects and classifies vehicles present at an intersection, distinguishing between cars, buses, trucks, motorcycles, and emergency vehicles such as ambulances. The model ensures high accuracy in recognizing objects within images or video feeds.

Key Functions:
Identifying and counting vehicles in each lane. Differentiating between various vehicle types.

Detecting emergency vehicles (ambulances) for priority handling.

© DEC 2025 | IRE Journals | Volume 9 Issue 6 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I6-1712839

Utilizing pre-trained models (YOLOv8) for real-time detection.

3. Traffic Density Estimation and Prioritization Module Description:

This module analyzes the number of vehicles in each lane and determines traffic congestion levels. It uses AI-driven logic to assign priority to lanes with higher vehicle density or emergency vehicles. Based on real-time traffic conditions, it dynamically adjusts the sequence and duration of green signals to optimize flow.

Key Functions:
Calculating the number of vehicles in each lane. Assigning priority to lanes based on congestion levels.

Detecting emergency vehicles and giving them highest priority.

Dynamically adjusting signal timings to optimize traffic movement.

4. Traffic Signal Control and Adaptation Module Description:

This module manages traffic lights based on the output from the traffic density estimation module. Using AI-based decision-making algorithms, it adapts signal timings dynamically, ensuring smooth traffic flow. The system applies green, yellow, and red signals appropriately while reducing unnecessary waiting times.

Key Functions:
Controlling traffic signals in real-time.

Implementing dynamic signal duration based on congestion levels.
Assigning higher green signal duration for heavily congested lanes.
Managing transitions between green, yellow, and red phases.

5. Emergency Vehicle Detection and Response Module Description:

This module ensures immediate response when an ambulance or emergency vehicle is detected in any lane. It overrides normal traffic flow rules and gives the lane with the ambulance the highest priority by immediately turning the signal green.

Key Functions:
Detecting ambulances in real-time using a dedicated AI model.

Instantly switching the respective lane to a green signal. Overriding standard signal timing to ensure quick passage of emergency vehicles.

7. Data Logging and Analysis Module Description:

This module records traffic patterns, vehicle counts, and signal adjustments over time. It helps city planners and traffic authorities analyze trends, improve traffic control strategies, and predict peak congestion times.

Key Functions:
Storing historical traffic data for future analysis. Generating reports on traffic flow and congestion levels. Analyzing long-term trends for improved traffic management.

8. User Interface and Monitoring Dashboard Description:

The graphical user interface (GUI) enables users to monitor real-time traffic conditions, upload images for analysis, and manually override signals if necessary. The dashboard displays detected vehicles, signal statuses, and time remaining for each phase.

Key Functions:
Displaying live traffic data in an interactive dashboard. Allowing users to upload images for vehicle detection. Providing manual control options for traffic managers. Showing real-time signal status and countdown timers.

9. System Integration and Cloud Connectivity Module Description:

This module ensures seamless integration of the system with existing traffic management infrastructure and cloud platforms for remote access. It enables scalability by connecting to central databases and IoT devices such as smart cameras.

© DEC 2025 | IRE Journals | Volume 9 Issue 6 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I6-1712839

Key Functions:
Connecting with city traffic management systems.
Enabling cloud-based access for remote monitoring.

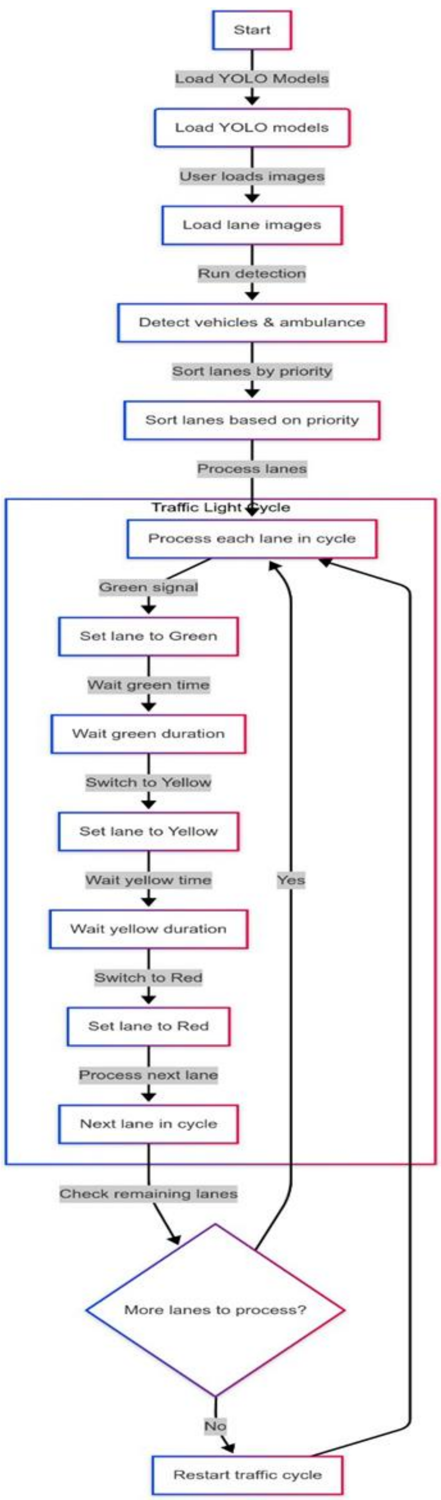


Fig. Flow Chart

VII. IMPLEMENTATION

1. 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.

2. 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.

3. 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.

4. 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.

5. 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.

6. 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.

7. Traffic Light Control Algorithm

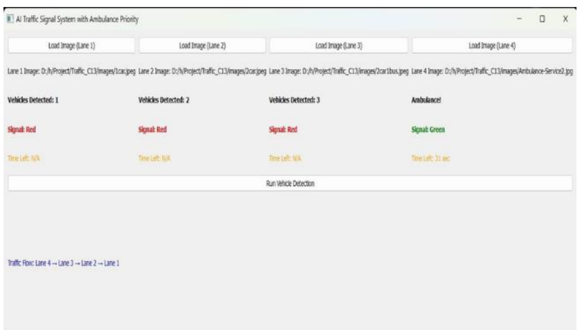
The model processes the detected vehicle data and determines the optimal sequence for signal changes. The cycle follows:

- 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.

8. 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.

VIII. RESULT



IX. CONCLUSION

In conclusion, the implementation of an AI-based smart traffic management system offers a transformative approach to addressing urban congestion and optimizing traffic flow. By integrating real-time monitoring, adaptive traffic signal control, and advanced machine learning techniques, the proposed system enhances road efficiency, reduces vehicle wait times, and prioritizes emergency vehicles. The use of deep learning models, such as YOLOv8 for object detection, combined with technologies like PyQt5 for GUI development and OpenCV for image processing, ensures a robust and scalable solution. Additionally, the system contributes to environmental sustainability by minimizing fuel consumption and lowering carbon emissions. With its potential to revolutionize traffic management, this AI-driven solution paves the way for smarter, safer, and more efficient urban mobility.

X. REFERENCES

[1] Chen, L., Xu, H., Song, J., & Xu, Y. (2020). A deep learning-based method for real-time traffic flow estimation. Sensors, 20(18), 5284. https://doi.org/10.3390/s20185284

[2] Gao, X., Huang, L., Wang, Y., & Zhang, K. (2021). Intelligent traffic signal control: A review. IEEE Transactions on Intelligent Transportation Systems, 22(11), 6994–7008. https://doi.org/10.1109/TITS.2020.3047806

[3] Agrahari, A., Dhabu, M. M., Deshpande, P. S., Tiwari, A., Baig, M. A., & Sawarkar, A. D. (2024). Artificial Intelligence-Based Adaptive Traffic Signal Control System: A Comprehensive Review. In Xin Geng (Ed.), Electronics (Vol. 13, p. 3875). https://doi.org/10.3390/electronics13193875

[4] Choudhary, A., Gupta, A., Dhuri, A., & Nikam, N. (2018). Artificial intelligence based smart traffic management system using video processing. International Research Journal of Engineering and Technology (IRJET), 5(3), 2271–2275. https://www.irjet.net/archives/V5/i3/IRJET-V5I3521.pdf

[5] Pan, T. (2023). Traffic Light Control with Reinforcement Learning. arXiv. https://arxiv.org/abs/2308.14295

[6] Gaur, A., Mavi, A., Tyagi, B., Anwar, N., & Department of Computer Science and Information Technology, Meerut Institute of Engineering and Technology, Meerut, Uttar Pradesh, India. (2024). Dynamic Traffic Light Management System using AI and ML. In International Journal of Engineering Research in Computer Science and Engineering (Vol. 11, Issue 4, pp. 20–21).

[7] Vision based intelligent traffic light management system using Faster R-CNN. (2024). In CAAI Transactions on Intelligence Technology. https://doi.org/10.1049/cit2.12309

[8] Yogesh Katre,Prof. Gajendra Singh Chandel “Image Forgery Detection Using Analysis of CFA Artifact”,2014 International Journal of Advanced Technology in Engineering and Science Volume No.02, Special Issue No. 01, September 2014 (IJATES), doi:

ijates.com/images/short_pdf/1412167558_292.pdf

[9] C. Vaidya, R. Borikar, S. Sharma, P. Tiwari, K. Ganar and V. Kharate, "Development of Multipurpose Smart Desk Assistant for a Department," 2024 First International Conference on Data, Computation and Communication (ICDCC), Sehore, India, 2024, pp. 374- 379, doi: 10.1109/ICDCC62744.2024.10961215.

[10] Santosh Kumar Sahu, Sachin U Balvir, A. Sahu, A.Anjikar, A.Shewale, S. Purve, "Parallel and High- Performance Computing in Artificial Intelligence", Auerbach Publications, Taylor & Francis Group, pp. 314-322, ISBN-9781003425458, 2025

[11] Dr. M. M Raghuwanshi[1], Yogesh Katre[2], Ayushi Sahu[3], Disha Sharma[4], Ankush Udapure[5], Chaitanya Lonarkar, "Weather Predisction with Machine Learning", International Journal of Innovative Science and Research Technology, Volume 9, Issue 9, September – 2024, IJISRT-ISSN No: -2456-2165
doi: doi.org/10.38124/ijisrt/IJISRT24SEP1682

[12] S. U. Balvir, M. M. Raghuwanshi and P. D. Shobhane, "Link Prediction in Social Networks: A Dual Perspective on Positive and Negative Links," 2024 Asian Conference on Intelligent Technologies (ACOIT), KOLAR, India, 2024, pp. 1-7, doi: 10.1109/ACOIT62457.2024.10939432.

[13] C. Vaidya, P. Yelure, S. Gonnade, R. Mohitkar, T. Burande and U. Sonkawade, "Auto Detection of Personal Protective Equipment on Human," 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal