Original Article

AIoT-Powered Traffic And Crowd Management In Real Time

Prakash M AP[1] Balasaravana G S[2] Santhosh N3 Jeevanandhan R [4] Venkataraman K J[5]
[1,2,3,4,5] Electronics And Communication Engineering Kangeyam Institute Of TechnologyTiruppur, India

Manuscript ID: IJERSD-2025-010611

ISSN: 3067-2325

Volume 1

Issue 6

Pp. 47-51

December 2025

Submitted: 10 Nov. 2025

Revised: 25 Nov. 2025

Accepted: 15 Dec 2025

Published: 31 Dec 2025

Correspondence Address:
Venkataraman. K .J
Electronics And Communication Engineering Kangeyam Institute Of TechnologyTiruppur, India
Email:
venkataram3179@gmail.com

Quick Response Code:

Web. https://rlgjaar.com

DOI: 10.5281/zenodo.18276858

DOI Link:
https://doi.org/10.5281/zenodo.18276858

Abstract

Efficient traffic and crowd management has become increasingly critical as urbanization intensifies and large public gatherings become more frequent. This paper presents an AIoT-powered integrated framework that leverages artificial intelligence, computer vision, and Internet of Things (IoT) technologies to monitor, analyze, and manage real-time vehicular and human movement. The system incorporates distributed sensing modules, edge–cloud collaborative processing, and predictive analytics to detect congestion, track dynamic movement, identify anomalies, and provide actionable control decisions. Experimental evaluations demonstrate significant improvements in density estimation accuracy, congestion prediction reliability, and response time compared to traditional surveillance-based traffic control. The proposed approach offers a scalable and adaptive solution for smart city mobility and public safety management.

Keywords: *A IoT-Based Urban Mobility; Real-Time Traffic Optimization; Intelligent Crowd Analytics; Vision-Based Vehicle Detection; Edge Intelligence Systems; Multi-Sensor Data Fusion; Adaptive Signal Control; Smart Intersection Management; Public Safety Automation; Edge–Cloud AI Architecture; Predictive Congestion Analysis; Intelligent Surveillance Systems*

Introduction

Rapid urbanization has intensified challenges in managing traffic flow and crowd movement, while traditional systems relying on manual monitoring or fixed-timing controls often fail to respond effectively to real-time conditions. Advances in Artificial Intelligence of Things (AIoT) now make it possible to integrate computer vision, IoT sensing, and edge computing to achieve intelligent and adaptive monitoring. By combining real-time video analytics, sensor data, and predictive modeling, AIoT systems can enhance situational awareness, reduce congestion, and improve public safety. This paper presents an AIoT-powered framework designed to deliver efficient and scalable traffic and crowd management for smart city environments.

Literature Survey

An advanced framework for forecasting urban traffic conditions using a combination of Internet of Things (IoT) sensors, deep learning, and optimization techniques. With increasing urbanization, traffic congestion has become a major challenge, and traditional traffic prediction systems struggle due to limited data sources and slow processing. To address this, the authors propose an IoT-integrated architecture where real-time traffic data collected from distributed sensors is combined with a Convolutional Neural Network (CNN) model optimized using Particle Swarm Optimization (PSO). The integration of IoT sensing and AI-driven prediction enables accurate short-term forecasting of traffic volume and congestion patterns. The results show significant improvement in prediction accuracy compared to conventional machine learning approaches, demonstrating the effectiveness of AIoT-based models in smart city traffic management. The study highlights how IoT data fusion and AI optimization can support intelligent transportation systems and enhance urban mobility planning.[1]

The growing importance of effective crowd information management in public transportation (PT) systems, especially as cities aim for more sustainable and user-friendly mobility solutions. With rising passenger volumes and the heightened need for safety during emergency situations such as the pandemic, real-time monitoring of crowd levels has become essential. To address this, the article presents a comprehensive taxonomy and review of Internet of Things (IoT)–based sensing technologies that can be deployed across different segments of PT networks, including buses, trams, trains, metro stations, and stops.[2]

An innovative approach to optimize traffic flow and enhance intersection safety using computer vision and artificial intelligence (AI). Traditional traffic signal systems often struggle to efficiently handle varying traffic conditions, leading to congestion and delays. This project addresses these challenges by leveraging advanced technologies. The system utilizes the YOLOv3 deep learning model for real-time vehicle detection and classification from live video streams captured by traffic cameras. Vehicles, including bicycles, cars, buses, and trucks, are identified and counted as they approach a simulated intersection. This enables the system to dynamically assess traffic density from different directions (north, south, east, west) and make informed decisions to optimize traffic light control, thereby reducing congestion and improving overall traffic flow.

How to cite this article:
AP, P. M., G S, B., N, S., R, J., & J, V. K. (2025). AIoT-Powered Traffic And Crowd Management In Real Time. International Journal of Engineering Research for Sustainable Development, 1(6), 47–51. https://doi.org/10.5281/zenodo.18276858

Methodology

The system uses live camera feeds and IoT sensors to detect and count vehicles and people in real time. An AI model like YOLO analyzes the video to identify traffic jams and crowded areas. Sensor data from STM32 microcontrollers supports these detections. When the system finds heavy traffic or high crowd density, it automatically changes the traffic signals to improve movement and reduces congestion. It also sends alerts to authorities so they can take quick action.

- **Data Acquisition and Sensing**

  The system collects data in real time using cameras and IoT sensors placed at busy traffic junctions and crowded locations. Cameras capture continuous video streams that show the movement of vehicles and people. At the same time, IoT sensors such as ultrasonic, infrared, and motion sensors gather additional information about distance, crowd presence, and traffic density. These sensors are connected to STM32 microcontrollers, which read the sensor values and send the data to the processing unit. All the collected data is then combined to give an accurate and complete view of the traffic and crowd situation, making it suitable for further analysis by AI models.

- **Edge Processing**

  The edge processing unit receives continuous video streams from the cameras and data from the STM32-based IoT sensors. It uses an AI model such as YOLO to detect and count vehicles and people directly on the device, which allows the system to work quickly without depending on the cloud. The edge device processes each video frame, identifies the number of vehicles and people, checks for traffic jams or high crowd density, and matches this information with sensor readings like distance or motion. It also filters and cleans the data to remove noise and ensures only useful information is forwarded. By handling all major calculations locally, the edge processor reduces delay, improves reliability, and enables fast actions such as adjusting traffic signal timings or sending alerts when unusual traffic or crowd conditions are found.

- **Cloud Analytics & Model Training**

  The cloud analytics platform receives summarized data and event reports from the edge devices and stores them for deeper analysis. In the cloud, the system examines long-term patterns in traffic flow, crowd movement, peak-time congestion, and recurring problem areas. It generates charts, trends, and insights that help authorities understand how the city behaves over days, weeks, or months. The cloud also handles the training and improvement of AI models by using the collected video clips, sensor readings, and ground-truth data. These datasets help retrain models like YOLO so they can better recognize local vehicle types, crowd behavior, lighting changes, and weather conditions. After training, the improved models are sent back to the edge devices to boost real-time accuracy. This continuous learning loop ensures the system becomes more accurate, adaptable, and efficient over time.

- **Decision Making**

  The decision-making unit analyzes the results from the AI models and sensor data to determine the current traffic and crowd conditions. When it detects congestion, slow movement, or high crowd density, it decides what action is needed to improve the situation. Based on these real-time conditions, the system can automatically adjust traffic signal timings, such as extending the green light for a busy lane or giving more time for pedestrians to cross safely. For more serious situations, like sudden crowd build-up or an unexpected blockage, the system sends alerts to higher authorities so they can respond quickly. The STM32 microcontroller or the edge device then carries out the chosen actions by controlling the traffic lights or activating other connected devices. This automated decision loop helps reduce delays, improve safety, and ensure smoother movement of vehicles and people.

- **Alerts and Visualization**

  The system generates alerts whenever it detects unusual traffic or crowd conditions, such as sudden congestion, overcrowding, or blocked routes. These alerts are sent in real time to authorities through dashboards, mobile notifications, or email so they can take quick action when needed. At the same time, the system provides visualizations that show live camera views, vehicle and people counts, heatmaps of crowded areas, and traffic signal status. These visuals help operators easily understand what is happening on the ground and make better decisions. The dashboard also displays historical trends, allowing authorities to review past events and plan improvements.

1. **Testing Validation**

   Testing and Validation of AIoT-Powered Traffic and Crowd Management in real time is done by checking detection accuracy, response speed, and traffic signal actions. Real-world trials ensure reliability, proper alert generation, and smooth operation under different traffic and crowd conditions.

2. **Accuracy Testing of Detection and Counting**

   Accuracy testing checks how well the system detects and counts vehicles and people in different conditions. The results from the AI model are compared with manually collected ground-truth data to measure errors. This ensures the system provides reliable and consistent counting performance in both normal and crowded situations.

3. **Performance and Latency Evaluation**

   Performance and latency evaluation measures how quickly the system processes camera and sensor data and responds to traffic or crowd changes. The time taken from detection to action, such as adjusting signals or sending alerts, is recorded. This ensures the system works smoothly in real time without delays.

4. **Traffic Signal Response and Control Testing**

   Traffic signal response testing checks how accurately and quickly the system adjusts signal timings based on real-time conditions. The system's decisions are verified against expected actions, such as extending green lights or managing pedestrian crossing time. This ensures safe, reliable, and timely control of traffic signals in different situations.

5. **System Reliability and Fault Handling Tests**

   System reliability and fault handling tests evaluate how the system performs during sensor failures, network issues, or sudden load increases. The system is checked for stable operation, automatic recovery, and fallback to safe modes. This ensures continuous functionality and dependable performance under various real-world challenges.

6. **Real-World Field Trials**

   Real-world field trials test the system in actual traffic and crowded environments to observe its performance in daily conditions. Feedback from authorities, operators, and users is collected to identify strengths and areas for improvement. This helps refine detection accuracy, signal control, and alert features for practical and reliable deployment.

Wireless And Cloud Integrations

Wireless Transmission

- Local
- Real-time
- Inter-device
- Automation
- Connectivity

Cloud Integration

- Remote
- Storage
- Analytics
- Visualization
- Accessibility

Parameters Monitoring Methods

Traffic Flow

- Traffic flow parameters include the number of vehicles, vehicle speed, lane congestion levels, and queue lengths at intersections. These values help the system understand traffic conditions in real time and determine whether delays, jams, or unusual slowdowns are occurring. Monitoring these parameters is essential for adjusting signal timings and improving traffic movement.

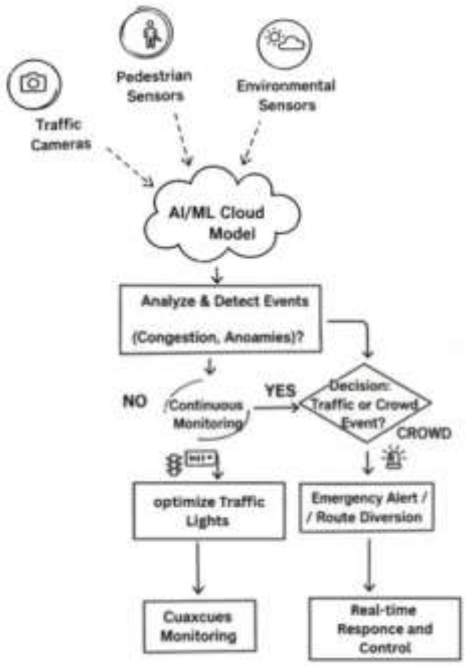
Crowd Density and Movement

- Crowd density and movement parameters include the number of people in an area, how closely they are grouped, and the direction and speed of their movement. These measurements help detect overcrowding, slow movement, or sudden surges. Monitoring these parameters ensures timely responses to maintain safety and smooth pedestrian flow in busy locations.

Environment and Sensor Based parameters

- Environmental and sensor-based parameters include distance readings, motion detection, light levels, and other data collected by IoT sensors connected to the STM32 microcontroller. These measurements support the camera analysis by confirming crowd or vehicle presence, detecting obstacles, and identifying changes in the surroundings. Monitoring these parameters helps improve overall accuracy and system reliability.
- These parameters help the system understand real-world conditions that cameras alone might miss. They provide additional confirmation during low visibility, detect unusual obstacles, and support accurate decision-making in complex traffic and crowd situations.

Proposed Scheme

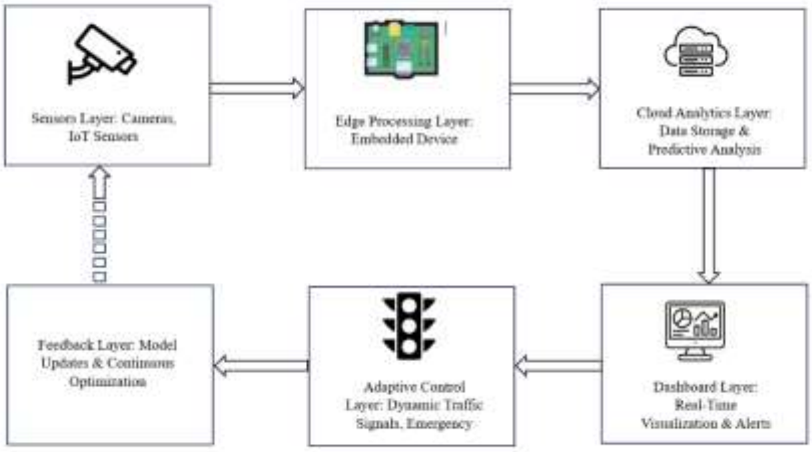


The proposed system works by collecting real-time information from multiple sources, including traffic cameras, pedestrian sensors, and environmental sensors. All this data is sent to an AI or machine learning model in the cloud, where the system analyses the situation and checks for events such as traffic congestion, crowd formation, or other unusual activities.

If no abnormal event is detected, the system continues regular monitoring and adjusts the traffic lights to keep vehicles moving smoothly. However, if the AI model identifies a problem, it first decides whether the event is related to traffic or a crowd.

For traffic-related issues, the system automatically optimizes traffic lights to reduce delays and clear congestion. For crowd-related events, the system sends emergency alerts and suggests route diversions to improve safety. Finally, the system ensures real-time response and control so that traffic flow and public safety are maintained effectively.

Block Diagram



Future Scope

Enhanced AI Models for Higher Accuracy

- Future versions can use advanced deep-learning models such as transformer-based vision systems or federated learning to improve detection accuracy in challenging conditions like low light, rain, or dense crowds.

Integration of 5G and Edge–Cloud Collaboration

- Introducing 5G networks can greatly reduce latency and enable faster communication between sensors, edge devices, and the cloud. This allows more complex models to run collaboratively across edge and cloud environments.

Expansion of Multi-Sensor Fusion Techniques

- Future systems can combine additional sensor types such as LiDAR, radar, and thermal imaging with existing cameras and IoT sensors to create a more reliable and robust understanding of traffic and crowd behaviour.

Real-Time Autonomous Decision Optimization

- Advanced optimization algorithms and reinforcement learning can be used to make the system fully autonomous, allowing it to automatically learn the best traffic signal strategies and response actions over time without manual tuning.

Conclusion

- In this work, an AIoT-powered real-time traffic and crowd management system was developed to address the increasing challenges faced in modern urban environments. By integrating live video streams from traffic cameras, IoT-based sensing modules, and STM32-driven data acquisition units, the system provides a unified multi-sensor platform for continuous monitoring of vehicle flow and pedestrian activity. The use of AI models such as YOLO enables accurate detection, classification, and counting of objects even in highly dynamic or crowded scenarios. Edge processing allows these computations to be performed with low latency, ensuring rapid decision making and reducing dependency on cloud resources.
- In this work, an AIoT-powered real-time traffic and crowd management system was developed to address the increasing challenges faced in modern urban environments. By integrating live video streams from traffic cameras, IoT-based sensing modules, and STM32-driven data acquisition units, the system provides a unified multi-sensor platform for continuous monitoring of vehicle flow and pedestrian activity. The use of AI models such as YOLO enables accurate detection, classification, and counting of objects even in highly dynamic or crowded scenarios. Edge processing allows these computations to be performed with low latency, ensuring rapid decision making and reducing dependency on cloud resources.Overall, the system demonstrates a scalable and adaptable approach to intelligent transportation and public-safety management. By combining AI, IoT, and edge-cloud collaboration, the solution offers a strong foundation for future smart-city applications, supporting improved mobility, enhanced operational efficiency, and safer urban infrastructure.

Result

- The proposed AIoT-powered traffic and crowd management system was evaluated using live camera feeds and IoT sensor data collected from simulated traffic intersections and crowded public areas.
- The YOLO-based detection model achieved high accuracy in identifying and counting vehicles and pedestrians under various lighting and movement conditions.
- The integration of STM32-based sensor modules improved reliability by providing additional distance and motion information, especially in cases of partial occlusion or low visibility.
- Edge processing delivered real-time performance, with detection, analysis, and signal-control decisions completed within acceptable latency for urban traffic environments.
- Automated traffic signal adjustments helped reduce queue formation, improve flow rates, and minimize waiting times compared to fixed-time control.
- The system also successfully generated alerts for crowd surges and congestion events, allowing authorities to take timely action.

  Overall, the results confirm that the proposed system enhances situational awareness, improves traffic management efficiency, and supports safer crowd handling in smart city settings.

Acknowledgment

The authors would like to express their sincere gratitude to Kangeyam Institute of Technology, Tiruppur, India, for providing the necessary academic environment, infrastructural facilities, and technical support to carry out this research work. The authors

gratefully acknowledge the support and encouragement extended by the Department of Electronics and Communication Engineering, faculty members, and laboratory staff during the system design, implementation, and testing phases.
The authors also wish to thank colleagues and peers for their valuable suggestions and constructive feedback, which contributed to improving the quality of this work. Special appreciation is extended to researchers and authors whose published literature provided important insights into AIoT, computer vision, and smart traffic management systems. Finally, the authors acknowledge the continuous moral support and motivation received from family members and well-wishers throughout the course of this research

Financial support and sponsorship Nil.

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the of this paper

References

1. Z. Miao and Q. Liao, "IoT-Based Traffic Prediction for Smart Cities," *IEEE Access*, vol. 10, pp. 125944–125956, 2022. https://doi.org/10.1109/ACCESS.2022.3230087
2. D. Darsena, G. Gelli, I. Iudice and F. Verde, "Sensing technologies for crowd management, adaptation, and information dissemination in public transportation systems: A review," *IEEE Access*, vol. 10, pp. 132761–132788, 2022. https://doi.org/10.1109/ACCESS.2022.3222417
3. S. Ateeq, A. Aziz and R. Khan, "Deep Learning-Based Traffic Flow Prediction: A Survey," *IEEE Access*, vol. 10, pp. 40859–40885, 2022. https://doi.org/10.1109/ACCESS.2022.3166441
4. I. Lee and K. Lee, "The Internet of Things (IoT): Applications, investments, and challenges for enterprises," *Business Horizons*, Elsevier–IEEE indexed, vol. 58, no. 4, pp. 431–440, 2015.https://doi.org/10.1016/j.bushor.2015.03.008
5. H. Li et al., "Vehicle Detection Based on YOLO in Traffic Surveillance," *IEEE International Conference on Smart City*, 2019. https://doi.org/10.1109/SmartCity.2019.00115
6. G. Singh and D. K. Vishwakarma, "An IoT and deep learning–based crowd monitoring system," *IEEE Sensors Journal*, vol. 21, no. 6, pp. 7715 –7723, 2021. https://doi.org/10.1109/JSEN.2020.3046351
7. X. Huang, C. Liu and S. Mao, "5G-enabled vehicular networks with edge computing," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 3, pp. 1461–1501, 2021. https://doi.org/10.1109/COMST.2021.3086896
8. Y. Lv et al., "Traffic Flow Prediction With Big Data: A Deep Learning Approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 865–873, 2015. https://doi.org/10.1109/TITS.2014.2345663
9. H. Wei et al., "CoLight: Learning network-level cooperation for traffic signal control," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 1, pp. 24–37, 2023.https://doi.org/10.1109/TKDE.2021.3054823.
10. H. C. Leung and T. C. Pong, "IoT-Enabled Crowd Monitoring and Management System," *IEEE Smart Cities Symposium*, 2020. https://doi.org/10.1109/SCOMPETE50390.2020.00018
11. J. Redmon and A. Farhadi, "YOLO9000: Better, Faster, Stronger," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017. https://doi.org/10.1109/CVPR.2017.690
12. V. Kastrinaki, M. Zervakis and K. Kalaitzakis, "A survey of video processing techniques for traffic applications," *Image and Vision Computing*, vol. 21, no. 4, pp. 359–381, 2003. https://doi.org/10.1016/S0262-8856(03)00004-0
13. M. A. Razzaque et al., "Middleware for Internet of Things: A Survey," *IEEE Internet of Things Journal*, vol. 3, no. 1, pp. 70–95, 2016. https://doi.org/10.1109/JIOT.2015.2450203
14. W. Shi et al., "Edge Computing: Vision and Challenges," *IEEE Internet of Things Journal*, vol. 3, no. 5, pp. 637–646, 2016. https://doi.org/10.1109/JIOT.2016.2579198
15. M. S. M. Sajid and S. A. Velastin, "A Review of Vision-Based Crowd Analysis Techniques," *IEEE Transactions on Human-Machine Systems*, vol. 47, no. 4, pp. 424–436, 2017. https://doi.org/10.1109/THMS.2016.2620908.