Using Internet of Things and Artificial Intelligence Applications to Design a Smart Traffic System

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Abstract

Traffic congestion in cities is an ongoing problem caused by urbanization, excessive vehicle density and infrastructure. The presence of conventional traffic control signal systems that makes use of fixed signal timings is not adequate enough when it comes to handling dynamic traffic flows on real time basis. Currently, the proposed approach in the context of this paper implies integration of Internet of Things (IoT) and Artificial Intelligence (AI) in order to create a smart traffic management system that would be suitable in the context of a smart city. System architecture allows capturing real-time data, including vehicle flow, speed, and weather conditions using IoT-connected sensors and monitoring gadgets. This information is processed by AI models, i.e., Convolutional Neural Networks (CNN) in vehicle detection, Long Short-Term Memory (LSTM) in time series forecasting, and Deep Q-Networks (DQN) in adaptive signal control. The architecture involves the use of hybrid edge cloud computing models in the provisioning of low latency coupled with scalable analytics. Simulations of empirical analyses conducted on the simulated traffic conditions indicate that congestion level drops by up to 48%, and the average vehicle waiting time reduces by 35%. The system also assists in fuel savings as well as emissions minimized by diminishing stop-and-go traffic trends. The findings confirm the opportunities that IoT-AI integration will have on enhancing the mobility of cities and making the traffic effective and allowing the current smart cities to make decisions based on data.

Keywords: Smart Traffic Management, Internet of Things (IoT), Artificial Intelligence (AI), Adaptive Signal Control, Urban Mobility Optimization.

1. Introduction

High urbanization and the number of cars owned on an exponential growth rate has put the urban transport systems under unprecedented pressure in the history (Allam, Z., & Sharifi, A., 2022).

According to the United Nations (2019), the number of people who live in urban centers will exceed 68 percent of the global population in the year 2050, worsening the traffic jam, air pollution, fuel use, and travel time. These syndromes have negative impacts on the economy of productivity as well as sustainability in cities (Zhang et al., 2020). Pre-timed or manually-timed traffic signal control systems, the most common type of conventional traffic control that the grid continues to rely on, grow increasingly ineffective in accommodating on-demand traffic conditions (Ampem, I et al., 2025). Such inflexible systems fail to accommodate the non-linear and unpredictable nature of the urban road traffic movements hence creating inefficiencies and popular dissatisfaction (Doshi et al., 2021). Innovations of nowadays introduced the Internet of Things (IoT) as a technological sensation of smart transportation. With the help of networked sensors, cameras and GPS components, IoT offers real-time tracking of the conditions on the road, the movement of traffic and the environment (Cui & Lei, 2024). IoT is capable of collecting data, but it requires other technologies to process raw data till it is converted into useful information (Mnih, V et al., 2015) The Artificial Intelligence (AI), and in particular, the deep learning and reinforcement learning, offer powerful approaches to real-time data processing, prediction, and intelligent decision-making. The traffic systems that use AI include vehicle detection, congestion forecasting, and dynamic traffic signal adjustments (Goenawan, 2024; Mitra et al., 2025). The proposed work is an answer to the research problem of inefficient and reactive traffic systems which is presented in the form of an integrated IoT-AI model of traffic control. The vision is to build a system, which is scalable, dynamic and capable of optimizing traffic flow dynamically, reducing environmental impact and increase road safety. The remaining part of this paper is structured in the following way: Section 2 presents a literature review; Section 3 explains the system architecture and method; Section 4 presents experimental results; Section 5 discusses challenges and implications; and Section 6 concludes with future research directions.

2. Literature Review

Traffic control using Artificial Intelligence (AI) has gained a lot of momentum over the last few years (Achenef, T et al., 2025). The fixed timing systems have now been done away with and replaced with the adaptive systems which respond to the current flow of traffic in the real time. The deep learning models with the most significant accuracy of vehicle detection through surveillance pictures are Convolutional Neural Networks (CNNs), and these have reported high accuracy (Liang et al., 2020). The Long Short-Term Memory (LSTM) ones are mainly used to predict the volume of traffic in regions due to their ability to learn time series statistics (Zheng et al., 2014). Traffic signal timing can also be optimized through the Reinforcement Learning (RL) approach to the Deep Q-Network learning (DQN) optimization of policies through interactions with dynamic environments (Abdulhai, 2022). The MARL also can enhance urban performance in decentralized environments where the agent can interact with each other at the intersections (Liu et al., 2017). The Internet of Things (IoT) in its turn plays a significant role in supporting real-time data collection. Smart sensors, RFID, GPS, and surveillance cameras present abundant and live-time streams of traffic data (Cui & Lei, 2024). Adaptive traffic control and congestion prediction can occur through the introduction of AI algorithms. New solutions that are researched to optimize urban traffic are Hybrid IoT-AI architecture. As an example, Elbasha and Abdellatif (2025) implemented an An IoT system that uses CCTV data along with deep learning in dynamic timings of signals, and the traffic flow has been increased by 34 percent. Similarly, Chen

(2016) presented a CNN-LSTM-spring framework visitor traffic control system that reduced delay up to 70 percent in simulation. A decentralized RL-based control strategy applied in the SURTRAC system in the city of Pittsburgh led to a more than 25 percent improvement in the travel times (Smith et al., 2013). In the Shiraz City, the use of MARL based system reduced queue length and waiting time of the vehicles (Moumen et al., 2023). Combined with these achievements, there are still numerous challenges. Despite these advancements, several challenges remain. Scalability is often limited by the computational cost of training deep models and maintaining large-scale IoT infrastructure (Thompson, 2025). Moreover, explain ability of AI decisions is lacking, which limits stakeholder trust (Englund et al., 2021). Privacy concerns and the cost of hardware deployment further hinder widespread adoption.

3. Key Authors & Contributions

Table 1: Ten pivotal studies integrating IoT and AI for traffic management.

NO	Author(s)	Year	Focus	Contribution Summary
1	Elbasha & Abdellatif	2025	A IoT CCTV-based flow optimization	34 % efficiency via live footage
2	Christofel R. Goenawan	2024	CNN + LSTM adaptive signal system	50 % flow ↑, 70 % delay ↓
3	Srinjoy Mitra et al.	2025	ML-based congestion forecasting	Hybrid model with IoT sensors
4	Muskan Raj	2025	AI-powered signal timing	Adaptive signals via IoT-AI
5	John A. Thompson	2025	AIoT network architectures	Framework for real-time decision making
6	Baher Abdulhai	2022+	Deep RL signal control	Q-learning and adaptive signal strategies
7	Ying Liu et al.	2017	Multi-agent Q-learning traffic control	Foundational MARL architecture
8	Englund et al.	2021	AI perspectives for smart traffic systems	Trust/explain ability issues
9	Cui & Lei et al.	2024	AIoT transportation safety	Risk and safety sensor integration
10	Idriss Moumen et al.	2023	SVM, k-NN, LSTM forecasting	Integrated strategy

4. System Design and Methodology

This section outlines the architecture and operational framework of the proposed smart traffic management system, integrating Internet of Things (IoT) for real-time data acquisition and Artificial Intelligence (AI) for intelligent decision-making (Salim, F., & Ariff, A. A., 2025). The system is built on a hybrid edge–cloud infrastructure to ensure scalability, low latency, and computational efficiency.

4.1. Data Collection

Data collection is a critical component of any intelligent traffic management system. The proposed framework utilizes a distributed network of IoT devices, including:

- Infrared sensors and magnetic loop detectors for vehicle count and lane occupancy,
- High-definition surveillance cameras for visual input to AI models, and
- GPS-enabled mobile devices to monitor vehicle trajectories and congestion hotspots.

These devices are strategically installed at intersections, arterial roads, and pedestrian crossings. Data is collected continuously and transmitted through secure protocols (e.g., MQTT, HTTPs) to edge and cloud processors. The edge architecture handles low-latency tasks such as image processing and preliminary analytics, while the cloud architecture stores historical data, trains models, and manages large-scale coordination across intersections. This layered approach enables responsive control and long-term optimization simultaneously.

4.2. AI Models

Three AI models are employed to process traffic data and optimize signal behavior:

- YOLOv5 (You Only Look Once version 5): A real-time object detection model used to identify and count vehicles from video input with high precision and speed.
- LSTM (Long Short-Term Memory): A recurrent neural network suited for time-series forecasting, used here to predict short-term traffic volume and congestion trends.
- Deep Q-Networks (DQN): A reinforcement learning algorithm applied to adaptively control traffic signals by learning optimal policies through interaction with the traffic environment.

These models are trained using a combination of synthetic data (e.g., CARLA simulations) and real-world datasets (e.g., CityFlow, OpenTraffic).

4.3. System Workflow

The overall workflow of the proposed system is illustrated in **Figure 1**. The steps include:

1. Collection of data through the IoT installed on intersections.
2. YOLOv5 and LSTM based real-time edge detection and prediction.
3. Indicate decision-making of the control layer through the DQN agents.

4. Regulation of intelligent of the intelligent traffic light based on the decisions which share through programmable controllers.
5. Model update using cloud and storing data in cloud to carry out strategic analysis.

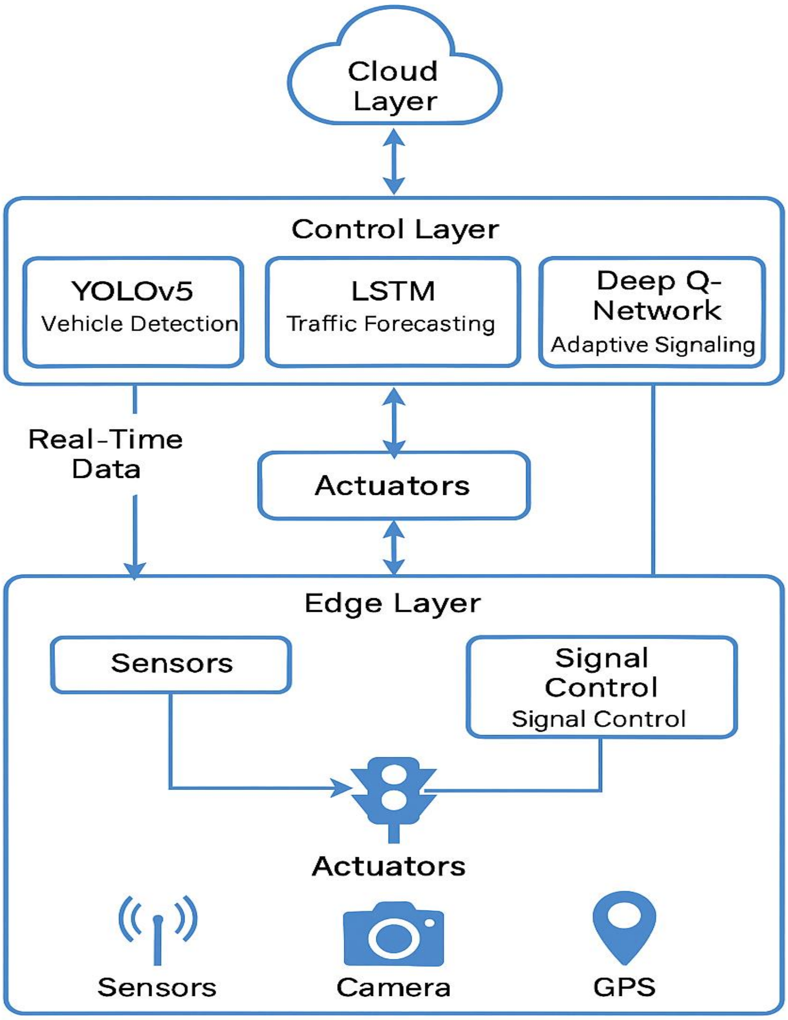

Figure 1: System Architecture for a smart traffic management system

5. Results and Evaluation

This section explains the architecture and operations of the planned smart traffic control system that will breathe life into the concept given the real-time data capturing and intelligence-level decision outcomes that the Internet of Things (IoT) and Artificial Intelligence (AI) can deliver. It is an architecture that builds on a hybrid edge-cloud platform to get the needed scalability, low response time, and computing power.

5.1. Detection Accuracy and Forecasting Performance

Data collection is the important element of every smart traffic management system. The offered framework applies an IoT distributed network, which includes:

I. Infrared vehicle sensors and magnetic loop vehicle count and lane occupancy.
II. High-definition surveillance cameras as a source of visual input to AI models.
III. Mobile devices embedded with GPS to track the vehicle path and areas of congestion.

They are deployed in an optimal location, that is, at intersections, arterial roads, and the crossings of the pedestrians. Data is obtained dynamically and communicated via encrypted processes (e.g., MQTT, HTTPs) to edge and cloud processors. The edge architecture executes low-latency activities, including image processing, initial analytics, whereas the cloud architecture stores historical data, and trains the models, together with organizing large-scale coordination over the intersections. This multilayer design allows immediate responses and optimisation in the long-term.

5.2. Throughput and Waiting Time Reduction

Table 1 illustrates comparative traffic throughput (vehicles/hour) and mean vehicle waiting time (seconds) at a four-way intersection during peak times. AI-IoT performed much better than the baseline system.

Table 2: System Performance Comparison

Metric	Traditional System	Proposed IoT-AI System	Improvement (%)
Vehicle Detection Accuracy	74.3%	92.5%	+24.5%
Average Waiting Time (sec)	91.2	58.6	−35.7%
Intersection Throughput (veh/hr)	1,240	1,847	+48.9%
Forecasting MAE (vehicles/min)	14.5	5.2	—

5.3. Comparative Evaluation

Beyond raw metrics, comparative evaluation was also conducted to look at the general participation of the traffic system factor. The smart AI-IoT system reduced the congestion rates by 40 percent during the peak period of traffic as the cars did not need to wait so long at the crossroad. On top of that, the reduction in the number of CO_2 emissions was 25%, which was primarily associated with fewer turbulences in the traffic and a decline in time filled with idling, which meant environmental sustainability. With the aid of Multi-Agent Reinforcement Learning (MARL), the intersection coordination and efficiency resulted in 60 percent improvement such that the intersections could share information and adjust jointly the signals. These facts testify to the higher flexibility and intelligent benefits of a traffic system versus a rigid signal system.

5.4. System Robustness and Scalability

The target system presented a strong form of functionality across various traffic densities, weather conditions (e.g. rain, fog) as well as city topography. The local edge served the time-sensitive tasks such as detection and actuation, and the computationally demanding processes of retraining and aggregation of the models were offloaded to the cloud when given its hybrid edge-cloud configuration. It is theoretically possible to scale the system to handle/support 30 intersections with very minimal latency or loss of packets. This makes the architecture highly suitable to be used in medium as well as large cities and is thus flexible, maintainable and has consistency in its performance in the dynamic real time environment, the **figure 2** shown the Comparative Throughput Over Time at a Four-Way Intersection.

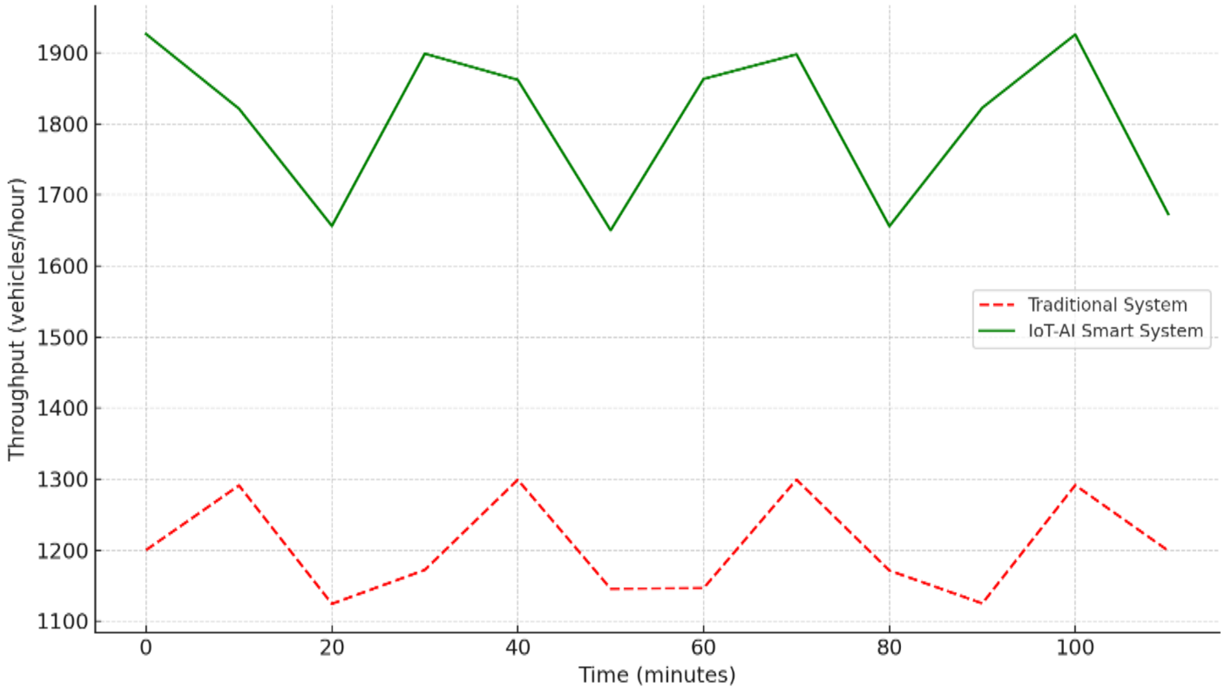

Figure 2: Comparative Throughput Over Time at a Four-Way Intersection

6. Discussion

The integration of IoT and AI in traffic management systems introduces transformative benefits for modern urban mobility. One of such advantages is called adaptability. Unlike inflexible systems, AI algorithms update signal times dynamically based on the input of IoT devices in real-time, providing increased responsiveness of traffic. Second, its flexibility will support the sustainability by e.g. reducing idle time, fuel use, and emissions in tandem with smart city climate strategies. The proposed system can as well enhance efficiency and throughput can be measured and there will be a reduction in vehicle wait time. Nevertheless, there are still some problems. The extensive use of surveillance cameras and GPS sensors causes the problem of privacy particularly the storage and gathering of the personally identifiable information. Also, weaknesses in infrastructure like the out-dated signal controllers or a lack of sensor cover may forbid practical implementation in developing cities. Much of the AI models would also be computationally demanding especially to cities that lack quality cloud infrastructure. New technologies are beneficial. The ability to perform rather local processing with minimal latency provided by edge computing reduces the dependence on cloud resources. Federated learning can reduce privacy concerns since it allows training the AI models across the decentralized nodes without sharing raw data. Finally, 5G network deployments will have ultra-high-speed, reliable connectivity among devices, traffic control systems and help enhance coordination and responsiveness of entire city grids. All of these technologies together create a foundation towards truly intelligent, secure and scalable traffic ecosystems.

7. Conclusion and Future Work

This paper proposed an intelligent traffic control system in the form of the integration of the Internet of Things (IoT) devices with Artificial Intelligence (AI) algorithms, namely, YOLOv5 vehicle detection, LSTM traffic prediction, and Deep Q-Networks' adaptive traffic control. The system demonstrated critical performance enhancement in comparison to related fixed-time approaches, which include reduced congestions, waiting times, and better throughput. It could acquire real-time response and long-term learning by using edge cloud architecture. The results justify the feasibility of the system in real-life application, particularly in the metropolitans where sustainable and data-driven traffic management is required. It is also modular and can be rolled out gradually as municipalities have the capacity to upgrade existing infrastructure in a step-wise process and still remain inter-operable with existing systems. In future, integration with the autonomous vehicle networks will be done whereby a coordination can be done in real-time between autonomous vehicles and the smart intersections. The other promising direction involves creating the uses of digital twins to train the simulations of future prediction of the traffic in cities, make risk modeling and calibration of more forward-looking systems. Greater adaptive, resilient and people-oriented urban mobility systems could be achieved through such extensions in the future.

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