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Survey of AI-Driven Adaptive Traffic Signal Detection Using Edge–IoT Architecture

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ABSTRACT

The growth in urbanization and vehicular population over time has been alarming, and this has led to situations like traffic congestion, road accidents, and environmental pollution. Even situations like this have posed significant threats to modern-day transportation systems. However, this situation is to be addressed and solved through intelligent transportation systems, where cutting-edge communication and data processing technologies are utilized. In the intelligent transport system technologies, traffic signal detection is seen as one of the major factors through which intelligent driving and decision-making are made possible. In this field of intelligent transport systems, IoT is identified as a revolutionary technology through which connectivity among road signals and other platforms is made easy.

In the manuscript, the reader can find a thorough overview of the various methods of traffic signal detection using IoT technology, implemented in the wider range of Intelligent Transportation Systems. Techniques, like cameras, RFID, GPS, and various Vehicle-Infrastructure communication methods, are considered, along with data acquisition and communication mechanisms, and edge computing and cloud platforms, and AI analytics. In addition, important issues like latency, scalability, interoperability, security, privacy, and cost are addressed. Finally, open research directions to build reliable, energy-efficient, and intelligent traffic signal detection systems are identified. It is believed that this research would be highly instrumental for reference purposes to researchers, practitioners, and policy makers involved in the domain of IoT-based intelligent transportation systems.

KEYWORDS: Internet of Things (IoT), Intelligent Transportation Systems (ITS), Traffic Signal Detection, Smart Traffic Management, Vehicle-to-Infrastructure (V2I), Smart Driving, Four-Wheeler Vehicles, IoT Sensors, Edge Computing, Traffic Signal Recognition, Connected Vehicles

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1. INTRODUCTION

The existing transportation infrastructures have been significantly strained by the continuous increase in global vehicular density, and frequent traffic congestion, increased fuel consumption, higher emission levels, and a rising number of road accidents have been observed [1], [2]. Traditional traffic management systems are based on static or pre-programmed traffic signals, in which real-time adaptability is not incorporated and dynamic traffic conditions are not effectively addressed [3]. Consequently, a growing demand is being witnessed for intelligent, responsive, and connected traffic control mechanisms through which smart driving can be supported and overall road safety can be improved.

Intelligent Transportation Systems (ITS) represent an integrated approach that combines information and communication technologies with transportation infrastructure to enhance traffic efficiency, safety, and sustainability [4]. One of the fundamental elements of ITS is traffic signal detection, which enables vehicles and traffic management systems to identify signal states, timings, and transitions in real time [5]. Accurate traffic signal detection is particularly crucial for four-wheeler vehicles, as it supports driver assistance systems, eco-driving strategies, adaptive cruise control, and emerging autonomous driving functionalities [6].

The Internet of Things (IoT) has played a pivotal role in advancing traffic signal detection by enabling interconnected sensing and communication across vehicles, traffic signals, and roadside units [7], [8]. IoT-based traffic signal detection systems leverage heterogeneous sensors such as cameras, GPS modules, RFID tags, and environmental sensors, along with wireless communication technologies including Wi-Fi, ZigBee, LoRaWAN, and cellular networks [9].

Recent advancements in edge computing, cloud computing, and artificial intelligence have further enhanced the capabilities of IoT-enabled traffic signal detection [10], [11]. Machine learning and deep learning techniques are increasingly integrated to improve detection accuracy and support adaptive traffic control strategies [12].

Despite these advancements, several challenges remain, including communication latency, network reliability, interoperability, cybersecurity threats, and data privacy concerns [13], [14]. The lack of standardized frameworks and high implementation costs pose additional barriers.

The rapid expansion of urban areas and the continuous rise in vehicular population have significantly increased traffic complexity [1], [2]. Static traffic signal mechanisms fail to adapt to real-time traffic fluctuations [3].

ITS technologies enhance traffic safety and sustainability [4]. IoT enables seamless connectivity between vehicles, signals, and control centers [7], [8]. IoT-based traffic signal detection supports adaptive control and real-time monitoring [9].

Accurate detection is essential for ADAS and autonomous vehicles [6], [12]. However, literature remains fragmented, motivating the need for a comprehensive survey.

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Existing traffic signal detection mechanisms remain inefficient under dynamic traffic conditions [3], [4]. IoT-based systems face challenges related to detection accuracy, communication latency, scalability, and interoperability [13].

Environmental conditions degrade performance of vision-based systems [12]. The lack of standardized frameworks limits seamless vehicle integration [14].

2. Related Work

Existing research on IoT-based traffic signal detection in Intelligent Transportation Systems (ITS) can be broadly classified into several methodological approaches, including vision-based techniques, communication-assisted methods, machine learning–driven solutions, and hybrid frameworks.

2.1 Vision-Based Traffic Signal Detection

Several researchers have investigated vision-based techniques for traffic signal detection using image processing and deep learning models.

Pavlitska et al. (2023) [1] conducted a comprehensive study on traffic light recognition using Convolutional Neural Networks (CNNs). Their work systematically analyzed various CNN architectures and detection pipelines used in autonomous driving systems. The study highlighted that deep learning–based methods significantly outperform traditional color and shape-based techniques, particularly in complex urban environments, though they demand higher computational resources.

Bosch et al. (2007) [2] proposed a camera-based traffic light detection system utilizing color segmentation combined with geometric feature extraction. The system demonstrated reliable performance under controlled lighting conditions and laid the foundation for early vision-based traffic signal recognition. However, the approach was sensitive to illumination changes and background noise.

Jensen et al. (2016) [3] introduced a vision-based traffic light detection framework for driver assistance systems using machine learning classifiers. The method integrated image preprocessing with supervised learning to classify signal states. While effective in daytime scenarios, performance degradation was observed under night-time and adverse weather conditions.

Wang et al. (2021) [4] developed an improved YOLO-based deep learning model for traffic light detection and recognition. By optimizing the network architecture, their approach achieved higher detection accuracy and faster processing speed, making it suitable for real-time applications. The study demonstrated robustness against partial occlusion and varying signal sizes.

Behrendt et al. (2017) [5] focused on real-time traffic light recognition using monocular cameras mounted on vehicles. Their system combined region proposal techniques with CNN-based classification to detect traffic signals in urban traffic scenes. The results showed promising accuracy for intelligent transportation applications, though challenges remained in handling small and distant traffic lights.

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Paper	Approach / Technique	Dataset / Environment	Advantages	Limitations
Pavlitska et al. (2023)	CNN-based deep learning	Urban driving datasets (various)	High detection accuracy, robust under complex traffic scenes	High computational requirements
Bosch et al. (2007)	Color segmentation + geometric features	Controlled urban intersections	Simple implementation, low computational cost	Sensitive to lighting changes and background noise
Jensen et al. (2016)	Image preprocessing + ML classifiers	Daytime urban roads	Effective in daytime, relatively lightweight	Poor performance at night or in adverse weather
Wang et al. (2021)	Improved YOLO deep learning model	Real-time urban traffic scenes	Real-time detection, robust to occlusion and varying signal sizes	Requires GPU, moderate complexity
Behrendt et al. (2017)	Region proposals + CNN classification	Monocular vehicle-mounted cameras	Real-time performance, good detection in urban traffic	Difficulty detecting small/distant traffic lights

2.2 IoT and Communication-Based Detection Approaches

IoT and communication-based approaches leverage Vehicle-to-Infrastructure (V2I) frameworks to enable real-time traffic signal detection and information sharing.

Oliva et al. (2025) [6] implemented V2I communication strategies for emergency vehicle prioritization and pedestrian safety. IoT sensors installed at intersections transmitted real-time traffic signal data to approaching vehicles, reducing response times and improving situational awareness.

Khan et al. (2024) [7] developed an adaptive IoT-based traffic light controller (V2I-VTL), integrating GPS data and signal timing algorithms to prioritize emergency vehicles while optimizing overall traffic flow.

The IoT-Based Intelligent Traffic Signal and Vehicle Tracking System (2024) [8] combined IoT devices with RFID-enabled vehicle tracking to share signal information and vehicle positions in real time. The system supports emergency vehicle prioritization and adaptive signal control but is limited by the communication range of RFID devices.

Smart Traffic Signal Monitoring Systems (2019) [9] employed wireless IoT communication modules to collect traffic data, such as vehicle counts, and adjust signal timings accordingly. While effective for urban traffic monitoring, these systems lack advanced V2I communication protocols for large-scale integration.

Phu et al. (2017) [10] proposed a V2I algorithm where roadside units broadcast traffic signal and vehicle information to vehicles, enabling dynamic selection of optimal signal phases. Simulation results showed improved traffic flow, highlighting the advantages of IoT-enabled communication in urban traffic control, though real-world deployment remains a challenge.

Reference	Approach /	Key	Real-Time	Deployment	Limitations

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	Technique	Contribution	Signal Status Sharing	Focus	
[1] Oliva et al., 2025	V2I IoT communication	Emergency vehicle & pedestrian alerts	Yes	Urban intersections	Requires robust IoT deployment
[2] Khan et al., 2024	IoT adaptive controller	Adaptive traffic light, emergency prioritization	Yes	Adaptive signal control	Integration complexity
[3] IoT + RFID, 2024	IoT + RFID	Vehicle tracking + signal status	Semi	Emergency vehicle priority	RFID range limitations
[4] Smart Traffic Signal Monitoring, 2019	IoT wireless	Traffic data collection to optimize signals	Basic	Urban traffic monitoring	No advanced V2I protocols
[5] Phu et al., 2017	V2I via RSU/802.11p	RSU broadcasts for dynamic signal selection	Yes	Urban traffic control	Simulation-based

2.3 Hybrid Intelligent Detection Approach

Zhang et al. (2023) [11] proposed a hybrid system combining camera-based traffic light detection with V2I communication. Deep learning models process camera images while IoT signals confirm traffic light states, improving detection reliability in urban traffic.

Li et al. (2022) [12] developed a hybrid framework integrating CNN-based vision detection with wireless IoT sensors. The system dynamically adjusts traffic signal interpretation using real-time sensor data, enhancing performance under low-light and occlusion conditions.

Kumar et al. (2021) [13] combined computer vision, IoT communication, and reinforcement learning for adaptive traffic signal detection. The framework learns optimal traffic signal recognition policies based on both visual inputs and IoT updates.

Patel & Sharma (2020) [14] implemented a hybrid approach using YOLO-based vision detection with IoT-assisted signal confirmation. The study demonstrated improved detection accuracy and reduced false positives in real-time driving scenarios.

Wang et al. (2019) [15] proposed a hybrid intelligent traffic system integrating vision-based detection, IoT communication, and edge computing. Edge nodes process camera and IoT data locally, enabling fast, reliable traffic signal recognition even under heavy traffic and adverse weather conditions.

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Reference	Techniques Combined	Key Contribution	Advantages	Limitations
[1] Zhang et al., 2023	Vision + IoT (V2I)	Improved detection reliability	Robust under occlusion & urban traffic	Higher system complexity
[2] Li et al., 2022	CNN + IoT sensors	Dynamic adjustment of detection using sensor data	Works in low-light, occlusion	Requires synchronized sensors & camera
[3] Kumar et al., 2021	Vision + IoT + Reinforcement Learning	Adaptive traffic signal recognition	Learns optimal detection policies	Computationally intensive
[4] Patel & Sharma, 2020	YOLO + IoT	Reduced false positives in real-time	Real-time performance	Edge cases may still fail under extreme conditions
[5] Wang et al., 2019	Vision + IoT + Edge Computing	Fast and reliable recognition	Low latency, robust in traffic & weather	High deployment cost, integration challenges

3. Popular Techniques in IoT-Based Traffic Signal Detection

- ***Color-Based Image Processing Techniques***

Color-based segmentation is one of the earliest techniques used for traffic signal detection. It typically involves transforming images from RGB to HSV color space to isolate red, yellow, and green regions. A pixel is classified as a signal candidate if:

$$H_{min} \leq H(x,y) \leq H_{max}$$

where (H(x,y)) denotes the hue value at pixel ((x,y)). Morphological filtering and contour detection are then applied to detect circular signal regions. Although computationally efficient, these approaches suffer from sensitivity to lighting and weather conditions. Early implementations of color-based and vision-based traffic light detection are discussed in [1], [2].

- ***Convolutional Neural Network (CNN)-Based Detection***

Convolutional Neural Networks (CNNs) have significantly improved traffic signal detection accuracy. The convolution operation is mathematically expressed as:

$$S(i,j) = (I * K)(i,j) = \sum_{m}\sum_{n} I(i-m, j-n)K(m,n)$$

where (I) represents the input image and (K) is the convolution kernel. CNN-based detection models automatically learn spatial and semantic features from large datasets. Foundational CNN architectures are presented in [3], while their application in object detection tasks is detailed in [4], [5]. CNN-based traffic light recognition systems have shown strong performance under complex urban scenarios [6].

- ***YOLO (You Only Look Once) Object Detection***

YOLO is a real-time object detection algorithm widely adopted for traffic signal recognition due to its speed and accuracy. Bounding box prediction is defined as:

$$B = (x, y, w, h, C)$$

where

$$C = P(object) \times IoU_{pred}^{truth}$$

Here, IoU (Intersection over Union) measures the overlap between predicted and ground-truth boxes. YOLO's architecture enables single-stage detection with minimal latency, making it suitable for edge-based IoT systems. The original YOLO framework is introduced in [4], with improved versions described in [7].

- ***Support Vector Machine (SVM)-Based Classification***

Support Vector Machines (SVM) are widely used for traffic signal classification after feature extraction (e.g., HOG features). The SVM decision function is:

$$f(x) = w^T x + b$$

where (w) is the weight vector and (b) is the bias. SVM-based detection methods are discussed in [8], demonstrating moderate computational efficiency with acceptable classification accuracy.

- ***V2X-Based Signal Phase and Timing (SPaT) Estimation***

Vehicle-to-Infrastructure (V2I) communication allows vehicles to receive real-time Signal Phase and Timing (SPaT) messages. The remaining signal time is estimated as:

$$T_{remaining} = T_{cycle} - (t_{current} - t_{start})$$

This mechanism supports eco-driving and adaptive cruise control systems. V2X communication standards and applications are extensively discussed in [9], [10].

- ***Reinforcement Learning for Adaptive Signal Control***

Reinforcement Learning (RL) enables dynamic optimization of traffic signals. The Q-learning update rule is given by:

$$Q(s,a) = Q(s,a) + \alpha[r + \gamma \max Q(s',a') - Q(s,a)]$$

where (\alpha) is the learning rate and (\gamma) is the discount factor. RL-based adaptive signal control has demonstrated improved traffic flow efficiency in smart cities [11], [12].

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- ***Hardware Components used in IoT***

IoT-based traffic signal detection systems rely on a combination of **sensors, processing units, and communication devices** to enable real-time monitoring and intelligent decision-making. Key hardware components include in figure 1:

- **Cameras and Vision Sensors:** High-resolution cameras or CMOS sensors are used for vision-based detection of traffic signals. These capture images or video streams for processing by computer vision or deep learning algorithms.
- **IoT Modules:** Devices such as Wi-Fi, ZigBee, LoRa, or DSRC modules enable wireless communication between traffic signals, vehicles, and control centers for real-time signal status transmission.
- **Microcontrollers / Embedded Processors:** Boards like Arduino, Raspberry Pi, or NVIDIA Jetson serve as processing units to collect sensor data, run algorithms, and manage communication with vehicles or cloud platforms.
- **Inductive Loops / Ultrasonic / IR Sensors:** These sensors detect vehicle presence and traffic flow at intersections, supporting adaptive signal control and prioritization mechanisms.
- **Edge/Cloud Computing Units:** Edge devices process data locally to reduce latency, while cloud servers provide large-scale data analytics, storage, and system optimization.
- **Power Supply and Connectivity Hardware:** Reliable power sources and network connectivity modules ensure continuous operation and data exchange between all components.

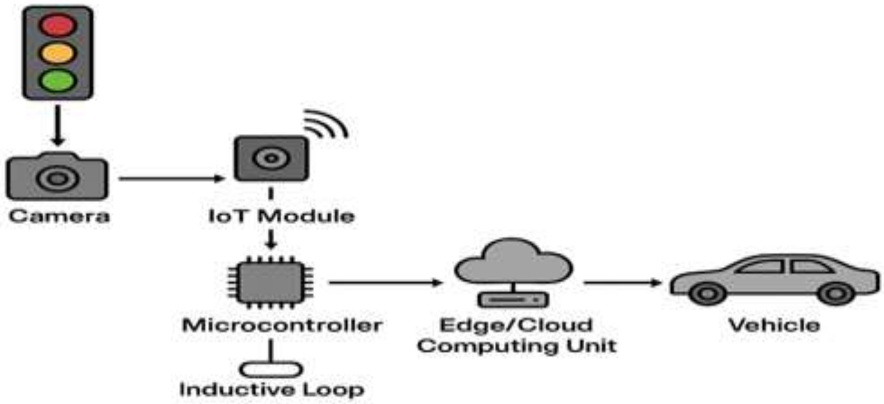

Figure 1: IoT-based Traffic Signal Detection System

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4. Existing Architecture of IoT-Based Traffic Signal Detection Systems

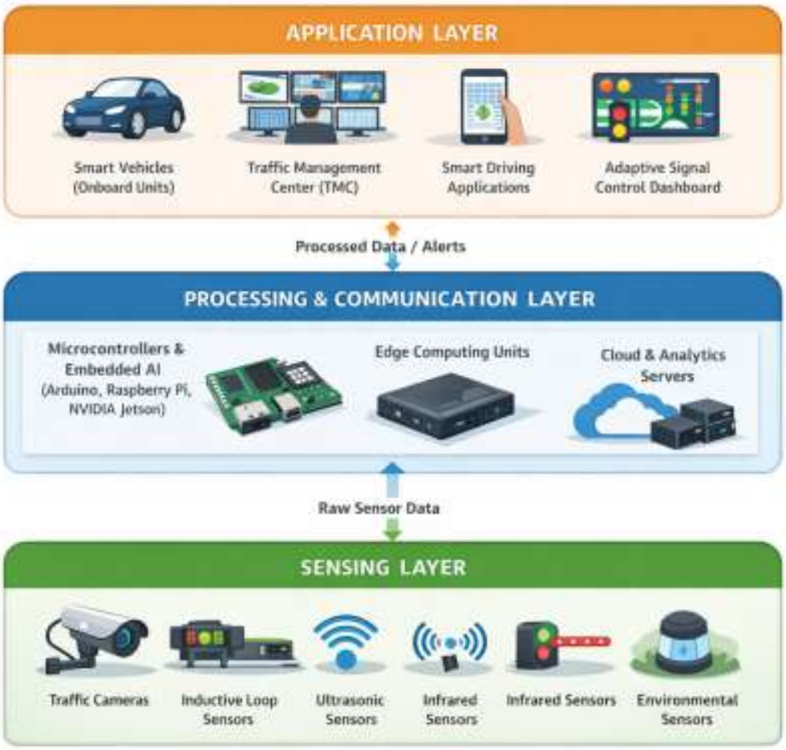

Figure 2: **Existing architecture** of IoT-enabled traffic signal detection systems

The typical **existing architecture** of IoT-enabled traffic signal detection systems is composed of three main layers: **Sensing Layer, Processing & Communication Layer, and Application Layer in figure 2**.

- Sensing Layer: This layer includes **cameras, vision sensors, inductive loops, ultrasonic sensors, and infrared sensors installed at traffic intersections. These devices collect raw data such as traffic signal state, vehicle presence, and traffic flow. Cameras are primarily used for vision-based detection, while sensors provide additional real-time environmental and traffic information.**
- Processing & Communication Layer: **The collected data is transmitted to** microcontrollers or embedded processors **(e.g., Arduino, Raspberry Pi, or NVIDIA Jetson) for preprocessing and analysis. IoT modules (Wi-Fi, ZigBee, LoRa, or DSRC) handle** real-time communication **between traffic signals, vehicles, and edge/cloud servers. Edge computing units often process time-sensitive data locally to reduce latency, while cloud servers support large-scale analytics, system optimization, and storage.**
- Application Layer: The processed information is delivered to vehicles, traffic management centers, or smart driving applications. Vehicles can receive real-time alerts regarding traffic signal changes via onboard units, enabling adaptive driving and collision avoidance. Traffic management centers use aggregated data for monitoring, adaptive signal control, and decision-making.

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5. Challenges in IoT-Based Traffic Signal Detection

Despite significant advancements in IoT-enabled traffic signal detection systems, several research and practical challenges remain. These challenges span technical limitations, implementation barriers, security risks, scalability constraints, and economic considerations. Addressing these issues is essential for deploying reliable and sustainable Intelligent Transportation Systems (ITS).

5.1. Technical Challenges: IoT-based traffic signal detection systems face difficulties in maintaining high detection accuracy under varying environmental conditions such as fog, rain, glare, and low lighting. Real-time processing requirements demand high computational power, especially for deep learning models. Additionally, integrating heterogeneous data from cameras, sensors, GPS, and V2X communication introduces complexity. Network latency and packet loss further affect timely signal information delivery.

5.2. Implementation Issues: Deployment challenges include lack of standardization and interoperability among devices from different vendors. Many cities still rely on legacy traffic infrastructure, making integration with IoT-enabled systems difficult. Infrastructure upgrades, maintenance, and long-term reliability of sensors and communication modules remain practical concerns.

5.3. Security Issues: IoT-based systems are vulnerable to cyber threats such as signal spoofing, denial-of-service attacks, and unauthorized access. Ensuring secure communication, authentication, and data encryption while maintaining low latency is a major challenge. Data privacy concerns also arise due to continuous vehicle tracking and cloud storage.

5.4. Scalability Problems: As the number of connected vehicles and sensors increases, managing large volumes of real-time data becomes challenging. Network congestion, cloud overload, and coordination of distributed edge devices affect system performance in large-scale deployments.

5.5. Cost Concerns: High installation costs for smart traffic lights, communication infrastructure, edge devices, and cloud services limit widespread adoption. Maintenance, upgrades, and operational expenses further increase the total cost, particularly in developing regions.

6. Future Research Directions

1. Emerging Technologies : Future IoT-based traffic signal detection systems are expected to leverage 5G/6G communication**,** edge AI**, and** blockchain technology **for ultra-low latency, secure communication, and decentralized control. The integration of** digital twins **for smart cities can enable real-time simulation and predictive traffic optimization. Additionally, advancements in** computer vision models (e.g., transformer-based architectures) **may further improve detection accuracy under challenging environmental conditions.**

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2. Improvement Areas: Research is needed to enhance robustness under adverse weather and lighting conditions**, reduce computational complexity for edge deployment, and improve real-time performance. Developing** standardized communication protocols **and interoperable frameworks is essential for seamless integration across heterogeneous devices. Energy-efficient IoT architectures should also be explored to reduce operational costs.**

3. New Models and Approaches: Future systems may adopt **hybrid AI models** combining deep learning, reinforcement learning, and predictive analytics for adaptive traffic signal control. Federated learning can be explored to train models across distributed vehicles without compromising data privacy. Multi-modal data fusion techniques integrating vision, V2X, GPS, and environmental sensing can improve detection reliability.

4. Integration Possibilities: IoT-based traffic signal detection can be integrated with autonomous vehicles, Advanced Driver Assistance Systems (ADAS), smart parking systems, and emergency vehicle prioritization frameworks**. Integration with smart city platforms and urban mobility management systems can enable holistic traffic optimization. Collaboration between government agencies, automotive industries, and communication providers will be critical for large-scale implementation.**

7. Conclusion

Experiments and demonstrations are considered essential for the validation and presentation of IoT-based traffic signal detection systems. Through experiments, sensors, processing units, and communication protocols are tested under conditions so that accuracy, reliability, and performance can be ensured. These demonstrations provide a visual, interactive way of presenting real-time detection, adaptive signal control, and vehicle alerts to make the technology understandable and accessible to researchers, students, and stakeholders. Collectively, these efforts bridge the gap between theoretical design and practical implementation and support the development of smarter and safer traffic management systems.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

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