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A Comprehensive Survey on AI-Driven IoT Traffic Control Systems with Collaborative Drones and Federated Intelligence

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Abstract—

The rapid rise in urban traffic coupled with the inability of traditional traffic control systems to adapt and expand to meet the needs of modern smart cities has created congestion, increased emissions, and reduced overall system efficiency. Advances in Artificial Intelligence (AI), the Internet of Things (IoT), and Unmanned Aerial Vehicles (UAV) have provided the opportunity to develop intelligent, decentralized, and adaptive solutions to the Urban Traffic Management (UTM) issues that cities face today. This survey provides an in-depth look at the development of IoT-based traffic control systems using AI and collaborative UAV networks, using the Distributed Learning (FL) framework. We examined cutting-edge solutions that have incorporated edge intelligence with real-time aerial monitoring and privacy-preserving learning methods from 2021 to 2025 to optimize traffic management and increase user safety. The paper categorizes the existing research into three primary technology layers—IoT Sensor, UAV Coordination, and Federated Learning—and provides comparative data on each layer with respect to performance metrics (latency, throughput, model accuracy, and energy efficiency). In addition, the paper identifies some of the main research challenges that remain, including heterogeneous data, communication constraints associated with UAVs, and protective measures for information security within a federated model. The overall results indicate that collaborative UAV networks operating on Federated Learning-based framework architecture will provide a scalable, secure, and resilient Intelligent Transportation Systems (ITS) for the future.

Keywords—

Artificial Intelligence (AI); Internet of Things (IoT); Federated Learning (FL); Drone Swarm; Intelligent Transportation Systems (ITS); Edge Computing; Real-Time Traffic Control; Smart Cities; Privacy Preservation; Aerial Collaboration.

1. Introduction

The increased demand for automobile use because of urban spread and the increased number of vehicles produced has become an overwhelming burden on the present traffic control systems found in cities around the globe. Conventional systems utilizing time-based signal control systems and Cloud Computing have difficulty reacting to rapid changes in traffic conditions. As a result, congestion, air pollution, and delays in travel emerge [1],[2]. With the recent combination of Artificial Intelligence (AI) and the Internet of Things (IoT), the operation of Intelligent Transportation Systems (ITS) has transformed into having the capability to obtain data in real-time; in addition, having predictive and adaptive control over traffic operations [3],[4],[5]. Through the use of IoT-based sensors and video cameras, sensors and video cameras develop a distributed network that autonomously monitors real-time traffic conditions as well as other environmental attributes, meanwhile, the AI algorithms use the information collected via the sensors as well as the video cameras located on-site, for immediate decision making related to the traffic flow [4],[5]. However, the focus on data through centralized clouds creates additional issues such as: high latency due to communication delays, privacy risks associated with data loss, loss of scalability associated with the centrally stored data bases, among many other problems [6]. As a solution to these problems, many scientists are developing Federated Learning (FL) framework designs that can be used to create a decentralized AI-based model that disburses AI models across multiple IoT-based nodes without having to share any of the raw data associated with the design or training of the AI model [7]. Likewise, the addition of collaborative, multi-rotor Unmanned Aerial Vehicles (UAVs) or drone swarms add another layer of dynamic data collection capabilities associated with aerial monitoring of traffic flow, congestion identification, and emergency response [8],[9]. Drones, IoT devices, and Federated Learning together form an excellent method of developing traffic management systems able to operate in real time, while providing both privacy and redundancy for Smart Cities [10]. Moreover, numerous recent studies have demonstrated applications of combining AI (Artificial Intelligence)-enabled IoT networks together with Edge Computing, (Edge Cloud Computing), and Aerial Intelligence to build new adaptable and more autonomous traffic management systems

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[11], [12]. Solutions involving hybrid deployments leverage a distributed spatial awareness, coupled with a collaborative approach to processing and disseminating information from various sources, to allow vehicles and intersections to operate in a fully coordinated manner, even while enabling localized decision-making based on their own data, in Real-Time. Even though many advances have occurred over the previous few years, most current approaches have either focused on the use of IoTs or on the use of Drones to monitor Traffic, rather than focusing on both in conjunction, while few works address the combined orchestration of both systems within a Federated Learning structure; [13]. In addition, while many challenges exist within the context of large scale deployments, such as Non-Independent and Identically Distributed (Non-IID), bottlenecks in Communication, and Security Flaws in Model Sharing, have yet to be fully resolved [14]. The objective of this survey is to fill these gaps, and it achieves this by completing a systematic review of the significant progress made (from 2021 to 2025) on automated Internet of Things traffic systems with the addition of collaborative drone intelligence and federated learning to AI capabilities. It provides a) a classification and comparison of current technology in terms of architecture, functionality, and performance b) identification of existing gaps in research, including scalability, energy efficiency, and communication c) recommendations for future research into the development of autonomous, privacy-preserving, and real-time traffic management ecosystems [15

2. Background and Enabling Technologies

Development of AI-enabled IoT traffic management systems based on Federated Learning (FL) and Drone Collaboration has been made possible by the convergence of four key technologies, these being; Artificial Intelligence (AI), Internet of Things (IoT), Federated Learning (FL) and Drone Swarm Networks. In this section, we outline these four enablers of Future Intelligent Transportation Systems (ITS).

2.1 Artificial Intelligence in Traffic Management

Artificial Intelligence provides automation and optimization for all aspects of Urban Traffic Management. Machine Learning (ML) and Deep Learning (DL) models are now being utilized for many tasks, including Vehicle Detection, Congestion Forecasting, Route Optimization and Incident Prediction. Convolutional Neural Networks (CNNs) are the most commonly used models for image analysis-based Vehicle Detection While Recurrent Neural Networks (RNNs) are used to predict traffic flow [16],[17]. Recent work has used Reinforcement Learning (RL) to create Adaptive Traffic Signal Control Systems that learn the optimum policy through repeated interaction with the environment [18]. More efficient use of AI models has led to less time spent waiting for green lights and lower emissions from vehicles due to optimized routing, thereby improving all aspects of the Mobility of Urban Citizens [19]

2.2 Internet of Things (IoT) and Edge Computing

The Internet of Things (IoT) provides the foundation for an intelligent traffic management system's ability to sense and communicate with each other. The use of the IoT has enabled roadside units (RSUs), cameras, inductive loops and vehicular sensors to provide a continuous flow of granular real-time data about the vehicle population, speed and weather conditions [21]. This data is transmitted to and from everything from vehicles to roadside infrastructure to edge servers using Vehicle-to-Everything (V2X) technology, allowing for coordinated decision-making and a comprehensive view of the traffic environment. The combination of IoT with Edge Computing provides information processing in proximity to the source and therefore reduces latency and bandwidth requirements [22]. The distributed nature of both of these technologies creates the ability to respond quickly to traffic congestion or accidents, thus making the combination of IoT and Edge Computing a necessity for providing efficient real-time traffic management systems [23].

2.3 Federated Learning (FL)

Federated Learning (FL) is a distributed way of doing machine learning that aims to solve the limitations that come with having a centralised way of processing data when it comes to privacy and scale. In FL, an IoT or drone will train a local model from its data, and send only updates about the model, instead of sending the raw data, to a central aggregation point [24]. This is why FL has produced versions of FedAvg, FedProx and FedPer that are specifically designed for use in situations where the environment is non-IID, resource-constrained and is typical of smart cities. This privacy-preserving method limits the amount of traffic on the network, while reducing potential disclosure risk related to sensitive information, and at the same time retaining accuracy of the

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collaboratively trained model. FL, therefore, helps provide a reliable way to move forward with learning in heterogeneous IoT and UAV technologies [25].

2.4 Drone Swarms and Aerial Intelligence

Unmanned Aerial Vehicles (UAVs), commonly known as drones, are ideally suited to integrate into an IoT-based environment so that they can enhance the capabilities of IoT-based sensing and decision support systems by providing high resolution aerial images to support the decision making process. With the support of drone swarms, drone systems can quickly reposition themselves to keep track of traffic flow, identify incidents and provide real-time video feeds back to a traffic control centre [26],[27]. Utilizing on-board Artificial Intelligence (AI) modules, drones can perform some limited analysis; such as counting vehicles, license plate recognition, and indicating areas of congestion [28]. Recent studies are focusing on creating collaborative UAV Networks in which multiple UAVs will exchange information or share knowledge regarding their respective models/algorithms to improve coverage and reliability [29]. In combination with Federated Learning, these UAV networks have the potential to create aerial-ground Co-operative Intelligence (CGI), thus allowing for a scalable, adaptable, resilient framework for smart traffic control [30].

3. Literature Review and Comparative Analysis

The combination of AI-based IoT traffic control systems, which leverage deeplearning and autonomous vehicles, with Edge Computing and Drone/Unmanned Aerial Vehicle (UAV) has led to an increase in research investigating how these technologies work together to create more effective traffic monitoring and control systems. This is the purpose of this paper – to examine representative research on this topic from 2021 until 2025, grouping them according to their technological focus and comparative performance, advantages and limitations. A summary of the primary contributions is presented in Table I.

3.1 Overview of Prior Studies

Initial IoT research efforts used permanent infrastructures placed alongside roadways as a means to monitor vehicle traffic and to provide optimized traffic signals [31]. Perera et al. (2022) proposed a hybrid system for an IoT-Based Edge Computing based on using Deep Learning Methods for image classification analysis to dynamically control signal phases, resulting in reduced latency, but did not provide means to protect privacy. Major advancements in technology regarding transportation can be found in the works of Zhang et al. (2024) and Moulahi et al. (2025), who presented Federated Learning as a method to train multiple Distributed Models in Intelligent Transportation System (ITS) applications while solving constraints relating to data-sharing and Non-IID Data [32], [33].

Research on the subject of using UAVs for improving the management of traffic has been limited to the use of aerial collection of data related to incidents and prediction of congested areas. Alahvirdi and Tuci (2025) showed that using Cooperative Drone Swarms increases aerial coverage of urban intersections by as much as 38% compared to using just one UAV [34]. Similarly, Wang et al. (2023) created an AI-Enabled UAV Surveillance (CSRV) Framework that had improved accuracy when detecting real-time events [35].

Integrated studies such as those by Li et al. (2024) and Aslan et al. (2021) have demonstrated benefits from integrating IoT with UAV usage and Edge Intelligence but lack many features including a coordinated FL layer that allows scaling and protecting the privacy of collected information [36], [37]. There is growing evidence that new architectures are needed to bring together Drone-IoT-FL Technologies to deliver flexible, efficient, autonomous and private security for heterogeneous environments [38]–[40].

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3.2 Comparative Summary of Representative Works

Ref.	Study (Year)	Core Technology	Key Contribution	Limitations
[31]	Perera et al., 2022	IoT + Edge AI	Adaptive signal control with CNNs	No privacy or FL integration
[32]	Zhang et al., 2024	Federated Learning (FL)	Privacy-preserving distributed training	Non-IID performance degradation
[33]	Moulahi et al., 2025	FL + Edge	Predictive model for congestion forecasting	Scalability limited to small nodes
[34]	Alahvirdi & Tuci, 2025	Drone Swarm	Wide-area traffic monitoring	High UAV energy consumption
[35]	Wang et al., 2023	AI + UAV Vision	Incident detection using onboard DL	High bandwidth requirement
[36]	Li et al., 2024	IoT + Edge Intelligence	Low-latency inference	Resource constraints at edge
[37]	Aslan et al., 2021	Drone-assisted Smart City	Flexible aerial deployment	Coordination complexity
[38]	Driss et al., 2022	FL in Vehicular Networks	Secure attack detection	Communication overhead
[39]	Pan et al., 2023	Decentralized UAV FL	Multi-drone learning scheme	Model drift across devices
[40]	Chen et al., 2023	UAV Vision Systems	YOLO-based traffic recognition	Limited to daylight conditions

Table I. *Comparative summary of representative AI-driven IoT and drone-based traffic control studies (2021–2025).*

3.3 Discussion and Insights

Three emerging patterns in research are detected in the studies reviewed:

1) An increasing trend toward decentralized systems (the centralized model of IoT having been replaced with distributed/federated architectures),

2) Collaboration between the aerial and terrestrial, whereby drone swarms enhance fixed sensors by allowing for nimble real-time sensor coverage, and

3) a trade-off: Because Federated Learning ensures that data is confidential, it incurs both communication and computation overhead.

Thus, there is an ongoing need for ways to mitigate these without compromising information confidentiality through lightweight aggregation and compression methods. In conclusion, there is still a significant gap in research with respect to fully-integrated Drone-IoT-Federated Learning frameworks that can optimise energy consumption, latency, and learning accuracy simultaneously at scale.

4. Taxonomy of Drone-Assisted IoT Traffic Systems

Various forms of architecture and learning paradigms in AI-driven IoT traffic control may be classified hierarchically by their functional layer, system configuration, and communication type. As shown in Figure 1 , each existing solution would fall into a classification based on their architectural hierarchy, their learning paradigm, and aerial-ground coordination model [41][41][41].

4.1 Architectural Hierarchy

There are three main types of drone-supported IoT Traffic Management Systems (TMS) by looking at them at a high level:

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1. Centralized Models:
Cloud or Central controller with all sensors' and drones' information to allow for the best decisions on a global basis. The central controller allows you to easily coordinate all drone activity, but there are several disadvantages including latency, a single point of failure and privacy concerns.

2. Decentralized Models:
Locally available data with each IoT device or drone will perform their own local analysis and make their own decisions. Improved resiliency and quicker responses due to decentralization, but may produce disparate decisions because of the heterogeneous nature of the data.

3. Hybrid Models:
More recent examples of TMS systems now combine both central clouds for intelligence and decisions while utilizing distributed edge and drone hardware for execution. Combining central intelligence for long-term goals along with the lower latency of edge/drones for near-term response provides the best of both worlds.

4.2 Learning Paradigms

The way that data-driven technologies develop is a reflection of the underlying learning strategies of the system:
-Supervised Learning: The application of supervised learning techniques has primarily included traffic image classification and vehicle detection through the use of labelled datasets (e.g. UA-DETRAC, CityFlow).
-Reinforcement Learning (RL): Controllers based on RL can automatically adjust their traffic signals (i.e. dynamically), independently of each other, based on their interactions with their environment (i.e., receive rewards or penalties for their actions), thus providing an improved level of adaptability when traffic conditions change.
-Federated Learning (FL): FL has quickly established itself as a key research direction for preserving privacy when using ITS. In federated learning systems, IoT devices and UAVs work together to build and share common ML models by sending only their local gradients (with no personal or private data) to preserve privacy while also ensuring the highest possible accuracy for their ML models at a global level.

New hybrid approaches to solving the challenges of the ITS involve a combination of RL and FL (e.g., FedRL) which allow UAVs and edge nodes to learn together and respond more effectively to changing traffic conditions.

4.3 Sensing and Communication Layers

A typical **Drone–IoT ITS architecture** includes three sensing and communication layers:

1. **IoT Edge Layer:**
   Comprises fixed roadside sensors, cameras, and RSUs that gather real-time traffic flow and environmental parameters [49][49][49].
2. **Drone Swarm Layer:**
   Provides dynamic, high-resolution aerial sensing. Drones use V2X and 5G/6G communication to relay video and telemetry data to nearby edge nodes. Swarm coordination algorithms such as Particle Swarm Optimization (PSO) and formation control enhance coverage efficiency.
3. **Federated Intelligence Layer:**
   Integrates all lower layers through distributed learning aggregation. Model updates from IoT and drone nodes are periodically aggregated at a central or regional coordinator, forming the foundation of **collaborative intelligence** in modern ITS [50][50][50].

4.4 Discussion:

The Taxonomy indicates that future integrated Traffic Control Systems for unmanned aerial vehicles (drones) will develop from a classical rigid hierarchical model to a multi-agent learning-based coordination model. Next-generation Traffic Control Systems will allow for the cooperation between Aerial, Earth, and Sea Vehicles with UAVs (Drones) not only acting as passive sensors but rather now as active Intelligent Agents participating in Decentralized Federated Decision Making. The Taxonomy also serves as a conceptual Framework for designing Scalable Adaptive Secure Drone– IoT–FL Architecture.

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5. Performance Matrices and Benchmarks:

In order to measure how well AI based IoT Traffic Systems work when combined with Collaborative Drones and Federated Intelligence, there needs to be a consistent set of established Performance Metrics that allow for the measurement of the Response Time, Model Performance, Privacy Protection, and Energy Sustainability of the AI based IoT Traffic Systems. The Comparative Performance Analysis in Figure 2 provides examples of the Performance Metrics derived from studies conducted in the years 2021 through 2025 [51][51][51].

5.1 Latency and Real-Time Responsiveness

Latency is used to measure the difference in timing in collecting data, processing it, and completing the corresponding control actions. Minimal latency is extremely important when looking to fulfill time-critical aspects of real-time applications such as dynamic signal management and emergency routing allocation [52][52]. The use of edge-based inference and drone-assisted sensing will help to decrease overall latency from beginning to end versus utilizing cloud-centric systems. If you utilize a hybrid IoT-UAV architecture, you should see a 30-40% decrease in average latency when you also incorporate local edge aggregation mechanisms [53][53].

5.2 Model Accuracy and Predictive Performance

Accuracy of model reflects how accurately the AI model predicts traffic patterns, detects incidents, or recognizes vehicles. There are many types of deep learning algorithms including state-of-the-art benchmarks for object recognition (YOLOv5) and temporal prediction using LSTM and ResNet [54][54].

In addition, accuracy may decrease in a federated system because of non-IID (non-identical distribution) data. However, adaptive Federated Learning algorithms, such as FedDyn or FedProx, will help keep the performance on par with that of centralized algorithms [55][55].

5.3 Communication Overhead & Bandwidth Utilization

Efficient communication impacts scalability in drone to IoT networks. The excessive amount of transmitting updates in Federated Learning (FL) frameworks results in drained bandwidth and increased level of energy usage [56] [56] [56]. Communication costs can be decreased by up to 60% using compression techniques such as quantized updates, sparse gradients, and asynchronous aggregation while still maintaining the fidelity of the model [57] [57] [57]. In addition, drone swarms equipped with 5G or mmWave communication technologies can further facilitate real-time synchronization between agents.

5.4 Energy Efficiency & UAV Endurance

Energy consumption is an important limiting factor for drone-based intelligent transportation systems (ITS). The available onboard battery capacity limits the amount of time the UAV can remain in the air and limits computation ability [58] [58] [58]. Several strategies, such as trajectory optimization, energy-aware task offloading, and solar-assisted UAV charging systems, improve endurance by approximately 20-35% [59] [59] [59]. Furthermore, dynamic voltage scaling and hardware acceleration (e.g., implementation on NVIDIA Jetson or Google Coral platforms) contribute to continual performance thus creating a reduced carbon footprint for IoT edge systems. [60] [60] [60]

5.5 Privacy Preservation and Security

While Federated Learning helps to preserve the privacy of data by removing the need for storing data centrally, it can still be compromised by model inversion and model poisoning attacks. The latest strategies for combating this problem use techniques such as differential privacy and secure multi-party computation (SMC) to alleviate these concerns [61][61][61]. The balancing of model performance with data privacy is one of the most difficult research problems today because of the use of high noise to ensure privacy, which negatively impacts the performance of models in real-time systems.

5.6 Benchmark Datasets

The three main benchmark datasets used for assessing AI based traffic systems are:

•**UA-DETRAC** (for vehicle tracking and object detection)
•**CityFlow-V2** (for multi-camera traffic analytics)
•**DeepUAV-Traffic** (for traffic scenes captured by drones)

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These datasets contain a variety of environmental/lighting conditions to help strengthen the model's performance evaluation and ability to generalize to new situations [62][62][62].

5.7 Highlights

The comparison in Figure 2 suggests that hybrid Drone-IoT-Federated Learning systems outperform traditional centralised models on nearly every metric, resulting in decreased latency, increased model flexibility, and improved privacy. However, these benefits result from increased communication complexity due to higher communication load per UAV and lower UAV endurance, indicating that more efficient model aggregation and cross-layer optimization will be important factors in future designs of Drone-IoT-Federated Learning systems.

6. Open Research Issues and Challenges

Despite the potential for AI-Enabled Traffic Control Systems, which integrate IoT devices with collaboration from Drones and Federated Intelligence, there remain many technical, operational, and ethical challenges that must be addressed prior to large-scale implementation in a real-world setting. This section highlights the key open issues and challenges in four areas: communication; coordination; privacy; and sustainability.

6.1 Bottlenecks and Reliability in Communication Networks

The Drone and IoT ecosystem is built upon a reliance on continuous data transfer between heterogeneous devices via 5G, Wi-Fi 6, and V2X networks. The combination of bandwidth bottlenecks; unreliable intermittent connections; and increased mobility create scenarios that lead to packet loss and delays in synchronisation; both of which have negative impacts on the overall Learning Performance of the UAVs [63][63][63]. Maintaining high levels of Quality of Service (QoS) over changing network conditions remains a significant challenge. There are promising solutions currently being studied, such as multi-access edge computing (MEC), and network slicing. Solutions that dynamically assign communication resources to priority communications nodes may prove to assist in improving QoS for priority levels of communications [64][64][64].

6.2 UAV Coordination and Task Scheduling

Coordinating large drone fleets for continuous communications and surveillance operations introduces a significant level of complexity. Many outstanding issues must still be addressed for improving coordination functionality, including collision avoidance; dynamic trajectory planning; and when to offload mission tasks based on limited drone battery power [65][65][65]. Development of systems for UAV scheduling through multi-agent reinforcement learning (MARL) and swarm intelligence algorithms are currently under development, yet the ability for these systems to converge and maintain stability is a considerable limitation [66][66][66].

6.3 Differences in Data Distributions Among Locations and Impact of Non-IID Data on the Convergence of Federated Learning Algorithms

Federated Learning (FL) assumes that the data distributions at local client sites will be equal contributors to the global FL Model. However, local FL data distributions can be Non-IID, or Non-Identically Distributed, resulting from geographic differences, traffic density differences, and weather differences in real-world traffic systems. As a result of these differences, convergence of the federated learning Model can take longer, and the accuracy of the global model can be unstable [67][67][67]. Several approaches, including Personalized Federated Learning; Clustered Federated Learning; and Meta-Learning, are being researched to mitigate such non-IID conditions; however, the computational resources needed to implement these approaches will continue to be a barrier to entry for edge and UAV devices [68][68][68].

6.4 Data privacy and security and trust

FL (Federated Learning) reduces the need to share raw data but still has vulnerabilities from model inversion attacks, gradient leakage, poisoning, etc., which can expose sensitive patterns in the underlying data. To provide privacy protection to model exchange while supporting real-time performance and scalability, lightweight Differential Privacy (DP) techniques/policies and Blockchain-based model exchange auditing frameworks are currently being developed [69][69][69]. In addition to the above issues, the establishment of trust between aerial and ground nodes in dynamic environments requires the use of reputation-aware consensus mechanisms and secure key distribution protocols.

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6.5 Energy Efficiency and Sustainability

Energy-aware task allocation is particularly essential for drone (UAVs) and IoT devices due to their limited energy supplies. UAVs experience accelerated battery depletion due to increased flight path changes, data transmission and onboard computation [70][70][70]. There is active research investigating Hybrid Energy solutions, including solar-assisted UAS (Unmanned Aerial Systems), Wireless Charging Stations, and Intelligent Sleep Scheduling of IoT sensors, however, the type and scale of deployment as well as the cost-effectiveness of implementing such solutions is still inconclusive.

6.6 Specific Ethical, Policy, And Societal Concerns.

In addition to being limited technically, several of the policies and regulations that govern how and where Drones fly and Capture data can also become a barrier to their successful deployment. Coordination between governments (as well as other organizations) that govern airspace and those who govern data, along with the need for coordinated efforts regarding citizen privacy is paramount. Governments and standardization organizations (such as IEEE and ETSI) are actively drafting and testing policies for Traffic Management of UAVs (UTM) and accountability for AI, however, actual Implementation of these policies is quite disjointed and refers to different jurisdictions throughout the world.

6.7 Summary

These issues collectively illustrate that systems developed along the lines of Drone–IoT–FL in the future must be able to integrate accuracy, and maintain a degree of confidentiality with energy efficiency as well as dependability. The development of these kinds of systems will require collaboration across the fields of AI Engineering and Communication, as well as collaboration with local, state, and national policymakers who support the development of well-functioning, socially acceptable, and scalable traffic ecosystems.8.

7. Conclusion

The survey presents developments in the use of AI-based IoT traffic control systems applying collaborative drones and federated learning (FL) to promote intelligent and decentralised transport networks and a solution that allows users to remain anonymous while contributing to the partnership. The report also reviews the key enabling technologies; categorises the various systems; lists the key performance parameters and identifies the current research gaps in developing scalable; reliable and energy efficient transportation systems. Comparative studies conducted between 2021 and 2025 have shown that Drone–IoT–FL systems have superior latency, adaptability and data privacy when compared to current centralised architectures. Future exploration will be focused on the use of 6G-V2X and Blockchain-supported Federated Learning and the introduction of MARL to build Sustainable, Self-Optimising and Real-Time Controllers. The combination of these technologies is expected to define the next generation of a smart, safe and resilient transport network.

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