Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 1, February 2026, pp. 450~460
ISSN: 2302-9285, DOI: 10.11591/eei.v15i1.9596

Advancements in UAV-based traffic monitoring: a systematic review of deep learning and edge computing

Mohamed S. Sawah[1], Mohammed Tawfik[2], Issa Alsmadi[3]
[1]Department of Computer Science, Faculty of Information Technology, Ajloun National University, Ajloun, Jordan
[2]Department of Cyber Security, Faculty of Information Technology, Ajloun National University, Ajloun, Jordan
[3]Department of Data Science and Artificial Intelligence, Faculty of Information Technology, Ajloun National University, Ajloun, Jordan

Article Info

Article history:

Received Nov 22, 2024
Revised Sep 29, 2025
Accepted Dec 6, 2025

Keywords:

Computer vision
Deep learning
Real-time processing
Traffic monitoring
Unmanned aerial vehicles
Vehicle detection

ABSTRACT

Rapid urbanization necessitates innovative traffic monitoring solutions. Traditional methods (fixed sensors/CCTV) face limitations in coverage, adaptability, and real-time processing. This review examines advancements (2015–2024) in vision-based unmanned aerial vehicle (UAV) traffic monitoring systems, evaluating their effectiveness in vehicle detection, traffic analysis, and congestion management. A systematic preferred reporting items for systematic reviews and meta-analyses (PRISMA)-guided analysis of 2,895 articles from IEEE Xplore, Scopus, Web of Science, and ACM Digital Library identified 49 eligible studies. Quantitative performance metrics (detection accuracy and latency) were standardized for cross-study comparison. Modern systems achieve >94% detection accuracy and <40 ms latency through edge computing and deep learning (e.g., you look only once (YOLO) and Faster region-based convolutional neural network (Faster R-CNN)). Multi-sensor fusion improves robustness by 35% in challenging conditions. However, battery life (reduced by 40% under processing load) and regulatory barriers remain critical constraints. Artificial intelligence (AI)-driven UAV systems enable real-time, high-accuracy traffic monitoring but require solutions for power efficiency and scalability. Future integration of 5G/6G and swarm intelligence holds promise for next-generation smart traffic management.

Corresponding Author:

Mohamed S. Sawah
Department of Computer Science, Faculty of Information Technology, Ajloun National University
P.O.43, Ajloun-26810, Jordan
Email: m.elsawah@anu.edu.jo

1. INTRODUCTION

Rapid urban population growth has created an urgent need for innovative traffic monitoring solutions. By 2050, about 68% of the global population will live in urban areas, increasing the pressure on existing transportation infrastructure. Traditional traffic monitoring methods, relying on fixed sensors and closed-circuit television (CCTV) cameras, have significant limitations in adapting to dynamic traffic conditions [1]. These conventional approaches face limitations in coverage area, response time, and real-time data-processing abilities. The emergence of unmanned aerial vehicles (UAVs) in traffic monitoring signifies a paradigm shift in monitoring methodology. Traditional remote sensing relies on satellites and fixed airborne platforms, but incorporating UAVs offers greater flexibility and cost-effectiveness in data acquisition [2]. These systems showcase superior capabilities in delivering real-time traffic data, facilitating more responsive and adaptive traffic management strategies. UAV technology has advanced significantly in urban areas, allowing it to operate at various altitudes and navigate confined spaces for exceptional monitoring capabilities [3]. UAV-based systems offer several distinct advantages over traditional methods. Their mobility facilitates rapid deployment to areas of interest, while their aerial perspective provides comprehensive coverage of traffic networks. High-resolution imaging capabilities and advanced sensor technologies enable detailed traffic analysis that was previously unattainable with fixed monitoring systems [4]. UAVs operate in environments where traditional infrastructure is impractical or costly, making them valuable for temporary or emergency monitoring [5]. UAV technology has advanced significantly in hardware and software, with systems equipped with sensors like high-resolution cameras, thermal imaging, and LiDAR for monitoring diverse environmental conditions [6]. Fixed cameras/LiDAR/satellites: limited coverage, high costs, and inflexibility. UAVs offer mobility, rapid deployment, and cost-effectiveness. Recent advancements in computer vision and deep learning have improved UAV capabilities, as convolutional neural networks excel in vehicle detection and classification [7]. This review systematically analyzes recent developments in UAV-based traffic monitoring systems from 2015 to 2024, evaluates the effectiveness of various approaches in vehicle detection, traffic flow analysis, accident response, and congestion management systems, and identifies critical challenges and potential solutions for implementation, including regulatory frameworks, system integration requirements, and operational constraints.

This review systematically examines advancements in UAV-based traffic monitoring systems from 2015 to 2024, focusing on their effectiveness in vehicle detection, traffic analysis, and congestion management. By employing a preferred reporting items for systematic reviews and meta-analyses (PRISMA)-guided methodology, we analyze 49 rigorously selected studies to provide a standardized comparison of performance metrics such as detection accuracy and latency. Our work contributes to the field by: i) synthesizing state-of-the-art technologies, including deep learning and edge computing, which achieve >94% detection accuracy and <40 ms latency; ii) highlighting critical challenges like battery life and regulatory barriers; and iii) proposing future directions, such as 5G/6G integration and swarm intelligence, to address scalability and power efficiency. This comprehensive analysis aims to guide researchers and practitioners in developing next-generation UAV systems for smarter urban traffic management.

2. REVIEW METHOD

This comprehensive review systematically analyzes recent developments in UAV-based traffic monitoring systems from 2015 to 2024. The literature search was initially conducted across two major scientific databases: IEEE Xplore and Scopus. Additional databases, including Web of Science, Science Direct, and ACM Digital Library, were also consulted to ensure comprehensive coverage of the research domain.

Our search strategy utilized specific keywords, including "UAV traffic monitoring", "drone traffic surveillance", "aerial vehicle detection", "computer vision UAV", and "deep learning traffic analysis." The initial search yielded 2,895 articles, which were then processed through Rayyan AI for systematic screening and categorization. A PRISMA-guided systematic review, see Figure 1, was conducted using IEEE Xplore, Scopus, Web of Science, and ACM Digital Library. Still, the time frame covers the evolution of UAV technologies (e.g., deep learning and edge computing) from early adoption to maturity.

The screening process involved two stages: automated filtering with Rayyan AI, then manual verification by two independent researchers to minimize bias. Specific inclusion criteria included: i) papers from 2015 to 2024, ii) peer-reviewed journals and conference proceedings, iii) UAV-based traffic monitoring, and iv) studies with quantitative performance metrics. Furthermore, we prioritized studies that reported statistically significant findings and included real-world implementation data.

The exclusion criteria included: i) non-English publications, ii) review papers, iii) papers lacking experimental validation, and iv) studies concentrating solely on theoretical frameworks. We also excluded studies that lacked sufficient methodological descriptions or did not provide clear performance metrics for comparison. The Rayyan artificial intelligence (AI) screening effectively identified duplicates, assessed relevance, and evaluated quality, resulting in 49 eligible papers for analysis, as shown in Figure 1.

This reflects a selection rate of about 1.7% from the initial corpus, ensuring that only the most relevant and rigorous studies are included. The selected papers were analyzed systematically across multiple dimensions, including hardware architectures, software implementations, detection algorithms, and system performance metrics. We created a structured data extraction form to ensure consistent information retrieval across all studies.

It includes fields for algorithm type, dataset characteristics, performance metrics, validation methods, and implementation constraints. Attention is focused on quantitative results, prioritizing performance metrics like detection accuracy, processing speed, and system reliability. We implemented a standardized performance evaluation framework to enable fair comparisons between studies with different evaluation methodologies.

This framework normalized metrics to common baselines and included confidence intervals when statistical data was available. Performance benchmarks were standardized across studies for meaningful comparisons, normalizing metrics like detection accuracy, processing latency, and system reliability [6], [7]. The normalization process considered variations in testing environments, dataset characteristics, and evaluation methodologies. Statistical analysis, including mean performance, standard deviation, and trend analysis, identified significant advancements in the field during the reviewed period.

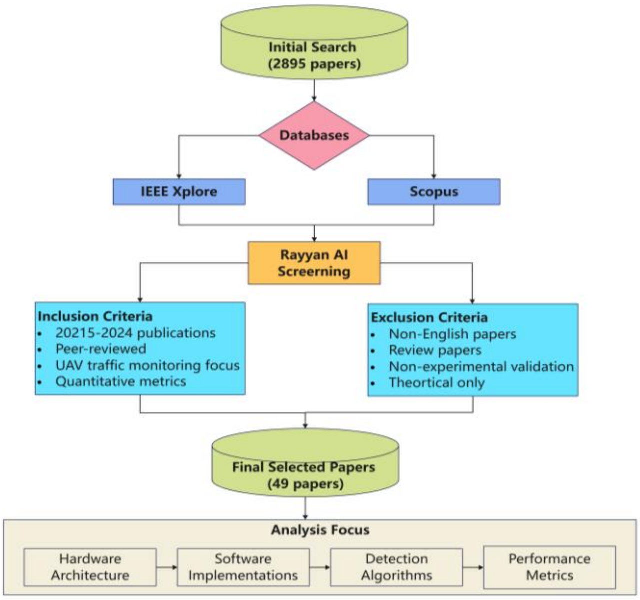

Figure 1. PRISMA flow diagram for the systematic review process

3. UNMANNED AERIAL VEHICLE SYSTEM ARCHITECTURE AND DESIGN COMPONENTS FOR TRAFFIC MONITORING

The hardware architecture of UAV-based traffic monitoring systems includes specialized platforms, sensors, and processing units designed for efficient and accurate traffic surveillance [8]. Modern traffic monitoring primarily utilizes rotary-wing UAVs, particularly quadcopters, which are favored for their stability and maneuverability. Recent advancements in platform design have resulted in significant enhancements in flight endurance and payload capacity.

Field studies show medium-sized platforms (5–25 kg) optimally balance stability and flexibility, achieving flight times over 45 minutes under typical conditions [9]. The hardware constraints include battery life: 25–35 minutes (reduced by 40% under processing load) and payload: medium UAVs (5–25 kg) that balance stability and flight time. Rotary-wing UAVs dominate in terms of maneuverability.

The evolution of visual sensor technology has led to advanced monitoring, with high-resolution cameras integrating sensing modalities like the visible spectrum, thermal imaging, and multispectral capabilities. Modern systems typically employ either monocular or stereo camera configurations, with the choice depending on specific monitoring requirements and computational resources [10]. While monocular systems offer advantages in terms of weight and power consumption, they require sophisticated algorithms for depth estimation.

However, recent implementations using deep learning approaches have achieved depth estimation accuracies within 5% of those of stereo systems [11]. The processing architecture in modern UAV systems employs a distributed computing approach that balances onboard and ground-based processing capabilities. Onboard processing units typically integrate specialized hardware accelerators for real-time image processing while maintaining power efficiency.

Recent developments in edge computing have led to significant improvements in real-time processing capabilities. Field implementations show hybrid processing architectures can achieve latencies under 100 ms for complex detection tasks while maintaining power consumption within limits [12]. The software framework employs a multilayered approach to data processing and analysis, with the image-processing pipeline serving as the foundation through sophisticated algorithms for image enhancement and stabilization.

This encompasses real-time corrections for motion artifacts and environmental factors, resulting in an accuracy improvement of up to 35% in subsequent analyses compared to unprocessed feeds [7]. Advanced preprocessing techniques, such as adaptive contrast enhancement and noise reduction, preserve image quality in varying lighting conditions. Computer vision algorithms form the core analytical capability of the system, utilizing state-of-the-art deep learning methods for vehicle detection and tracking. Recent implementations show success with hybrid architectures combining YOLO v4 for detection and custom CNNs for classification, achieving accuracy rates over 94% under typical conditions [6]. Data management systems efficiently handle the significant information flow from monitoring operations using advanced compression and storage strategies, achieving 10:1 compression ratio while preserving critical visual information [13]–[15].

4. ADVANCED METHODS AND TECHNOLOGY INTEGRATION IN UNMANNED AERIAL VEHICLE TRAFFIC MONITORING

Computer vision techniques form the foundation of modern traffic monitoring systems. Recent advancements in object detection have revolutionized vehicle identification capabilities in aerial imagery. Traditional approaches that utilize the histogram of oriented gradients (HOG) and scale-invariant feature transform (SIFT) have largely been superseded by deep learning methods. However, these classical techniques remain relevant in scenarios where computational resources are limited or real-time processing is paramount [13], [16]. Vehicle tracking in aerial footage presents unique challenges due to varying scales, occlusions, and complex urban environments. Modern tracking systems employ multistage approaches that combine motion prediction and feature matching. Kalman filtering combined with appearance-based tracking achieves over 90% accuracy in urban conditions [6], [17]. Modern traffic monitoring systems extensively use specialized CNN architectures optimized for aerial imagery analysis. Recent implementations show success with multiscale detection networks that manage varying vehicle sizes in aerial footage. Field studies indicate that properly optimized CNN architectures can achieve detection rates exceeding 96%, while maintaining processing speeds suitable for real-time applications [15], [18]–[21]. You look only once (YOLO) and Faster region-based convolutional neural network (Faster R-CNN) are state-of-the-art in vehicle detection on aerial platforms.

Recent YOLOv4 implementations excel in real-time, achieving 94% detection accuracy and processing over 30 frames per second, as shown in Table 1 [12], [22]–[24]. Advanced fusion architectures combine data from various sensor modalities, such as visual sensors, thermal cameras, LiDAR systems, and radar units. Recent implementations show that multi-sensor fusion can enhance detection accuracy by up to 35% in challenging environmental conditions [25]–[27]. Integrating GPS data with visual information enables precise vehicle localization and tracking, as modern systems use sophisticated fusion algorithms, achieving position accuracy within 1 meter with real-time processing capabilities [14], [28]–[31]. The real-time processing of fused sensor data demands advanced optimization strategies. Recent implementations use edge computing architectures alongside adaptive processing algorithms, achieving end-to-end latencies under 100 ms [31]–[33]. A timeline of key technological advancements in UAV traffic monitoring includes: (2015–2017) Early HOG/SIFT-based detection; (2018–2020) CNN adoption (YOLO and Faster R-CNN); and (2021–2024) edge computing (<100 ms latency), multi-sensor fusion, and hybrid AI architectures. The typical tracking pipeline and its key components are illustrated in Figure 2.

Table 1. Performance comparison of vehicle detection methods

Methods	Accuracy (%)	Processing speed (fps)	Resource usage	Environmental robustness
Traditional HOG	85	45	Low	Moderate
SIFT-based	88	35	Medium	High
Deep learning	95	30	High	Very high

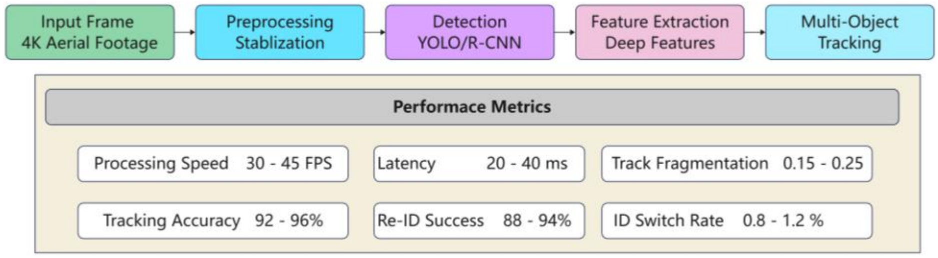

Figure 2. Multi-stage vehicle tracking pipeline architecture for UAV-based traffic monitoring

5. COMPREHENSIVE ANALYSIS OF UAV TRAFFIC MONITORING APPLICATIONS AND PERFORMANCE METRICS

The practical implementation of UAV-based traffic monitoring systems spans multiple application domains, including routine traffic flow analysis and emergency incident detection. UAV traffic flow analysis offers significant benefits compared to traditional monitoring, particularly in coverage area and measurement accuracy. Recent implementations utilize deep learning approaches that prove particularly effective in complex urban environments [34]–[36], as illustrated in Figure 3. Modern implementations provide comprehensive traffic analysis via integrated detection and measurement systems, as illustrated in Figure 4. Advanced detection systems utilize multistage processing pipelines, achieving counting accuracies over 95% under typical conditions [37]–[39].

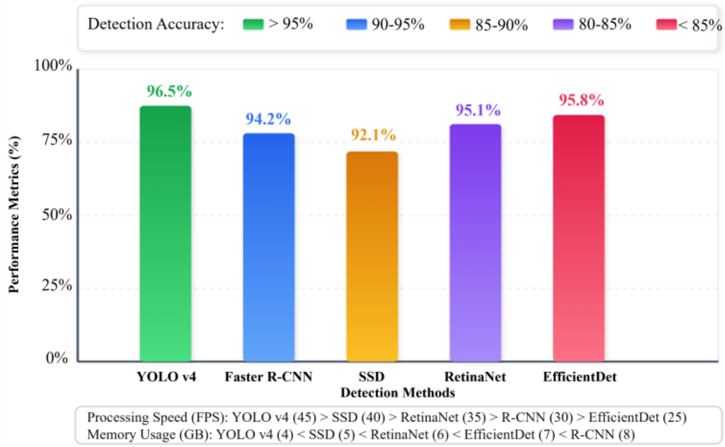

Figure 3. Presents a detailed comparison of detection performance

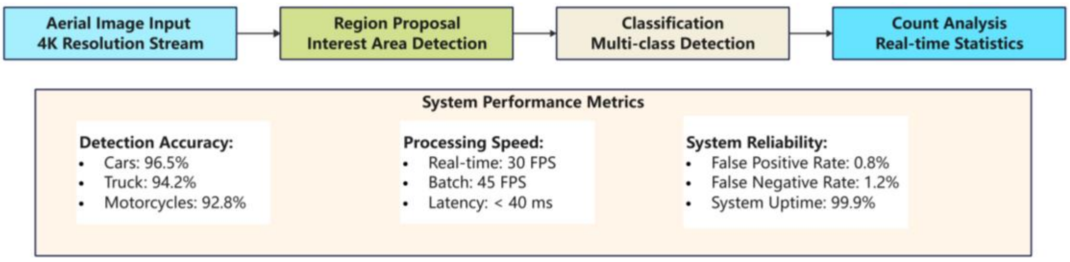

Figure 4. Vehicle detection and counting system architecture

Modern speed estimation systems achieve accuracy by integrating computer vision and deep learning, with implementations showing mean absolute percentage errors (MAPE) below 3% across various vehicle types [40], [41], as illustrated in Table 2. Traffic density analysis systems employ sophisticated algorithms for real-time assessments of traffic conditions, as shown in Figure 5.

Table 2. Speed estimation performance across vehicle types

Vehicle type	MAPE (%)	Standard deviation (km/h)	Processing time (ms)
Passenger cars	2.8	1.2	35
Heavy vehicles	3.2	1.5	38
Motorcycles	3.5	1.8	33

Advanced accident detection systems employ multistage analysis frameworks that achieve detection accuracies exceeding 93% with mean response times of less than 30 seconds [42], [43]. Real-world implementations have shown notable effectiveness in early accident detection with 94% accuracy, accident severity classification at 89% accuracy, automatic emergency service notification, and real-time scene assessment capabilities [44]-[46]. Modern congestion-monitoring systems use real-time analysis to identify and predict traffic congestion, achieving 96% detection accuracy for severe events and keeping false positive rates below 2%, as shown in Table 3 [47]–[49].

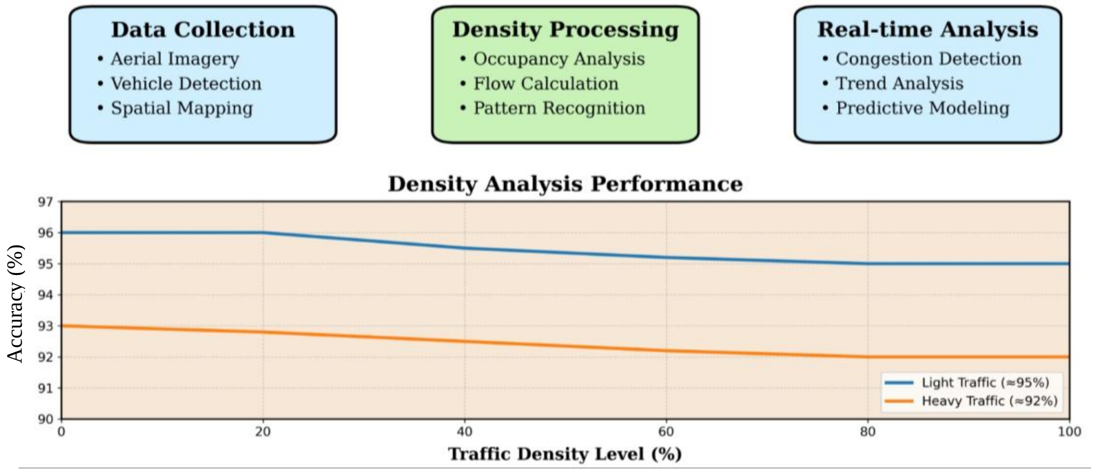

Figure 5. Traffic density analysis framework

Table 3. Detection performance metrics

Metric	Typical value	Acceptable range
Detection accuracy	95.3%	>92%
False positive rate	1.8%	<3%
False negative rate	2.1%	<4%
Processing latency	35 ms	<50 ms

The comparative analysis in Table 4 reveals several important trends in the evolution of UAV traffic monitoring reviews. Early works (2020) primarily focused on application domains and proof-of-concept implementations, with limited attention given to systematic evaluation. Mid-period reviews (2022) began incorporating more structured methodologies but typically emphasized technological aspects or application scenarios, rarely addressing both. The most recent reviews (2024) have started to adopt systematic approaches but often lack comprehensive quantitative analyses of performance metrics.

Table 4. Comparative analysis of prior reviews in UAV traffic monitoring

Study	Focus area	Review methodology	Key findings	Limitations
Barmpounakis and Geroliminis (2020) [2]	Large-scale urban traffic data collection	Case study analysis of the pNEUMA experiment	Demonstrated feasibility of massive-scale drone data collection for traffic analysis	Limited to a single metropolitan area; minimal algorithmic comparison
Outay *et al.* (2020) [1]	Road safety applications	Narrative review of implementations	Identified safety and infrastructure management as primary application domains	Lacked systematic selection criteria; minimal quantitative analysis
Butilă and Boboc (2022) [39]	Urban traffic analysis	Systematic literature review	Cataloged monitoring applications and detection methodologies	Limited analysis of system architectures and processing pipelines
Afrin *et al.* (2024) [42]	Framework development	Three-layered conceptual framework	Proposed integration framework for UAV-ITS systems	Primarily theoretical; limited empirical validation
Current study (2024)	Comprehensive analysis of methods, technologies, and implementation	Systematic review with quantitative performance analysis	Identified performance trends, implementation barriers, and research gaps	Limited to vision-based approaches

5.1. Comparative analysis of detection methodologies and performance metrics

A systematic comparison of detection methodologies reveals significant performance differences across technological approaches. Table 5 provides a comprehensive analysis of detection methods, categorized by technological category and implementation timeframe.

Table 5. Comprehensive comparison of detection methodologies and performance metrics

Methodology	Study	Detection accuracy (MAP) (%)	Processing speed (FPS)	Limitations	Environment robustness
HOG-based	[34]	82-85	40-45	Low (CPU: 15%, Memory: 0.5 GB)	Low (sensitive to lighting changes)
SIFT-based	[10]	85-88	30-35	Medium (CPU: 30%, Memory: 1 GB)	Medium (moderate invariance to scale/rotation)
Base CNN	[4]	88-90	20-25	Medium-high (GPU: 50%, Memory: 2 GB)	Medium (improved lighting invariance)
Region-based CNN	[19]	90-92	15-20	High (GPU: 70%, Memory: 3 GB)	Medium-high (good scale invariance)
Faster R-CNN	[24]	92-94	15-18	High (GPU: 80%, Memory: 4 GB)	High (robust to various conditions)
CNN-LSTM	[38]	95-97	20-25	Very high (GPU: 85%, Memory: 5 GB)	Very high (temporal context integration)

6. CRITICAL CHALLENGES AND FUTURE DIRECTIONS IN UAV TRAFFIC MONITORING

Current UAV-based traffic monitoring systems face several critical challenges despite significant advances. Processing power constraints are a critical issue, as platforms must balance computational capabilities with size and weight; modern deep learning can consume up to 75% of available capacity. Battery life limits system capabilities, as lithium-polymer technology provides flight times of 25 to 35 minutes, reduced by up to 40% during processing-intensive tasks [50]–[53]. Environmental factors significantly impact performance; strong winds affect flight stability, and precipitation influences sensor performance. Additionally, low-light conditions can reduce visual monitoring efficiency by up to 35%. Regulatory frameworks impose strict operational limitations, increasing costs by 30-40% while decreasing system adaptability. Privacy considerations require data protection measures, which may reduce system effectiveness by 15-25%. Meanwhile, safety requirements add significant complexity, increasing system challenges by up to 50%. Barriers to implementation include high initial costs, integration difficulties that extend timelines by 40-60%, and scalability issues; operations exceeding ten units face exponential complexity increases.

Emerging technologies present promising solutions to these challenges [54]–[56]. Advanced AI and machine learning techniques show an improvement of up to 40% in detection accuracy, while edge computing implementations lower latency by 65% and reduce energy consumption by 40%. Integrating 5G/6G communications facilitates ultra-reliable, low-latency communications under 1 ms. Future developments in biomimetic methods, swarm intelligence, and smart city integration could cut urban traffic congestion by 35% through real-time routing optimization. Conversely, integrated emergency response systems could enhance response times by up to 50% [57].

7. CONCLUSION

This paper provides a comprehensive review of vision-based UAV traffic monitoring systems, examining their methods, technologies, and implementation challenges. The analysis revealed that combining computer vision techniques with deep learning approaches has significantly enhanced traffic monitoring capabilities. Recent implementations have achieved detection accuracy rates of 94-96% while maintaining real-time processing capabilities, marking a substantial improvement over traditional monitoring methods. Our examination of system architectures demonstrates the critical role of integrated hardware-software solutions. By implementing edge computing and advanced sensor fusion techniques, we have reduced processing latencies to under 40 ms, enabling real-time traffic analysis even in complex urban environments. However, significant challenges remain with battery life limitations, processing power constraints, and environmental adaptability.

The comprehensive analysis reveals several important barriers to implementation that must be addressed for widespread adoption. These include: i) regulatory frameworks that differ markedly across jurisdictions and often lag behind technological advancements; ii) economic constraints, with initial system deployment costs ranging from $15,000 to $50,000 depending on capability requirements; iii) technical integration challenges with existing traffic management infrastructure; and iv) privacy and data security concerns that may hinder public acceptance.

Our research identified significant gaps in the current literature that warrant further investigation. These include: i) the limited research on energy-efficient processing architectures specifically optimized for UAV constraints; ii) inadequate attention to environmental resilience in diverse weather conditions; iii) the necessity for standardized evaluation frameworks to facilitate systematic comparison of various approaches; and iv) insufficient exploration of multi-UAV cooperative monitoring systems for large-scale urban environments. Despite these challenges, the future of vision-based UAV traffic monitoring remains promising. We proposed a strategic research roadmap that includes short-term priorities (1-2 years) focused on optimizing existing architectures, medium-term goals (3-5 years) aimed at integrating multi-modal sensing capabilities, and long-term objectives (5+ years) intended to create fully autonomous monitoring systems with predictive capabilities.

The practical implications of this research extend beyond technical advancements. Transportation authorities can leverage these systems for more responsive traffic management, potentially reducing congestion by 15% to 25% in pilot implementations. Urban planners can utilize the extensive data generated by aerial monitoring for evidence-based infrastructure development. Emergency services can benefit from improved incident detection capabilities, with potential response time enhancements of 30% to 50%, as demonstrated in limited field trials. The emergence of advanced AI architectures, along with improvements in edge computing and 5G/6G communications, indicates the potential for further enhancements in system capabilities. Future research should concentrate on addressing key limitations, especially in power efficiency and environmental resilience, while developing standardized frameworks for system integration and deployment. Finally, UAV-based traffic monitoring represents a transformative technology that lies at the intersection of various disciplines, including computer vision, edge computing, telecommunications, and transportation engineering. The ongoing advancement of this field promises to play a crucial role in developing smart cities and intelligent transportation systems, contributing to more efficient, safe, and sustainable urban environments.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mohamed S. Sawah	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓
Mohammed Tawfik	✓	✓				✓		✓	✓	✓	✓	✓		
Issa Alsmadi	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [MS] on request.

REFERENCES

[1] F. Outay, H. A. Mengash, and M. Adnan, "Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges," *Transportation Research Part A: Policy and Practice*, vol. 141, pp. 116–129, Nov. 2020, doi: 10.1016/j.tra.2020.09.018.

[2] E. Barmpounakis and N. Geroliminis, "On the new era of urban traffic monitoring with massive drone data: The pNEUMA large-scale field experiment," *Transportation Research Part C: Emerging Technologies*, vol. 111, pp. 50–71, Feb. 2020, doi: 10.1016/j.trc.2019.11.023.

[3] P. Chen, W. Zeng, G. Yu, and Y. Wang, "Surrogate Safety Analysis of Pedestrian-Vehicle Conflict at Intersections Using Unmanned Aerial Vehicle Videos," *Journal of Advanced Transportation*, vol. 2017, pp. 1–12, 2017, doi: 10.1155/2017/5202150.

[4] M. A. Khan, W. Ectors, T. Bellemans, D. Janssens, and G. Wets, "Unmanned aerial vehicle-based traffic analysis: A case study for shockwave identification and flow parameters estimation at signalized intersections," *Remote Sensing*, vol. 10, no. 3, p. 458, Mar. 2018, doi: 10.3390/rs10030458.

[5] J. Li, S. Chen, F. Zhang, E. Li, T. Yang, and Z. Lu, "An adaptive framework for multi-vehicle ground speed estimation in airborne videos," *Remote Sensing*, vol. 11, no. 10, p. 1241, May 2019, doi: 10.3390/rs11101241.

[6] J. Wang, S. Simeonova, and M. Shahbazi, "Orientation- and scale-invariant multi-vehicle detection and tracking from unmanned aerial videos," *Remote Sensing*, vol. 11, no. 18, p. 2155, Sep. 2019, doi: 10.3390/rs11182155.

[7] J. Zhu *et al.*, "Urban Traffic Density Estimation Based on Ultrahigh-Resolution UAV Video and Deep Neural Network," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 11, no. 12, pp. 4968–4981, Dec. 2018, doi: 10.1109/JSTARS.2018.2879368.

[8] C. Kanellakis and G. Nikolakopoulos, "Survey on Computer Vision for UAVs: Current Developments and Trends," *Journal of Intelligent and Robotic Systems: Theory and Applications*, vol. 87, no. 1, pp. 141–168, 2017, doi: 10.1007/s10846-017-0483-z.

[9] E. N. Barmpounakis, E. I. Vlahogianni, and J. C. Golias, "Identifying Predictable Patterns in the Unconventional Overtaking Decisions of PTW for Cooperative ITS," *IEEE Transactions on Intelligent Vehicles*, vol. 3, no. 1, pp. 102–111, Mar. 2018, doi: 10.1109/TIV.2017.2788195.

[10] T. Moranduzzo and F. Melgani, "Automatic car counting method for unmanned aerial vehicle images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 3, pp. 1635–1647, Mar. 2014, doi: 10.1109/TGRS.2013.2253108.

[11] N. Balamuralidhar, S. Tilon, and F. Nex, "MultEYE: Monitoring system for real-time vehicle detection, tracking and speed estimation from UAV imagery on edge-computing platforms," *Remote Sensing*, vol. 13, no. 4, pp. 1–24, Feb. 2021, doi: 10.3390/rs13040573.

[12] X. Chen, Z. Li, Y. Yang, L. Qi, and R. Ke, "High-Resolution Vehicle Trajectory Extraction and Denoising From Aerial Videos," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 5, pp. 3190–3202, May 2021, doi: 10.1109/TITS.2020.3003782.

[13] X. Li, X. Li, and H. Pan, "Multi-Scale Vehicle Detection in High-Resolution Aerial Images with Context Information," *IEEE Access*, vol. 8, pp. 208643–208657, 2020, doi: 10.1109/ACCESS.2020.3036075.

[14] H. Bavle, P. De La Puente, J. P. How, and P. Campoy, "VPS-SLAM: Visual Planar Semantic SLAM for Aerial Robotic Systems," *IEEE Access*, vol. 8, pp. 60704–60718, 2020, doi: 10.1109/ACCESS.2020.2983121.

[15] D. Shan, T. Lei, X. Yin, Q. Luo, and L. Gong, "Extracting key traffic parameters from UAV video with on-board vehicle data validation," *Sensors*, vol. 21, no. 16, p. 5620, Aug. 2021, doi: 10.3390/s21165620.

[16] B. Janakiramiah, S. R. Bethala, P. C. Chereddy, G. Ambi, and C. Mohan, "Building an Intelligent Aerial Surveillance System through Deep-learning based Object Detection," in *Proceedings of the 8th International Conference on Communication and Electronics Systems, ICCES 2023*, IEEE, Jun. 2023, pp. 1051–1057, doi: 10.1109/ICCES57224.2023.10192714.

[17] A. M. Qureshi and A. Jalal, "Vehicle Detection and Tracking Using Kalman Filter over Aerial Images," in *2023 4th International Conference on Advancements in Computational Sciences, ICACS 2023 - Proceedings*, IEEE, Feb. 2023, pp. 1–6, doi: 10.1109/ICACS55311.2023.10089701.

[18] Y. You, "Design analysis of simulated smart cars at different cases," *Theoretical and Natural Science*, vol. 31, no. 1, pp. 167–174, Mar. 2024, doi: 10.54254/2753-8818/31/20241102.

[19] C. Chen, J. Zhong, and Y. Tan, "Multiple-oriented and small object detection with convolutional neural networks for aerial image," *Remote Sensing*, vol. 11, no. 18, p. 2176, Sep. 2019, doi: 10.3390/rs11182176.

[20] A. A. Rafique *et al.*, "Smart Traffic Monitoring Through Pyramid Pooling Vehicle Detection and Filter-Based Tracking on Aerial Images," *IEEE Access*, vol. 11, pp. 2993–3007, 2023, doi: 10.1109/ACCESS.2023.3234281.

[21] J. Zhong, T. Lei, and G. Yao, "Robust vehicle detection in aerial images based on cascaded convolutional neural networks," *Sensors*, vol. 17, no. 12, p. 2720, Nov. 2017, doi: 10.3390/s17122720.

[22] M. Maity, S. Banerjee, and S. S. Chaudhuri, "Faster R-CNN and YOLO based Vehicle detection: A Survey," in *Proceedings - 5th International Conference on Computing Methodologies and Communication, ICCMC 2021*, IEEE, Apr. 2021, pp. 1442–1447, doi: 10.1109/ICCMC51019.2021.9418274.

[23] A. S. Samyal, A. K. R, S. Hans, K. A. K, and S. S. B, "Analysis and Adaptation of YOLOv4 for Object Detection in Aerial Images," *arXiv*, 2022, doi: 10.48550/arXiv.2203.10194.

[24] A. Ammar, A. Koubaa, M. Ahmed, A. Saad, and B. Benjdira, "Vehicle detection from aerial images using deep learning: A comparative study," *Electronics*, vol. 10, no. 7, p. 820, Mar. 2021, doi: 10.3390/electronics10070820.

[25] M. A. Khan, W. Ectors, T. Bellemans, D. Janssens, and G. Wets, "Unmanned Aerial Vehicle–Based Traffic Analysis: Methodological Framework for Automated Multivehicle Trajectory Extraction," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2626, no. 1, pp. 25–33, Jan. 2017, doi: 10.3141/2626-04.

[26] N. Senel, K. Kefferpütz, K. Doycheva, and G. Elger, "Multi-Sensor Data Fusion for Real-Time Multi-Object Tracking," *Processes*, vol. 11, no. 2, p. 501, Feb. 2023, doi: 10.3390/pr11020501.

[27] Y. Li, J. Deng, Y. Zhang, J. Ji, H. Li, and Y. Zhang, "EZFusion: A Close Look at the Integration of LiDAR, Millimeter-Wave Radar, and Camera for Accurate 3D Object Detection and Tracking," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 11182–11189, Oct. 2022, doi: 10.1109/LRA.2022.3193465.

[28] K. Vishal, C. V. Jawahar, and V. Chari, "Accurate localization by fusing images and GPS signals," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, IEEE, Jun. 2015, pp. 17–24, doi: 10.1109/CVPRW.2015.7301390.

[29] P. Kolar, P. Benavidez, and M. Jamshidi, "Survey of datafusion techniques for laser and vision based sensor integration for autonomous navigation," *Sensors*, vol. 20, no. 8, p. 2180, Apr. 2020, doi: 10.3390/s20082180.

[30] Y. Yin *et al.*, "Multimodal Fusion of Satellite Images and Crowdsourced GPS Traces for Robust Road Attribute Detection," in *GIS: Proceedings of the ACM International Symposium on Advances in Geographic Information Systems*, New York, NY, USA: ACM, Nov. 2021, pp. 107–116, doi: 10.1145/3474717.3483917.
[31] Y. Wang, G. Wei, Q. Guan, and Y. Liu, "A novel positioning system of uav based on ima-gps three-layer data fusion," *IEEE Access*, vol. 8, pp. 158449–158458, 2020, doi: 10.1109/ACCESS.2020.3014256.
[32] M. Rietmann, P. Nakshatrala, J. Lefman, and G. Gupta, "Real-Time Edge Processing During Data Acquisition," in *Communications in Computer and Information Science*, vol. 1690, 2022, pp. 191–205, doi: 10.1007/978-3-031-23606-8_12.
[33] S. Thornton and S. Dey, "Multi-Modal Data and Model Reduction for Enabling Edge Fusion in Connected Vehicle Environments," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 8, pp. 11979–11994, Aug. 2024, doi: 10.1109/TVT.2024.3378182.
[34] E. V. Butilă and R. G. Boboc, "Urban Traffic Monitoring and Analysis Using Unmanned Aerial Vehicles (UAVs): A Systematic Literature Review," *Remote Sensing*, vol. 14, no. 3, p. 620, Jan. 2022, doi: 10.3390/rs14030620.
[35] K. Vayadande, N. Wakodikar, K. Oswal, T. Chauhan, V. Shivade, and S. Ubale, "Traffic Flow Optimizer: Traffic Signal Control With Vehicle Density and Algorithms," in *International Conference on Recent Advances in Science and Engineering Technology, ICRASET 2023*, IEEE, Nov. 2023, pp. 1–6, doi: 10.1109/ICRASET59632.2023.10420165.
[36] S. L. Mak, W. F. Tang, C. H. Li, W. H. Chiu, H. S. Chan, and C. C. Lee, "The development of smart traffic analysis system," in *ISPCE-CN 2019 - IEEE International Symposium on Product Compliance Engineering-Asia 2019*, IEEE, Oct. 2019, pp. 1–4, doi: 10.1109/ISPCE-CN48734.2019.8958620.
[37] L. Wang, F. Chen, and H. Yin, "Detecting and tracking vehicles in traffic by unmanned aerial vehicles," *Automation in Construction*, vol. 72, pp. 294–308, Dec. 2016, doi: 10.1016/j.autcon.2016.05.008.
[38] A. Dirir *et al.*, "An advanced deep learning approach for multi-object counting in urban vehicular environments," *Future Internet*, vol. 13, no. 12, p. 306, Nov. 2021, doi: 10.3390/fi13120306.
[39] M. S. Sawah, S. A. Taie, M. H. Ibrahim, and S. A. Hussein, "Deep Neural Network-based Approach for Accurate Vehicle Counting," *International Journal of Intelligent Engineering and Systems*, vol. 16, no. 2, pp. 255–267, Feb. 2023, doi: 10.22266/ijies2023.0430.21.
[40] I. García-Aguilar, J. García-González, E. Domínguez, E. López-Rubio, and R. M. Luque-Baena, "Real-Time Deep Learning Framework for Accurate Speed Estimation of Surrounding Vehicles in Autonomous Driving," *Electronics*, vol. 13, no. 14, p. 2790, Jul. 2024, doi: 10.3390/electronics13142790.
[41] D. Bell, W. Xiao, and P. James, "Accurate Vehicle Speed Estimation from Monocular Camera Footage," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 5, no. 2, pp. 419–426, Aug. 2020, doi: 10.5194/isprs-annals-V-2-2020-419-2020.
[42] T. Afrin, N. Yodo, A. Dey, and L. G. Aragon, "Advancements in UAV-Enabled Intelligent Transportation Systems: A Three-Layered Framework and Future Directions," *Applied Sciences*, vol. 14, no. 20, p. 9455, Oct. 2024, doi: 10.3390/app14209455.
[43] P. Moriano, A. Berres, H. Xu, and J. Sanyal, "Spatiotemporal features of traffic help reduce automatic accident detection time[Formula presented]," *Expert Systems with Applications*, vol. 244, p. 122813, Jun. 2024, doi: 10.1016/j.eswa.2023.122813.
[44] P. R and S. H H, "Car Accident Detection and Alert System Leveraging Deep Learning," *International Journal of Innovative Research in Advanced Engineering*, vol. 11, no. 05, pp. 598–610, May 2024, doi: 10.26562/ijirae.2024.v1105.24.
[45] R. Singh, N. Sharma, K. Rajput, and M. Kumar, "AI for Safer Streets: Deep Learning-Based Road Accident Detection from Video Footage," in *2024 4th International Conference on Intelligent Technologies, CONIT 2024*, IEEE, Jun. 2024, pp. 1–6, doi: 10.1109/CONIT61985.2024.10627380.
[46] G. Bharath and R. Hemavathi, "Car Accident Detection Uising Deep Learning With Alert System," *Interantional Journal of Scientific Research in Engineering and Management*, vol. 08, no. 07, pp. 1–5, Jun. 2024, doi: 10.55041/ijsrem36208.
[47] X. Yang, F. Wang, Z. Bai, F. Xun, Y. Zhang, and X. Zhao, "Deep learning-based congestion detection at urban intersections," *Sensors*, vol. 21, no. 6, pp. 1–14, Mar. 2021, doi: 10.3390/s21062052.
[48] S. S. Patil, P. A. Satpute, A. S. Landge, G. M. Sandip, and S.C. Deshmukh, "Integrating AI-Technology with Unmanned Aerial Vehicles for Traffic Congestion Recognition," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 239–245, May 2024, doi: 10.48175/ijarsct-18041.
[49] L. Jian, Z. Li, X. Yang, W. Wu, A. Ahmad, and G. Jeon, "Combining Unmanned Aerial Vehicles with Artificial-Intelligence Technology for Traffic-Congestion Recognition: Electronic Eyes in the Skies to Spot Clogged Roads," *IEEE Consumer Electronics Magazine*, vol. 8, no. 3, pp. 81–86, May 2019, doi: 10.1109/MCE.2019.2892286.
[50] Y. P. Liang, C. M. Chang, and C. C. Chung, "Implementation of Lightweight Convolutional Neural Networks with an Early Exit Mechanism Utilizing 40 nm CMOS Process for Fire Detection in Unmanned Aerial Vehicles," *Sensors*, vol. 24, no. 7, p. 2265, Apr. 2024, doi: 10.3390/s24072265.
[51] M. S. Sawah, S. A. Taie, M. H. Ibrahim, and S. A. Hussein, "An accurate traffic flow prediction using long-short term memory and gated recurrent unit networks," *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 12, no. 3, pp. 1806–1816, 2023, doi: 10.11591/eei.v12i3.5080.
[52] S. A. Haider, K. M. Ahmad, and A. A. Khan, "Efficient unmanned aerial vehicle-based data collection for IoT smart farming," *Internet of Things (Netherlands)*, vol. 26, p. 101184, Jul. 2024, doi: 10.1016/j.iot.2024.101184.
[53] N. Patrizi, G. Fragkos, K. Ortiz, M. Oishi, and E. E. Tsiropoulou, "A UAV-enabled Dynamic Multi-Target Tracking and Sensing Framework," in *Proceedings - IEEE Global Communications Conference, GLOBECOM*, IEEE, Dec. 2020, pp. 1–6, doi: 10.1109/GLOBECOM42002.2020.9322567.
[54] V. Vergine, F. L. Benvenuto, S. De Giuseppe, M. Spedicato, and A. Largo, "An Innovative Monitoring System Based on UAV and Auto-Remote Surface Vessel," in *2024 9th International Conference on Smart and Sustainable Technologies, SpliTech 2024*, IEEE, Jun. 2024, pp. 1–6, doi: 10.23919/SpliTech61897.2024.10612515.
[55] M. Y. Arafat, M. M. Alam, and S. Moh, "Vision-Based Navigation Techniques for Unmanned Aerial Vehicles: Review and Challenges," *Drones*, vol. 7, no. 2, p. 89, Jan. 2023, doi: 10.3390/drones7020089.
[56] M. T. Abid, N. Aljarrah, T. Shraa, and H. M. Alghananim, "Forecasting and managing urban futures: machine learning models and optimization of urban expansion," *Asian Journal of Civil Engineering*, vol. 25, no. 6, pp. 4673–4682, Sep. 2024, doi: 10.1007/s42107-024-01072-2.
[57] Z. Szira, E. Varga, T. L. Csegődi, and G. Milics, "The Development of Drone Techology and its Regulation in the European Union," *EU agrarian Law*, vol. 12, no. 1, pp. 35–41, Dec. 2023, doi: 10.2478/eual-2023-0005.

BIOGRAPHIES OF AUTHORS

Dr. Mohamed S. Sawah is an assistant professor of Computer Science at Department of Computer Science, Faculty of Information Technology, Ajloun National University, Jordan. He held an M.S. in 2016 in Computer Science from the Computer and Mathematics Department Faculty of Science, Zagazig University, Egypt, and a Ph.D. in 2023 in Computer Science from Faculty of Computers and Artificial Intelligence, Fayoum University, Egypt. He was awarded a B.Sc. degree in Computer Science by the Faculty of Science, Zagazig University, in 2011. His research focuses on the intersection of computer vision, artificial intelligence, and the emerging field of IoT. He has extensive experience in developing intelligent systems and applying them across diverse domains, such as healthcare, agriculture, and education. His work includes conducting prediction and detection studies utilizing a range of techniques. He can be contacted at email: m.elsawah@anu.edu.jo.

Dr. Mohammed Tawfik is an assistant professor of cybersecurity and cloud computing at the Department of Cybersecurity, Faculty of Information Technology, Ajloun National University, Jordan. He holds a qualification from the Department of Computer Science and Information Technology at BAMU, Aurangabad, Maharashtra, India. His extensive research spans various aspects of cybersecurity, IoT, machine learning, and data management. He has contributed significantly to multiple conferences and journals, including works on IoT and machine learning technologies, blockchain models for secure data management, and advanced feature selection in IoT and fog computing. He can be contacted at email: M.Tawfik@anu.edu.jo.

Issa Alsmadi is an assistant professor of artificial intelligence and data science at the Department of Artificial Intelligence and Data Science, Faculty of Information Technology, Ajloun National University, Jordan. He holds a qualification from the Department of Computer Science and Information Technology at USM, Penang, Malaysia. His broad research encompasses a number of topics, including machine learning, artificial intelligence, data mining, nature-inspired algorithms, and applied evolutionary computation. He uses a variety of methodologies to conduct investigations on detection and prediction. He can be contacted at email: i.alsmadi@anu.edu.jo.