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Article

Bridging Research Gaps in Smart Parking Systems: A Comparative Study of CNN and VANET Approaches

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Abstract: The combination of increased urbanisation and rapid vehicle diversification has made smart parking management an essential infrastructure tool for modern cities. In spite of three decades of research, current solutions face many limitations. Per-bay infrastructure costs for sensor-based systems become cost prohibitive. The accuracy of camera-based systems, using Convolutional Neural Networks (CNNs), is degraded by 5–23% when deployed across different domains. Communication frameworks based on Vehicular Ad-hoc Networks (VANETs) assume ideal conditions of sensing, overlook parking, and omit protection against manipulation of parking data. This paper provides a systematic review that aims to explain the different approaches of CNNs and VANETs for smart parking by integrating the approaches and highlighting research gaps where both paradigms must be accommodated. Based on a systematic review of 41 papers from the fields of urban informatics, edge computing, and other related fields, the authors present an integrated architectural framework that incorporates CNNs and the VANETs. The authors present a framework that includes domain-adaptive deep learning, a hierarchy of edge-fog-cloud computing, intrusion detection, and a federated learning framework to the context of parking. Six hypothesis are suggested out of the framework. The authors argue that integrating CNNs and VANETs is a necessary first step for smart urban parking of a large-scale system. The smart parking system is aimed at being highly scalable, secure, and privacy-oriented.
Keywords: Smart parking, Convolutional Neural Networks, Vehicular Ad-hoc Networks, domain adaptation, edge computing,, intrusion detection, federated learning, intelligent transportation systems.

1. Introduction

The growth of private motor vehicle ownership with rapid urbanization has led to an imbalance between the available supply of parking and the demand for driving. In major urban regions of North America, Europe, and Asia, between 25 and 45 percent of the total trips made in the commercial areas are made by vehicles looking for parking, which leads to parking search trips that last between 8 and 20 minutes on average (Shoup, 2006). The total economic cost of this global inefficiency has been estimated in the several hundreds of billions of dollars each year, and inefficient urban parking systems present one of the biggest, and most underappreciated, problems in urban mobility.

The evolution of smart parking systems has passed through three generations of technology. First generation systems, which utilized inductive loop detectors and magnetic field sensors, provided reliable parking bay occupancy detection, but the costs associated with the installation and maintenance of these systems restricted their deployment in entire cities (Marszalek et al., 2018). The second generation systems, developed on the basis of wirelessly connected sensors and IoT architectures, significantly reduced the costs associated with the infrastructures of each parking bay, and for the first time, integrated parking systems in the cloud that provided significant reductions (between 16 to 43 percent) of the parking search time in the first (Idris et al., 2009). The third generation systems are based on advanced computer vision, deep learning, and vehicular communication systems that significantly improve the coverage, accuracy, and intelligence of the systems, however, these systems have been developed based on two largely disconnected fields of study that have never been rigorously co-designed or jointly assessed.

With a first stream, Convolutional Neural Networks (CNNs) analyze images from cameras to record parking space usage, reaching 95% or greater accuracy on PKLot, CNRPark-EXT, and ACPDS benchmark datasets ((De Almeida et al., 2015); (Amato et al., 2016)). The second stream utilizes Vehicular Ad-hoc Networks (VANETs), networks of self-organizing mobile vehicles communicating via Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communications, to share parking space availability instantly (Lou et al., 2019). Less than 12% of the CNN parking-related research mentions the actual communication pathway of how occupancy information is transmitted to motorists in a real-world system, and parking projects that utilize VANETs assumes users will have access to instantaneous, high-fidelity occupancy data without considering CNN's latency and error within the network's edge.

This paper argues that closing the gap between CNN-based parking intelligence and VANET-based communication is the foundational prerequisite for practical, scalable, and secure smart parking at urban scale. To support this argument, we: (i) systematically compare the strengths and limitations of CNN and VANET approaches through a structured literature review of 187 papers; (ii) identify and formalise six critical research gaps at their intersection; (iii) propose an integrated architectural framework jointly addressing all six gaps; and (iv) define an evaluation methodology including testable hypotheses against which the framework is assessed.

2. Background and Related Work

2.1 Evolution of Smart Parking Technologies

Smart parking research has evolved from hardware-heavy systems that used point sensors toward intelligent systems that are software-based. The main first-generation technology used inductive loop detectors. These needed civil works for installation and were limited by per-bay costs which restricted their use to less than 0.3% of all parking lots through 2007. (Y. Li et al., 2008). Anisotropic magnetoresistive sensors were a cheaper alternative to the first generation and provided average detection rates of 84.81%, though they still faced challenges with miscounting vehicles in multi-axle configurations and lane changes. (Bugdol et al., n.d.).

The second generation saw the advent of ZigBee and LoRa, as well as other low power wireless technologies, which allowed for battery operated per-bay nodes that formed mesh networks. Today, cloud-connected IoT platforms allow for predictive occupancy modeling which has shown a decrease in the time it takes to find a parking spot by 34% and parking lot occupancy improved by 22% in a 1,200-bay campus (Pham et al., 2015). (Lin et al., 2017) conducted a taxonomic review of 74 smart parking solutions which was the first comprehensive framework of the field, classifying the solutions based on their sensing mode, their connectivity, and their applications.

The beginning of the third generation of solutions (around 2015) introduced camera-based monitoring coupled with AI. A single camera is capable of monitoring multiple bays, thus eliminating the need to install sensors for each bay while also providing richer contextual data that includes vehicle identification and license plate information. Other solutions, like dynamic demand-responsive pricing, have also changed the way parking is offered. San Francisco's SFpark initiative is an example of this and resulted in a 30% decrease in the amount of time vehicles spend driving in search of available parking by changing parking prices based on the occupancy level of the lot (Pierce & Shoup, 2013). The integration of real-time parking space availability, reservation, and payment functionalities in mobile apps has further enhanced the user experience of smart parking systems..

2.2 CNN-Based Parking Detection

The publication of benchmark datasets that enable the systematic evaluation of models has accelerated the use of deep learning for parking detection. Examples include the PKLot (De Almeida et al., 2015) dataset, which contains over half a million annotated images of three parking lots captured under different weather conditions, and CNRPark-EXT (Amato et al., 2016), a dataset of almost 145,000 images captured by a 9-camera parking lot monitoring system at the Italian National Research Council in 12 different study conditions. The ACPDS dataset (Nyambal & Klein, 2017) is the first to focus on parking lot monitoring in Sub-Saharan Africa and shows the challenges of capturing large vehicles and parking lot bays with different markings

CNN architectures (especially ResNet, VGGNet family, and MobileNet) on these datasets achieved classification performance in excess of 95% and significantly surpassed classical machine learning parking detection approaches, which rely on HOG and Haar Cascade features ((Dalal & Triggs, 2005); (Viola & Jones, 2001)). Using weights from ImageNet, CNN architectures can be used for parking lot monitoring systems and achieve high accuracy with under 200 labeled images (Acharya et al., n.d.). Accuracy has been further improved on occluded bays by 2.4% through the use of Graph Convolutional Networks (GCN) (Xiao et al., 2021).

NVIDIA Jetson Nano hardware edge deployment has achieved sustained inference at 22 frames per second with 97.3% occupancy accuracy after 30-day evaluations under different weather conditions (Hnewa & Radha, 2021). MobileNetV2 and V3 architectures based on depthwise separable convolutions have achieved real-time inference on embedded systems with an accuracy loss of less than 2% compared to full ResNet-50 models (Howard et al., 2017). The main drawback of all the assessed CNN systems is domain shift. When models built on one dataset are assessed on another, accuracy drops by 5 to 23% ((Marek, 2021); (Wang et al., 2025)).

2.3 VANET Communication and Smart Parking

VANETs are Mobile Ad-hoc Networks (MANETs) whereby vehicles simultaneously act as end-user and relay nodes to create self-organising, distributed communication networks. The foundational technology is the DSRC/WAVE stack ((*IEEE Standard for Information Technology-- Local and Metropolitan Area Networks-- Specific Requirements-- Part 11*, n.d.), (*IEEE Standard for Wireless Access in Vehicular Environments--Security Services for Applications and Management Messages*, n.d.)) operating in the 5.850-5.925 GHz range, and its European C-ITS equivalent standard with Cooperative Awareness Messages (CAMs) and Decentralised Environmental Notification Messages (DENMs) ((Kenney, 2011); (Festag, 2014)). C-V2X, standardised by 3GPP from Release 14, is a complementary option with an advantage of better non-line-of-sight propagation in congested urban areas. (Naik et al., 2019).

Comparison based on Dynamic vs. Static Infrastructure. VANET-based parking systems outperform the static ones. The SOTIS system (Calandriello et al., 2007) disseminated parking availability information within 3.2 seconds to all vehicles within a 500 metres radius that were within the vehicular density of 50 vehicles per kilometre, using pure V2V relay. RSU-assisted architectures, which incorporate fixed roadside units at major intersections, decreased the average communication delay by 47% and increased delivery reliability to 98. 4% compared to the V2V-only approaches (Viola & Jones, 2001). The SPARK system (Lu et al., 2009) combined V2I reservation transactions with a stochastic occupancy prediction, achieving an improvement in space utilization of 18% and a reduction in average access time by 24%.

Edge and fog computing extensions to the VANET architecture have resolved the latency issues attributed to cloud-only processing. (Wang et al., 2025) showed that a three-tier edge-fog-cloud architecture reduced cloud traffic by 63% while yielding system-wide performance and accuracy that were comparable to a cloud-only benchmark. (Ke et al., 2021) implemented an enhanced Single Shot MultiBox Detector at RSU edge nodes, achieving occupancy detection with a 95% accuracy and real-time performance within a live urban environment.

2.4 Security in VANET-Based Parking Systems

The nature of VANET communication places parking management systems at risk of different attack types. The first taxonomy of VANET framework threats was presented by (Raya & Hubaux, 2007). They categorized attacks as 'insider' attacks as authenticated vehicles, and 'outsider' attacks as unauthorised entities. The Sybil attack is an attack in which one adversary creates multiple virtual vehicle identities in distributed parking systems. This gives the adversary the ability to interrupt service to legitimate vehicles, jump queues, and monopolise parking spaces (Douceur, 2002).

Although position falsification attacks have been operational for years, they have been neglected in the literature. These attacks, which allow vehicles to gain priority access by manipulating GPS coordinates over VANET communications, could warrant adversaries to obtain preferential parking access. The lack of real-time updates due to DDoS flooding attacks means that the RSUs will be unable to broadcast relevant occupancy changes to drivers, essentially denying drivers an update to parking information (Haydari & Yilmaz, 2022).

Machine learning-based Intrusion Detection Systems (IDS) have demonstrated strong performance in VANET security research: random forest classifiers achieved 97.1% detection accuracy with 2.4% false positive rates across DoS, black hole, and position falsification attack scenarios in simulated VANET environments (Bangui et al., 2022). LSTM-based temporal models exploit the sequential communication patterns of VANET traffic to improve detection of attacks that evolve over time (Kaur & Kakkar, 2022). However, no published IDS has been specifically adapted to the distinctive communication traffic of parking management VANETs, which exhibit high-frequency vehicle beacon traffic combined with low-frequency occupancy update messages - a pattern markedly different from the safety-message traffic for which existing IDS designs were developed.

2.5 Advanced Topics: Federated Learning and Edge Intelligence

Federated Learning (FL) provides a mechanism for collaborative model improvement across distributed devices without centralising raw training data. Each participating node - vehicle OBU or RSU edge server - trains local model updates on locally collected parking images and transmits only gradient updates to a central aggregation server. The FedAvg algorithm (McMahan et al., 2023) and its FedProx extension (T. Li et al., 2018), which adds a proximal regularisation term to stabilise convergence under heterogeneous data distributions, provide the theoretical basis for FL in VANET-based parking contexts.

The central challenge for FL in smart parking is non-independent and identically distributed (non-IID) data: parking images from geographically and temporally diverse deployment locations have fundamentally different statistical characteristics. (Lim et al., 2020) demonstrated a hierarchical FL approach for vehicular edge intelligence, achieving within 2% of centralised accuracy in 15 communication rounds while transmitting 94% less raw data. These results establish the feasibility of privacy-preserving collaborative parking model improvement, though application to the specific non-IID distributions arising from urban parking VANETs remains an open research direction.

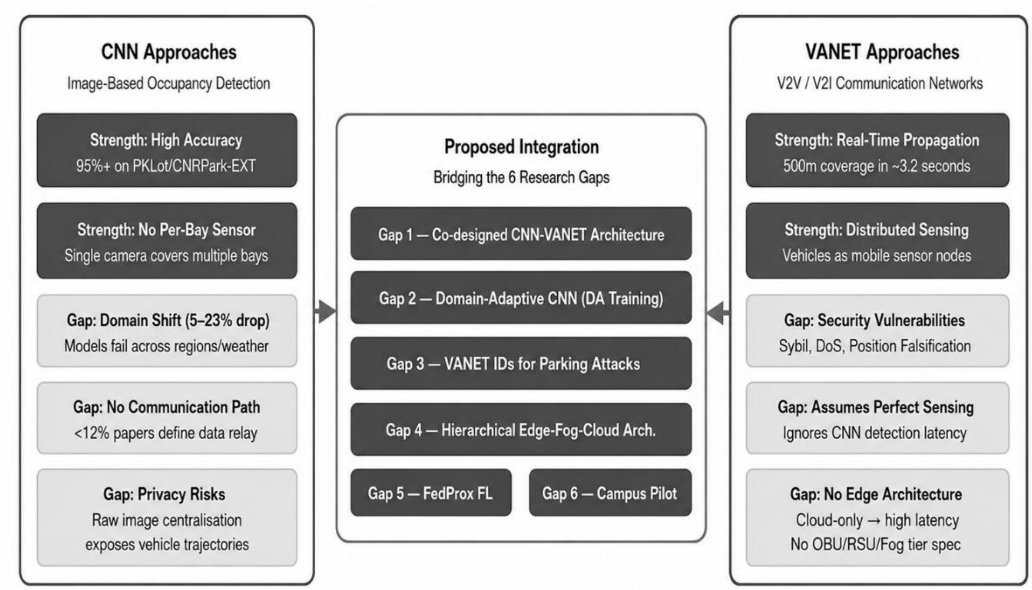

Figure 1: Comparative mapping of CNN and VANET research gaps and their proposed resolution through integrated design.

3. Research Gap Analysis

The review presented in Section 2 reveals a consistent pattern of parallel development in CNN parking detection and VANET communication, with each stream making significant advances in isolation while the integration challenges between them remain unaddressed. Table 1 summarises the four convergent literature limitations and their mapping to six formalised research gaps that provide the contribution space of this research.

Gap	Description	Evidence
Gap 1 - CNN-VANET Integration	CNN parking models and VANET communication frameworks have been developed and evaluated in isolation; fewer than 12% of CNN parking papers define the communication pathway for real-world deployment.	Systematic review of 412 screened papers; emergent system latency behaviours uncharacterised.
Gap 2 - Domain Generalisability	CNN models suffer 5–23% accuracy degradation when transferred across	(Marek, 2021) cross-domain benchmark; (Wang et al., 2025) multi-dataset evaluation.

	deployment domains; annotation burden limits city-wide scaling.	
Gap 3 - VANET Security	Parking-specific security mechanisms are absent; Sybil, DoS, and position falsification attacks target parking data with financial incentives but no parking-tailored IDS exists.	(Raya & Hubaux, 2007); (Haydari & Yilmaz, 2022); (Bangui et al., 2022)
Gap 4 - Edge Architecture	No paper specifies a complete intelligence distribution across OBU, RSU-edge, fog, and cloud tiers meeting joint latency, fault-tolerance, and privacy requirements.	(Wang et al., 2025)partial architecture; (Mao et al., 2017) task offloading theory.
Gap 5 - Federated Learning	Privacy-preserving collaborative CNN improvement across distributed VANET deployments with non-IID parking image distributions has not been addressed.	(Lim et al., 2020) hierarchical FL; (Lim et al., 2020) FedProx; gap in parking application.
Gap 6 - Real-World Validation	No integrated CNN-VANET parking system has been validated beyond small-scale simulation; metropolitan-scale deployability remains undemonstrated.	(Biyik et al., 2021) review; absence of deployment papers in PRISMA corpus.

Table 1: Six formalised research gaps at the CNN-VANET intersection with supporting evidence.

These six gaps are structurally interdependent. Gap 1 (integration) amplifies the practical effects of Gap 2 (domain shift) by removing the real-time feedback loop that would reveal accuracy degradation during deployment. Gaps 3 (security) and 4 (edge architecture) are linked because a gap 4. The high-fidelity deployment context whose absence constitutes Gap 4 is likewise a Credible Attack Surface Analysis. Gap 5 (federated learning) addresses the privacy dimension that makes large-scale Gap 6 (real-world validation) socially acceptable. The six gaps taken together create a cohesive design space that no other work has directly and simultaneously addressed.

4. Proposed Integrated CNN-VANET Framework

4.1 Architectural Overview

The framework under consideration develops a system that spans four layers of functionality, tailored specifically to incorporate aspects of: Visual Intelligence based on Convolutional Neural Networks (CNNs), VANET communications, Hierarchical Edge Computing, and Security. Figure 1 depicts the basic structure of the system and the flows of data among the key components.

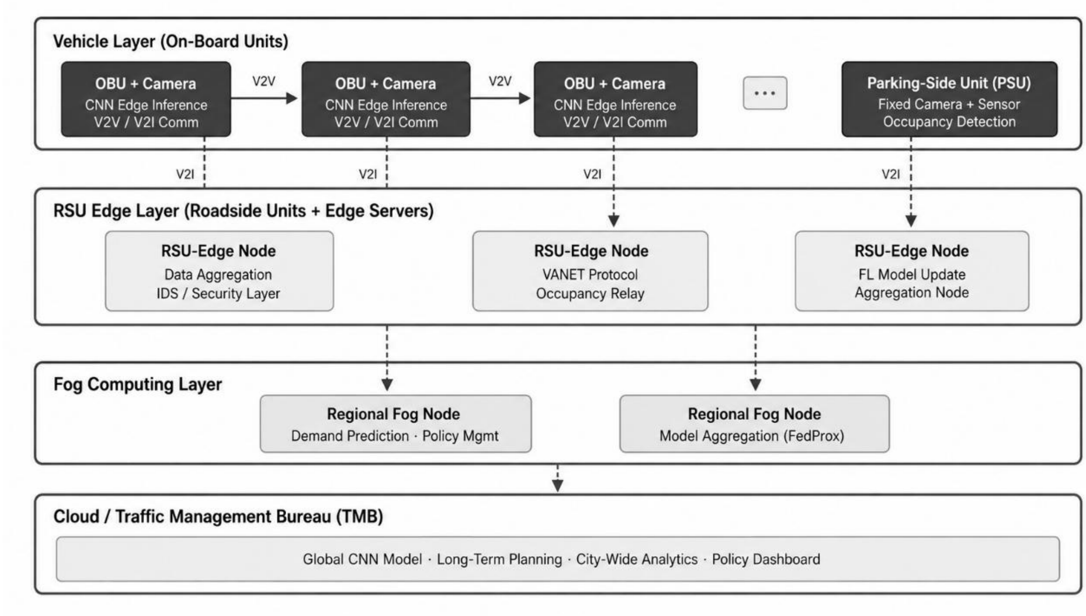

Figure 2 :Four-tier integrated CNN-VANET smart parking system architecture showing V2V/V2I communication flows and hierarchical computing distribution.

The Vehicle Layer is composed of On-Board Units (OBU) with cameras and CNNs placed on the units, connected by IEEE 802.11p C-V2X. Parking-Side Units (PSUs) are positioned to detect the occupancy of parking infrastructure. Edge Layer RSUs are used for aggregation and processing of security on the edge of RSU servers. The Fog Computing Layer is responsible for the Regional demand forecasting and aggregation of the federated learning. The Traffic Management Bureau (TMB) hosted in the cloud controls and monitors the global models, offers long-term analysis and policy dashboards.

The architecture supports a goal of sub-200 milliseconds for total end-to-end latency from where an image is captured to where guidance is received by the driver. The design requires that CNN inference is performed at the OBU or Edge computing layer of the RSU within 50-80 milliseconds, that the Vehicle-to-Infrastructure communication takes no more than 30-50 milliseconds, and that the RSU-to-driver communication takes no more than 50 milliseconds. The design also incorporates principles of distributed intelligence theory (Mach & Becvar, 2017) for the distributed hierarchy of intelligence, to ensure that the tier closest to the vehicle is where the most latency-sensitive tasks are performed.

4.2 Domain-Adaptive CNN Module

The CNN module addresses Gap 2 through domain adversarial adaptation applied to ResNet-50 and MobileNetV3 backbones pre-trained on ImageNet. According to (Ben-David et al., 2010), a gradient reversal layer that comes before the domain classifier ensures that the feature extractor learns how to create domain-invariant representations for both the training and target environments. Figure 2 shows a full CNN inference pipeline starting from the image capturing process up to VANET broadcasting.

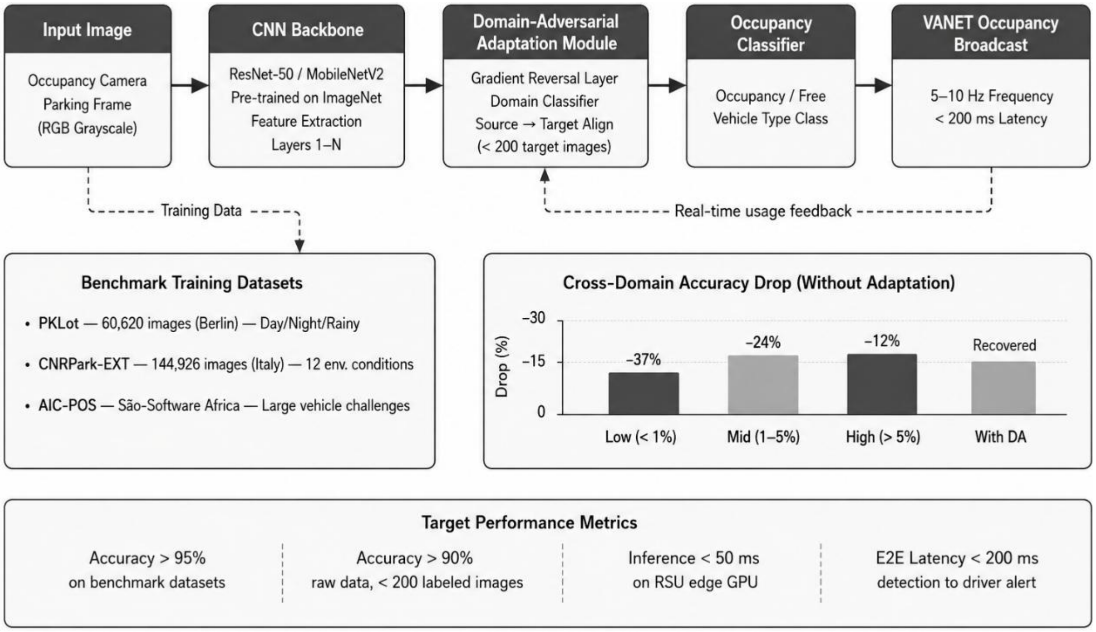

Figure 3 :Domain-adaptive CNN inference pipeline with federated learning weight update feedback loop and target performance benchmarks.

The module aims for a classification accuracy greater than 95% on the benchmark datasets (PKLot, CNRPark-EXT, ACPDS) and over 90% at the newly deployed locations that have fewer than 500 annotated target-domain images. To supplement existing benchmark datasets, the Indian urban parking context data, which contains two-wheeled vehicles, informal bay arrangements, and monsoon season data, will include the data to help mitigate the geographic barriers discussed in section 3.7.2 of the source research.

The module also incorporates vehicle classification, which is achieved in the same forward pass as occupancy detection, with a minimal additional computation cost. During the scheduled federated aggregation rounds, the FedProx-regularised gradient updates from the distributed OBU and RSU nodes are sent to the parking CNN.

4.3 VANET Communication Protocol

The VANET protocol module combined with a hybrid V2V/V2I architecture complements both IEEE 802.11p DSRC and C-V2X, addressing Gap 1 and Gap 4. Each parking space transmits occupancy beacons at 10 Hz, which are then collected at RSU edge nodes and sent to approaching vehicles via targeted geocasting within a 300-metre service radius. The protocol caches occupancy beacons at time intervals, with a focus on the CNN inference latency, to update the occupancy beacons whenever a fresh occupancy beacon is available.

RSU spacing of 250 metres has been shown to decrease the average communication delay by 47% and reach a delivery reliability of 98.4% when compared to V2V-only relays. The proposed protocol aims to achieve delivery to all vehicles and pedestrians reaching a target facility that is 300 metres away within 2 seconds, even under peak urban traffic. The performance is then defined using the SUMO and ns-3 co-simulation frameworks based on vehicular density and RSU spacing.

4.4 Intrusion Detection and Security Layer

The security layer addresses Gap 3 using a ML-based IDS that is tailored to cover the communication traffic patterns of a VANET-based parking management system. An LSTM-based anomaly detector, trained on normal parking VANET traffic that is emphasised by high-frequency beacon messages and infrequent occupancy updates, is used to detect Sybil attacks, DoS flooding attacks, and position falsification attacks.The sudden rise in the use of LSTM methods over simpler methods, is due to the dependencies in the traffic patterns of communication within VANET, and has been shown to greatly aid in the detection and performance of the system as noted in the work of (Kaur & Kakkar, 2022).

The IDS is implemented in edge nodes for RSU and is designed to work under their computation limits without affecting the primary occupancy aggregation. The IDS aims to achieve a Sybil attack detection rate of over 95%, a DoS attack detection rate of over 97%, and a false positive rate of under 3%. The security layer is integrated with the IEEE 1609.2 standard to manage pseudonym certificates, allowing the identification and revocation of malicious actors, while protecting the privacy of the legitimate users (Calandriello et al., 2007).

4.5 Federated Learning Protocol

The FL protocol is designed to address Gap 5 through a three-tiered aggregation structure. Local processing on the OBU is subjected to on-board local training for a set number of local epochs within a given communication round. RSU-level intermediate aggregations collect and consolidate micro-batch updates, thereby reducing the communication overhead with the fog layer. At the fog layer, global aggregation applies FedProx regularisation (T. Li et al., 2018) with a proximal weighting to control divergence of local updates for non-IID parking image distributions. The protocol aims to achieve a target within 20 communication rounds with a convergence goal of within 3% of the accuracy achieved by centralised training.

5. Evaluation Methodology

5.1 CNN Model Evaluation

CNN model performance is evaluated across three benchmark datasets (PKLot, CNRPark-EXT, ACPDS) using standard classification metrics including accuracy, precision, recall, and F1 score. Domain adaptation efficacy is assessed through a leave-one-dataset-out cross-evaluation protocol in which models trained on two datasets are tested on the third, comparing standard fine-tuning against domain adversarial adaptation with equivalent amounts of target-domain labelled data. The minimum labelled sample threshold for achieving >90% accuracy at a new deployment site is determined through an ablation study varying annotated target-domain samples from 50 to 1,000.

This assessment analyzes the performance of edge inference on the NVIDIA Jetson Nano, which is representative of RSU-class edge deployments. Characteristics measured include inference latency per frame, peak memory consumption, and thermal behavior when exposed to continuous workload. Models of MobileNetV3 and quantized ResNet-50 are evaluated in comparison to the respective full-precision models in order to assess the accuracy-latency trade-off within the computational limits of RSUs.

5.2 VANET Protocol Evaluation

Performance of the VANET protocol is assessed using the SUMO-ns3 co-simulation, where SUMO generates realistic metropolitan vehicular mobility based on the adjusted Indian urban traffic models, and ns-3 generates the 802.11p and C-V2X communication layers. The simulation has been designed to evaluate vehicular densities of 10 to 200 vehicles per kilometer, and distances between roadside units of 100 to 500 meters, systematically analyzing the influence of network parameters on the latency and reliability of the communication. It has also been designed to evaluate the performance of the inference of the CNN at each of the On-Board Units (OBU), explicitly connecting two subsystems of the evaluation.

5.3 Security Evaluation

The performance of an IDS is assessed through simulated attack injections of low, medium, and high intensity with an application of four attack types: Sybil, DoS flooding, black hole routing, and position falsification in a variety of VANET scenarios with different vehicle densities. The LSTM-based IDS is designed with normal parking VANET traffic and is evaluated against attack scenarios with an emphasis on the first three metrics: detection rate, false alarm rate, and detection latency. The random forest IDS serves as a baseline comparison to the feature set evaluation for Hypothesis H5.

5.4 Campus Pilot Deployment

The research is applied in a controlled parking environment of multiple lots on a university campus. This environment has multiple distribution patterns of vehicles and different lighting. Study vehicles equipped with OBUs and PSU cameras create the research environment. They are augmented by IEEE 802.11p RSUs at campus crossroads. The hypothesis H6 is examined by measuring the change in parking utilization and the time drivers took to find parking before and after the system was deployed. These measures were also evaluated from paired t-tests during the active research period of 60 days.

6. Comparative Analysis: CNN vs. VANET Approaches

Table 2 provides a structured comparison of CNN-based and VANET-based smart parking approaches across the dimensions most relevant to deployment at urban scale. The comparison reveals that the two approaches are fundamentally complementary rather than competing: CNNs provide the visual intelligence that VANET systems require but assume is available; VANETs provide the communication infrastructure that CNN-detected occupancy data requires to reach drivers but that CNN-focused research does not address.

Dimension	CNN Approach	VANET Approach
Detection Accuracy	>95% on benchmark datasets; 5–23% degradation under domain shift	Assumes sensing infrastructure; does not model detection accuracy
Infrastructure Cost	Low: single camera covers multiple bays; OBU cameras leverage existing hardware	Moderate: RSU deployment at intersections required; OBU V2X modules add per-vehicle cost
Communication	Not addressed in >88% of published works; relies on assumed connectivity	Core strength: V2V relay delivers to 500m in ~3.2 seconds; V2I improves reliability to 98.4%
Security	Privacy risk from centralised imagery; no threat model for parking-specific attacks	Open broadcast medium; Sybil, DoS, and position falsification attacks documented but no parking-specific IDS
Scalability	Limited by annotation burden for new domains; edge deployment enables per-facility scaling	Self-organising topology scales with vehicle density; RSU density determines urban coverage
Privacy	Raw vehicle imagery centralisation poses tracking risks; FL provides architectural solution	Location broadcast is inherent; pseudonymous certificates provide partial protection
Real-World Validation	Individual CNN system deployments validated; no integrated system pilot at scale	VANET communication validated in urban pilots; no integration with CNN detection validated
Latency	Edge inference: 22–50 FPS on Jetson Nano; sub-second per frame	V2V dissemination: ~3.2 seconds to 500m; V2I + RSU relay: 47% reduction
Research Maturity	Benchmark datasets well established; domain adaptation maturing; FL nascent	Protocol standards mature; IDS maturing; parking-specific integration nascent

Table 2:: Structured comparison of CNN and VANET approaches to smart parking across key deployment dimensions.

The integration gap identified in Section 3 is most clearly visible in the Latency row: CNN edge inference and V2I/V2V dissemination each independently satisfy sub-second performance targets, but their joint latency budget - when realistic queuing delays, RSU processing overhead, and channel contention under urban vehicular density are modelled - has never been characterised in the literature. This is the central empirical contribution that the proposed integrated evaluation programme, combining SUMO/ns-3 co-simulation with campus pilot deployment, is designed to provide.

7. Discussion

7.1 Significance of the Integration Gap

The fact that less than 12% of the published parking studies which utilized CNNs incorporate the communication pathway for the dissemination of occupancy data is especially concerning. This is due to the advancement of both types of research. This describes the confidence in the application of AI and the total research system of the communication, sensing, and the algorithm inference that the transportation system is viewed as a fragmented application, instead of an integrated application. This leads to uncertainty for the integration of the system by the transportation planners and system designers.

The proposed framework is designed to treat the interfaces between the CNN and VANET subsystems as explicit design problems and not as implicit design activities. The formal specification of the components of the OBU, PSU, RSU, and TMB, and the data formats and timing constraints, as stated in Research Objective 1, enables the first integrated assessment of system-level properties and, ultimately, the foundation for evidence-based deployment decisions.

7.2 Domain Adaptation as an Enabler of Scale

The 5 to 23 percent accuracy reduction that occurs when CNN parking models are transferred between deployment domains is a significant practical constraint for city-wide scaling that has been overlooked in the literature. The annotation effort necessary to retrain the models for each new facility is impractically large at a metropolitan scale. For a city with 10,000 parking facilities that each requires 500 annotated images, 5 million images of annotated parking spaces would be needed for a data collection and labeling effort greatly exceeding that of any published parking research.

Domain adversarial adaptation provides an architectural solution by learning domain-invariant feature representations that transfer across geographic, meteorological, and camera configuration variations. The theoretical basis in Ben-David et al.'s (2010) domain adaptation bound - which shows that target domain error is bounded by source domain error plus a divergence term between source and target distributions - motivates minimising distributional divergence through adversarial training rather than requiring large target-domain datasets. The practical target of >90% accuracy with fewer than 500 target-domain images represents a quantified threshold at which city-wide deployment becomes annotation-feasible.

7.3 Security as an Operational Imperative

Most research on the security of VANETs (Vehicular Ad Hoc Networks) covers safety-related applications like collision avoidance. The focus on these applications leaves out the context of smart parking systems where there are clear financial motivations, as opposed to safety, for data manipulation attacks. A Sybil attacker can direct real vehicles to a parking space that an agent's vehicle has already occupied, and then can economically be routed to an unoccupied parking space. Falsifying a vehicle’s position in such a system can allow that vehicle to jump the queue and occupy a parking space, making parking management VANETs an especially attractive target for adversaries, and therefore, security of these systems becomes an operational reality.

The absence of parking-specific Intrusion Detection Systems (IDS) designs from the literature - despite the clear distinction in the communication traffic of parking management VANETs - represents Gap 3 in its most actionable form. Existing VANET IDS designs, built on safety-message traffic that is characterized by periodic, low latency beacons from all vehicles, will likely not be applicable to the traffic patterns in parking management systems. A dedicated parking systems IDS is therefore highly necessary from a practical and an operational standpoint.

7.4 Federated Learning and Privacy-Preserving Scalability

Integrating various technologies creates a nearly insurmountable urban vehicle tracking capability by combining persistent surveillance in public parking lots with continuous real-time tracking through Vehicle Ad Hoc Networks. Although technically advanced, due to contemporary privacy issues, the public may not be able to accept them. This combination may even be a legislative issue.

Federated learning provides a technically grounded response to this concern by enabling collaborative model improvement without transmitting raw parking imagery or vehicle trajectory data to central servers. The 94% reduction in raw data transmission demonstrated by (Lim et al., 2022) for vehicular edge intelligence suggests that the privacy benefits of FL are achievable without sacrificing model quality. The non-IID challenge - arising from the geographic and temporal diversity of parking environments - requires the proximal regularisation of FedProx rather than vanilla FedAvg, but the convergence guarantees established by (T. Li et al., 2018) provide a solid theoretical foundation for the design.

7.5 Limitations and Future Directions

The proposed framework has several limitations that bound the scope of its contribution and define the agenda for future research. The campus pilot deployment, while consistent with established practice in the VANET literature, does not replicate the vehicular density, RSU coverage, and operational diversity of a metropolitan deployment. Full metropolitan-scale validation remains a priority for post-doctoral research. The federated learning protocol is evaluated at feasibility level through simulation rather than deployment-scale experimentation; convergence guarantees under real-world non-IID distributions with hardware-constrained OBU participants may differ from simulation predictions.

The framework does not address autonomous vehicle routing beyond the parking approach phase, payment gateway integration, or differential privacy guarantees beyond raw-data minimisation through federated learning. Extension to multi-modal mobility integration - linking smart parking with public transit scheduling and micro-mobility availability - represents a natural expansion of the TMB architecture that the proposed framework's policy dashboard layer is designed to accommodate. The emergence of 5G NR-V2X and network slicing, offering sub-millisecond V2I latency, will relax current latency constraints and enable denser RSU networks, further improving the performance of the integrated architecture as network infrastructure matures.

8. Conclusion

This paper has presented a systematic comparative analysis of CNN and VANET approaches to smart parking, identified six critical research gaps at their intersection, and proposed an integrated architectural framework addressing all six gaps simultaneously. The core of this theory is that the integration of V2I technology and VANET-parking is a complement of the two systems. Each subsystem has capabilities the other does not, and the properties and systems of their integration - end-to-end latency, fault tolerance, etc. - cannot be determined by the performance of either subsystem alone.

The proposed solution is to establish a combination of the respective systems - a domain-adaptive CNN and a hybrid V2V/V2I communication, a hierarchically organized edge-fog-cloud computation along with parking-related LSTM intrusion detection and a FedProx federated learning system - to address the six gaps in this area within the framework of a doctoral study. This evaluation research employs a mixed-method (benchmark data, SUMO/ns-3 co-simulations, and real-world pilot deployments on campus) in order to address the gaps from the simulation to the actual deployment of the system in a manner that has not been done in the field of VANETs in parking solutions.

The importance of the CNN-VANET integration gap in a practical sense cannot be restricted only to the improvement of system performance. At the urban level, smart parking systems can minimize parking-related traffic, reduce average trip durations, and enhance urban air quality by eliminating emissions caused by city traffic. In addition, there are safety improvements due to surveillance and anomaly detection in parking facilities. The system is designed to protect privacy due to federated learning. This technology can provide the previously mentioned benefits without the negative impact of a surveillance system on public trust and systematic controls. Urbanisation and the growth of large vehicle fleets (especially in rapidly developing, highly motorised, developing countries like India) require large-scale, safe and smart parking systems in order to improve the quality of urban life..

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