Management Strategies and Engineering Sciences 2027; 9(1):1-8

AI-Driven Innovations in Smart Parking and Graph Neural Networks: A Survey

Muhtada Zuhair Ali [1], Jamshid Bagherzadeh[2] Parviz Rashidi-Khazaee[3*]

[1] Department of Electrical and Computer Engineering, Urmia University, Urmia, Iran
[2] Professor, Department of Electrical and Computer Engineering, Urmia University, Urmia, Iran
[3] Assistant Professor, Department of Information Technology and Computer Engineering, Urmia University of Technology, Urmia, Iran

*** Corresponding author email address**: p.rashidi@uut.ac.ir

Received: 2025-10-01 **Revised:** 2026-02-15 **Accepted:** 2026-02-23 **Initial Publish:** 2026-05-31 **Final Publish:** 2027-01-01

Abstract

The rapid progress of Intelligent transportation systems (ITS) is desperately needed to reduce the challenges of urbanism; today, a major challenge is to "cruising for parking" that causes around 30% of urban traffic, systemic density, and environmental impacts such as carbon emissions. In this paper, a comprehensive review of the evolution of urban mobility from fundamental hardware sensors and statistical baselines to high-rise learning and large-language model architecture (LLM) is presented. Despite significant gains in predictive accuracy, current deep learning paradigms exhibit substantial research gaps, notably the "black-box" nature of model inference, which lacks an intuitive mapping from multi-modal inputs to predicted results. Methodologically, existing spatio-temporal models are frequently constrained by fixed distance-based adjacency matrices, which fail to capture the "functional synchronization" between urban functional areas that are functionally similar but geographically non-adjacent. Furthermore, the transition to large-scale urban grids is currently hindered by unsustainable training overhead and a significant domain gap between natural language and structured traffic data. The scope of this review encompasses visual occupancy detection backbones, hierarchical graph-based predictors, and the emerging generative AI frameworks for explainable forecasting. We conclude that while the integration of Graph Neural Networks (GNNs) and recurrent units has improved non-linear modeling, the LLM paradigm offers superior representation for few-shot learning and context-aware reasoning. However, critical limitations regarding inference latency and the scarcity of seasonally diverse benchmarks remain unresolved. Future research must prioritize adaptive, efficient, and transparent frameworks capable of modeling complex dependencies across heterogeneous urban environments.

Keywords: *Intelligent Transportation Systems (ITS), Parking demand forecasting, AI-driven decision support, Real-time parking-lot detection, Predictive Traffic Analytics*

How to cite this article:
Zuhair Ali, M., Bagherzadeh, J., & Rashidi-Khazaee, P. (2027). AI-Driven Innovations in Smart Parking and Graph Neural Networks: A Survey. Management Strategies and Engineering Sciences, 9(1), 1-8.

1. Introduction

In the large metropolises, the average daily traffic has increased by more than 10% over the past ten years, which has aggravated the shortage of existing berths [1]. In such cities, the search process is not just a logistical problem; it also causes the search time for the park to be averaged over seven minutes per vehicle, resulting in consequences such as a significant increase in workload, stress and driver fatigue. From the social and environmental dimension, these inefficiencies result in unnecessary emissions of carbon dioxide, fuel waste and high risk of traffic accidents because drivers are forced to resort to the illegal parking [1-3].

To reduce these challenges, development and deployment of intelligent transportation systems (ITS) are necessary. For this purpose, modern smart parking spaces have been used in the city level and they are trying to use cutting-edge technologies, such as the Internet of Things (IOT), cloud computing and digital twins to solve the information asymmetry problem between users and existing parking resources [4, 5]. In these platforms, by integrating thousands of parking in a unified platform, real-time access controls, parking reserved services and precision navigation are presented. In addition, by accurate recognition of the actual time and the close prediction of the future area of the parking area, there is another essential service set that includes dynamic pricing and space division [6, 7]. These functions increase the satisfaction rate of drivers due to reduced traffic time and enables the city managers to allocate the required space for the city park, thereby optimizing the overall efficiency of urban traffic flows [4, 5].

There are fundamental changes in the literature of this field, so that the main focus of researchers and its users is the use of hardware-based algorithms to modeling data-driven forecasting [7, 8]. This means that initial attempts to monitor the parking occupation heavily rely on non-visual hardware, such as radio frequency identification chips (RFID), ultrasonic detector, magnetic field sensors, and inductive rings [9]. In the early systems such as rPark, which were able to show close to 100% accuracy, they were often criticized for high installation and maintenance costs, energy requirements, and sensitivity to environmental stressors such as high temperatures. As a result, the second type of systems was considered severe. in these methods, when the spine is composed of deep learning strategies, they use for simultaneous monitoring of hundreds of parking spaces [1, 8, 9]. Unlike traditional sensors, these visual systems are able to treat parking as a problem-understanding problem, providing resistance to hidden and hidden changes.

Nowadays, most researchers focus on forecasting through simple linear time series analysis to complex Spatio-temporal modeling. Early statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Historical Average (HA) have a good function in the early stages of entry to this field, but they failed to manage the nonlinear dynamics of traffic during intense oscillations. For these professionals, machine learning methods such as support vector regression (SVR) and the nearest neighbor (SVM) have been used to remove linear assumptions [10-12]. There is currently a focus on applying deep learning architectures, especially Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM). In this research, we try to use Graph Neural Networks (GNNs) to record non-Euclidean space dependencies.

Despite such advances, there is a major research gap and methodological limitations in the literature. The deficiency of existing approaches lies in the proximity-based adjacency matrices, and the solution lies in the current GNN frameworks [5, 10]. In most of the available models, the correlations between adjacent parking space and distance can be calculated and in them the "functional synchronization" between distant nodes is ignored. ignoring these higher-order equations limit the accuracy and consistency of regional predictions [10]. In addition, by expanding the scale of urban information networks, computational overhead and training time required for traditional spatial-temporal applications are unstable. While researchers have begun to examine dimensionality reduction through techniques such as graph coarsening, only a few fixed models successfully scaled the graph structure complexity by compressing the properties of high-dimensional nodes without significant loss[4].

Another important challenge is the nature of the "black box " of deep learning architectures. While the results of modern models are high, but in most cases, how and with what data and philosophies have been achieved, they cannot explain it and cannot be understood for its users. This lack of clarity is an important barrier to the industrialization of these technologies [13, 14].

Another challenge is the integrity of available data to use and generalize, and often lack environmental diversity such as winter imagery or various blockage scenarios; thus, limiting the generalizability of the trained models in the ideal conditions. Currently, specialists have developed large-language models (LLMs) to overcome these challenges, in which cross-sectional knowledge transfer and learning capabilities are presented [13, 15, 16]. However, the application of the generator artificial intelligence for structured traffic data is still in its infancy, which is structured with a considerable range of natural language and spatio-temporal tensors, as well as significant concerns about the delay of inference[14, 16-18].

Considering such challenges, it is necessary to consider and use consistent, efficient and transparent structure. Hence, in this paper, at first, a comprehensive survey of the current status is presented and the required components for the current technology are reviewed. The remainder of this paper is organized as follows. Section II reviews the evolution of vehicle detection methods, from hardware-based systems to global context-aware visual architectures. Section III analyzes the progression of spatio-temporal predictive modeling, focusing on the integration of GNNs and the shift toward adaptive adjacency matrices. Section IV examines the emerging paradigm of LLMs and Generative AI in transportation, emphasizing few-shot generalization and explainability. Section V discusses the critical limitations regarding scalability, dataset diversity, and inference speed. Finally, Section VI summarizes the key findings and provides insights for future research directions in autonomous urban management.

2. Methodology

In this research, in order to investigate the evolution of technologies related to prediction and identification of park position, a wide range of traditional hardware-based systems to modern approaches of smart city and artificial intelligence algorithms have been used. The data collection process was performed based on the web of science web (wos). The search strategy was developed in such a way that all the resources that were identified in the three areas of title, abstract and keywords have parking, detection, prediction, occupancy and smart. This search led to the identification of 532475 entries. To further carefully and restrict research scope, the results were reduced solely to the sources that the word parking was inserted as or keywords. In the next step, 105 papers were identified by applying the subject filter and selection of articles based on computer science category. After extraction of complete details of these works, the process of precise and case study was done which finally led to the selection of 65 articles eligible for final analysis. Finally, the findings of the analysis of these articles are presented.

3. Literature Review

Considering that urban traffic is one of the most important challenges of modern urbanism and 30 percent of existing traffic in cities is due to finding a place for car park [19], it is necessary to use sophisticated data-based methods in intelligent transportation systems. The process, often referred to as " patrolling for park" increases the average search time for more than seven minutes per device, resulting in significant driver fatigue, physiological stress, and systemic inefficiency such as increased carbon emissions and fuel waste [20]. To address these challenges, research from fundamental hardware sensors to the spine of complex visual recognition, spatial-temporal architectures have been predicted and recently the application of large linguistic models (LLMs) for autonomous urban management has evolved [21].

Considering data mining results, first, the evolution of real-time vehicle detection was briefly reviewed. Then, Spatio-Temporal Prediction and regional synchronization is discussed. In the next step, Efficiency and Sustainability in large-scale systems were evaluated. Then the trend to the large-language model (LLM) has been studied. In the next step, the existing Dataset in this field and existing standards have been discussed and finally research gaps have been presented.

3.1. Evolution of Real-Time Vehicle Detection: From Sensors to Computer Vision

Early detection methods rely on non-visual hardware that are classified as global and global settlement approaches [22]. Global systems using gate-arm valves or inductive loop detectors provide a general enumeration, but cannot provide a precise location [23]. In contrast, local occupation sensors, such as ultrasonic systems, magnetic field or radio frequency identification (RFID) provide an individual slit state [24]. In this domain, rPark is considered as the most perfect watershed in the domain, in which static RFID chips with very high frequency and high frequencies are used to achieve the accuracy of detection close to 100%[25]. Nevertheless, the most challenging and objections to these problems are: high installation costs, energy requirements, and sensitivity to stressors such as temperature and wind power [26].

consideration of such results is preferred to apply the visual methods of existing monitoring infrastructure [27]. The primary visual methods in which shallow learning techniques are used and they have high accuracy in respect of standard criteria. The disadvantage of these approaches were that they were sensitive to ambient noise [28]. By introducing the deep learning algorithms, the Convolutional neural network algorithm (CNNs) appeared, in which the desired features were automatically extracted [29]. Primary visual architectures have been focused on a cluster-based subspace. In order to optimize processing speed, reduced models such as mAlexNet and CmAlexNet have been used [22, 27].

Despite these achievements, patch-based methods were still ineffective under the influence of illumination variations, perspective distortions, and dysfunctional occlusions. To overcome these limitations, Multi-Branch Output ConvNeXt Network (MBONN) was proposed in which all the scenes have been used to simultaneously process all the scenes from a common feature map [1]. Each output branch in MBONN infers the state of a specific gap using global contextual information, allowing the system to control the background of occlusions and distortions of the lens. The EfficientNet-P model uses extended and compact blocks with a reduced parameter effect to record global features, which significantly crosses the base line on a diverse seasonal data set [3]. In addition, Attentional Graph Neural Networks (GNNs) were introduced to model the marking points as the structured data of the graph, thus eliminating the need for geometric manual processing after the parking [30].

3.2. *Spatio-Temporal Prediction and regional synchronization*

Forecasting the situation of near future traffic or vacant parking spaces (VPS) requires the registration of linear historical trends and complex non-Euclidean spatial correlations [5, 10, 11] [31]. While statistical models such as ARIMA and historical average (HA) affect short-term and flat data cycles, and cannot record nonlinear dynamics during severe oscillations [5, 10, 12]. To overcome these limitations, machine learning methods developed improvements, but the problem with which these models had was that those models treated the first degree of parking as a univariate problem regardless of spatial interactions [10, 11].

To overcome these limitations, researchers have proposed multi-view and adaptive approaches. The Hybrid Graph Convolution Network with Long Short-Term Memory (HGLT) model combines a global similarity matrix using the Pearson correlation coefficient to construct a similarity matrix beside the local adjacency. The overall assessments indicate that this view has been associated with an average of 28.19% of the prediction improvement [10]. In addition, in some of researches, the multi-GRU repetitive unit model has been modeled, in which using graph-based networks, spatial-temporal data has been integrated using gated networks to increase the prediction of parking space. This model combines the use of an adaptive proximity matrix that adjusts the spatial weights during training based on real-time data changes, multi-modal context. These developments allow models to record both the individual-level and macro-level urban layout characteristics [23].

3.3. *Efficiency and Sustainability in Large-Scale Systems*

With the expansion of the internet of things in the field of urban management, which is expected to manage thousands of sensors, traditional spatial-temporal learning models cannot be responsive [32]. These challenges led to research in the context of dimensionality reduction techniques. The PRGAT framework employs a ParkingRank-based focus mechanism that connects real-time evaluation of the parking service capacity to the graph attention network. By combining this method with the coarse meshes of the graph in hypernodes and preserving structural features-the framework will be improved by 30.5% [4].

Additionally, researchers used Temporal Convolutional Autoencoders to reduce the unified dimensionality of graph structures and node features. Unlike conventional coarse methods that reduce only the size of the graph structure, the TCN-ae module transforms the high-dimensional sparse data into low-dimensional compact, and facilitates the near-loss compression [32].

3.4. *The Large Language Model (LLM) Paradigm Shift*

The initial deep learning models were usually criticized for the nature of the "black box" because there was not sufficient intuitive understanding of the input-output roadmap. Integrating and documenting the models of the generating foundation shows that fundamental changes have been made to predict the traffic in these models. By applying the LLMs models, capabilities are provided that by applying it in areas with limited historical data, it is possible to provide accurate prediction [13, 15].

Another innovation introduced in this field is LEAF framework, in which the discriminative ability of LLMs has been used as selectors. To produce self-selection sets, the LEAF uses two branches (graph and hypergraph), in which the frozen LLM selects the most likely outcome, thus improving consistency under test temporal distribution shifts. Likewise, the LSDM diffusion model integrates models with the developed environment to obtain high uncertainty in personal traffic patterns [33].

3.5. *Critical Analysis of Datasets and Evaluation Standards*

The review of the literature suggests that there is a serious criticism of the high diversity of quality and standards of evaluation within the whole dataset in this area, The PKLot dataset is one of the common dataset for visual recognition, but its clear line-of-sight views oversimplify real-world tasks [34]. On the contrary, the SPKL dataset in which a set of challenging scenarios were introduced, vehicles often blend into snowy backgrounds [3].

In summary, it can be said that although visual occupancy detection and spatio-temporal GNNs have created excellent benchmarks for high accuracy, but such technologies have suffered from limitations such as rigid spatial assumptions and a lack of transparency [5, 10, 13]. The movement toward adaptive, efficient, and explainable frameworks imply that there is an urgent need for a unified approach so that we can simultaneously capture the multi-view dependencies and leverages generative prior knowledge to be able to overcome the rarity of dataset in this field. Addressing the tension between inference latency and model interpretability remains the primary unresolved problem for the next generation of autonomous urban management systems[15, 33]

4. Discussion

The findings of this study indicate that in the field of intelligent transportation systems (ITS), significant progress has been made, so that from static and hardware-based observations to time-adaptive modeling and recently developed models of generating foundation have been developed. This transformation is related to the urgent need to reduce the urban inefficiencies in which the " patrol for parking " forms about 30% of urban traffic, and the search time for finding a parking place in the city requires more than seven minutes of time, which has various consequences, including significant environmental degradation [10].

4.1. Synthesis of Sensing and Occupancy Detection

When the vehicle detection methods are evaluated, it can be realized with a clear change in the tools and tools used in this field so that non-visual hardware is modified to modern computer vision [1]. Comparing the accuracy and the outputs of these two methods, it can be said that the primary systems such as rPark in which static RFID chips are used are almost 100% accuracy. However, the main difficulty of using these solutions is high maintenance costs and high sensitivity to stressors such as high and high temperatures which make the work and their use difficult [7]. That is why the use of existing monitoring infrastructure has emerged as a common paradigm paradigm.

Methodologically, this field has transitioned from based on patch-based classification, in which individual slots with benefiting from reduced architectures such as mAlexNet were processed individually, to global context-aware frameworks [1]. One of the most important criticisms that has been introduced to the patchwork models is their vulnerability to illumination variations, perspective distortions, and occlusions within the car. In contrast, modern architectures such as the multi–branch output ConvNeXt network (MBONN) maximize the contextual information to simultaneously process and evaluate the state of all parking spaces [1]. This change reflects the theoretical development in which the practice of settlement recognition is performed not as a set of independent classification tasks but as a problem of understanding the integrated scene. In addition, the introduction of Dilated Convolutional Neural Networks has proven that the recording of high– frequency features on a large scale for tasks of binary occupation is more than the deeper and additional layers found in the spinal column of the standard ImageNet [8].

4.2. Comparative Spatio-Temporal Prediction Paradigms

Forecasting the state of traffic and VPS has changed from the linear statistical line (ARIMA) and has reached complex nonlinear modeling [10]. While the iterative neural networks (RNNs) and LSTMs successfully extract the temporal frequency, historically, they were historically constrained to not use non-euclidean space dependences [11, 35]. The integration of Graph Neural Networks (GNNs) addressed this by representing road networks as directed graphs.

However, there is considerable methodological weaknesses in the reliance on fixed-distance matrices. Traditional GNNs often assume that spatial autocorrelation is strictly a function of geographical proximity, thus ignoring the "functional synchronization" [36]. As identified within the framework of HGLT, remote business areas may show similar occupation patterns during the holidays, even though geographically far away. to overcome this gap, multi-point approaches using Pearson correlation coefficients and adaptive graph models (AGCRU) to the system allows the system to learn dynamic weights based on functional similarity and multi-sided factors such as interest points (POIs) and land use [10].

4.3. The Large Language Model Paradigm: Explainability and Adaptation

The newest and most influential technology which has recently been introduced into this field, is using large-language models (LLMs) to predict traffic. In the previous description, it can be said that traditional deep learning is inherently black box systems and no intuitive mapping of multi-modal inputs to the predicted results. While the alternative is replaced by a "white box" alternative by using textualizing traffic data into natural language and allows an intuitive prediction through Chain-of-Thought (CoT) reasoning [13].

Theoretical significance lies in the LLMs' ability to perform few-shot and zero-shot learning by activating inherent pre-trained world knowledge. Frameworks like TPLLM and GSF-LLM demonstrate superior accuracy in data-scarce regions where traditional GNNs typically overfit. Additionally, discriminative frameworks like LEAF utilize LLMs as selectors to identify the most likely future outcomes from choice sets generated by dual-branch predictors, significantly improving adaptability to test-time distribution shifts[14, 33].

4.4. *Systemic Limitations and Research Gaps*

Despite these advancements, several systemic gaps remain unresolved. A primary challenge is the trade-off between explainability and computational efficiency. Analysis of inference latency reveals that a 13B LLM can take over 26 seconds for a single prediction task that an LSTM completes in 0.011 seconds, making real-time deployment on edge devices currently unsustainable [15]. Furthermore, there is a persistent "domain gap" between natural language and structured traffic tensors that limits the transferability of pre-trained knowledge [13].

The second limitation is the lack of environmental variation in standard benchmarks. Most of the data sets, such as PKLot, provide clear vision that oversimplify the real world conditions. A recent introduction of SPKL data sets has shown that current models are struggling with winter images, where snow causes visual distortions that cause vehicles in the background [3].

Finally, as urban IoT networks expand to city-wide scales, the training overhead for spatio-temporal GNNs becomes prohibitive [4]. While dimensionality reduction techniques like graph coarsening combined with Temporal Convolutional Autoencoders (TCN-AE) have achieved training efficiency gains of 30.5%, unified reduction that preserves both structural topology and high-dimensional node features remains an active area of investigation [34].

4.5. *Theoretical and Practical Significance*

In practice, these enhancements facilitate the transition from simple monitoring to traffic and parking information that can play a significant role in drivers' direction and can help reduce traffic bottlenecks [32]. Theoretically, moving toward adaptive and adaptive hybrid models represents the convergence of structural graph learning and human contextual reasoning. The future research route should be prioritized by reducing the delay of LLM from knowledge distillation and the spread of diverse seasonal criteria to ensure the realization of fully integrated and flexible cities.

5. Conclusion

In this paper, the comprehensive evolution of intelligent transportation systems (ITS) has been investigated. It has been tried to emphasize on the approaches that clarify how and why the transition occurred from foundational hardware-centric monitoring to advanced generative spatio-temporal modeling. The integration of Deep Learning (DL) has transformed the landscape of urban mobility, enabling the transition from simple statistical models like ARIMA and Historical Average (HA)-which struggle with nonlinear traffic fluctuations-to complex architectures capable of capturing intricate high-dimensional patterns. Major findings indicate that Graph Neural Networks (GNNs), when coupled with recurrent units such as LSTMs or GRUs, offer superior performance in modeling non-Euclidean spatial dependencies. Furthermore, the recent emergence of Large Language Models (LLMs) has introduced a new paradigm for few-shot learning and explainable forecasting, effectively leveraging pre-trained world knowledge to predict traffic patterns in data-scarce environments.

Although technically, these approaches are responsive and have created positive and fundamental changes, however, there are various researches that need to be discussed more. A primary methodological limitation is the continued reliance on fixed distance-based adjacency matrices in GNN frameworks, which inherently fail to capture "functional synchronization" between geographically distant but functionally similar urban areas. While adaptive graph models and multi-view approaches have begun to address this, the computational overhead of training such models on city-wide scales remains a significant barrier. Furthermore, visual occupancy detection continues to struggle with environmental generalization; most established models are susceptible to failure under extreme weather conditions, such as winter snowfall or intense glare, primarily due to the lack of diverse, seasonally representative datasets. Additionally, the transition toward LLM-based predictors has introduced a critical trade-off between explainability and efficiency, as the high parameter counts of these foundation models result in inference latencies that are currently unsuitable for real-time edge deployment.

Future research is better focused on two issues: coordinating computational efficiency and predictive transparency. It seems that the development of advanced graph dimensionality reduction techniques is very important and necessary to enable sustainable forecasting in cities. To be able to communicate between the gap between the " black box " gap and discriminative LLM agents, it is necessary to provide stakeholders with intuitive, human-readable rationales for autonomous decisions. Moreover, research should prioritize the expansion of multi-modal datasets to include wintertime imagery and complex occlusion scenarios to ensure model robustness. Finally, the potential for cross-domain expansion-applying these learned spatio-temporal patterns to other transportation hubs like airports and high-speed rail systems-represents a vital frontier for the realization of truly integrated smart cities. By addressing these challenges, this field can move beyond the sheer data-based accuracy towards a more efficient urban management framework.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] L. Encío, C. Díaz, C. R. del-Blanco, F. Jaureguizar, and N. García, "Visual Parking Occupancy Detection Using Extended Contextual Image Information via a Multi-Branch Output ConvNeXt Network," *Sensors,* vol. 23, no. 6, p. 3329, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/6/3329.

[2] C. T. Ponnambalam and B. Donmez, "Searching for Street Parking: Effects on Driver Vehicle Control, Workload, Physiology, and Glances," *Frontiers in Psychology,* vol. 11, p. 574262, 2020. [Online]. Available: https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2020.574262/full.

[3] A. Martynova, "Revising deep learning methods in parking lot occupancy detection," *arXiv preprint arXiv:2306.04288,* 2023. [Online]. Available: https://arxiv.org/abs/2306.04288.

[4] Y. Wang, Z. Chen, K. Zhang, Y. Cui, Y. Yang, and L. Peng, "Efficient Large-Scale Urban Parking Prediction: Graph Coarsening Based on Real-Time Parking Service Capability," *IEEE Transactions on Intelligent Transportation Systems,* 2024. [Online]. Available: https://arxiv.org/abs/2410.04022.

[5] X. Xiao, Z. Jin, Y. Hui, Y. Xu, and W. Shao, "Hybrid Spatial–Temporal Graph Convolutional Networks for On-Street Parking Availability Prediction," *Remote Sensing,* vol. 13, no. 16, p. 3338, 2021. [Online]. Available: https://www.mdpi.com/2072-4292/13/16/3338.

[6] J. Li, H. Qu, and L. You, "An integrated approach for the near real-time parking occupancy prediction," *IEEE transactions on intelligent transportation systems,* vol. 24, no. 4, pp. 3769-3778, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9997228.

[7] A. Rahman and E. Ufiteyezu, "Smart parking occupancy detection method using smart app," *International Journal of Wireless and Mobile Computing,* vol. 26, no. 1, pp. 99-105, 2024. [Online]. Available: https://www.inderscience.com/info/inarticle.php?artid=136588.

[8] S. Nurullayev and S.-W. Lee, "Generalized Parking Occupancy Analysis Based on Dilated Convolutional Neural Network," *Sensors,* vol. 19, no. 2, p. 277, 2019. [Online]. Available: https://www.mdpi.com/1424-8220/19/2/277.

[9] M. K. Chitirala, T. Devarakonda, L. V. H. Chaluvudi, and G. B. A. Avvaru, "Car Parking Occupancy Detection Using Deep Learning," *International Journal of Scientific Research in Engineering and Management (IJSREM),* vol. 8, no. 4, 2024. [Online]. Available: https://www.researchgate.net/publication/380010414_Car_Parking_Occupancy_Detection_Using_Deep_Learning.

[10] W. Ye, H. Kuang, X. Lai, and J. Li, "A Multi-View Approach for Regional Parking Occupancy Prediction with Attention Mechanisms," *Mathematics,* vol. 11, no. 21, p. 4510, 2023. [Online]. Available: https://www.mdpi.com/2227-7390/11/21/4510.

[11] Y. Feng, Q. Hu, and Z. Tang, "Predicting vacant parking space availability zone-wisely: a graph based spatio-temporal prediction approach," *arXiv preprint arXiv:2205.02113,* 2022. [Online]. Available: https://ieeexplore.ieee.org/document/10098887.

[12] C. Zeng, X. Zhou, L. Yu, and C. Ma, "Parking Generating Rate Prediction Method Based on Grey Correlation Analysis and SSA-GRNN," *Sustainability,* vol. 15, no. 17, p. 13016, 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/17/13016.

[13] X. Guo, "Towards Explainable Traffic Flow Prediction with Large Language Models," *Communications in Transportation Research,* vol. 4, p. 100150, 2024. [Online]. Available: https://arxiv.org/abs/2404.02937.

[14] Y. Ren, Y. Chen, S. Liu, B. Wang, H. Yu, and Z. Cui, "TPLLM: A Traffic Prediction Framework Based on Pretrained Large Language Models," *arXiv preprint arXiv:2403.02221,* 2024. [Online]. Available: https://arxiv.org/abs/2403.02221.

[15] M. Peng, X. Guo, X. Chen, M. Zhu, and K. Chen, "LC-LLM: Explainable Lane-Change Intention and Trajectory Predictions with Large Language Models," *arXiv preprint arXiv:2403.18344,* 2024. [Online]. Available: https://arxiv.org/abs/2403.18344.

[16] C. Hu, "Self-Refined Generative Foundation Models for Wireless Traffic Prediction," *arXiv preprint arXiv:2408.10390,* 2024. [Online]. Available: https://arxiv.org/abs/2408.10390.

[17] H. Wang, "GSF-LLM: Graph-Enhanced Spatio-Temporal Fusion-Based Large Language Model for Traffic Prediction," *Sensors,* vol. 25, no. 21, p. 6698, 2025. [Online]. Available: https://www.mdpi.com/1424-8220/25/21/6698.

[18] Y. Zhao, X. Luo, H. Wen, Z. Xiao, W. Ju, and M. Zhang, "Embracing large language models in traffic flow forecasting," in *Findings of the Association for Computational Linguistics: ACL 2025*, 2025, pp. 8108-8123. [Online]. Available: https://arxiv.org/abs/2412.12201.

[19] C. N. Badii, P; Paoli, I, "Predicting Available Parking Slots on Critical and Regular Services by Exploiting a Range of Open Data," *IEEE ACCESS,* vol. 6, 2018, doi: 10.1109/ACCESS.2018.2864157.

[20] H. Z. Qin, F; Yu, BH; Wang, ZF, "Analysis of the Effect of Demand-Driven Dynamic Parking Pricing on on-Street Parking Demand," *IEEE ACCESS,* vol. 10, 2022, doi: 10.1109/ACCESS.2022.3187534.

[21] R. Z. Zheng, HF; Wu, XH; Meng, W, "T-psd: T-shape parking slot detection with self-calibrated convolution network," *JOURNAL OF REAL-TIME IMAGE PROCESSING,* vol. 21, 2024, doi: 10.1007/s11554-024-01460-6.

[22] G. C. Amato, F; Falchi, F; Gennaro, C; Meghini, C; Vairo, C, "Deep learning for decentralized parking lot occupancy detection," *EXPERT SYSTEMS WITH APPLICATIONS,* vol. 72, 2017, doi: 10.1016/j.eswa.2016.10.055.

[23] C. Y. Qian, KX; He, JP; Peng, XJ; Huang, HJ, "Curb parking occupancy prediction based on real-time fusion of multi-view spatial-temporal information using graph attention gated networks," *APPLIED SOFT COMPUTING,* vol. 171, 2025, doi: 10.1016/j.asoc.2025.112781.

[24] L. M. Mainetti, I; Patrono, L; Solic, P; Stefanizzi, ML; Vergallo, R, "A Novel IoT-aware Smart Parking System based on the integration of RFID and WSN technologies," *INTERNATIONAL JOURNAL OF RF TECHNOLOGIES-RESEARCH AND APPLICATIONS,* vol. 4, 2016, doi: 10.3233/RFT-161523.

[25] V. L. Rajyalakshmi, K, "Detection of car parking space by using Hybrid Deep DenseNet Optimization algorithm," *INTERNATIONAL JOURNAL OF NETWORK MANAGEMENT,* vol. 34, 2024, doi: 10.1002/nem.2228.

[26] S. S. Verma, A; Sunil, MP; Islam, SMN; Kumar, DS; Jebarani, MRE, "Deep learning enabled real time parking monitoring using YOLOv7 for intelligent and secure critical infrastructure," *DISCOVER COMPUTING,* vol. 28, 2025, doi: 10.1007/s10791-025-09789-7.

[27] S. B. Hudda, R; Khurana, A; Haribabu, K, "A WSN and vision based smart, energy efficient, scalable, and reliable parking surveillance system with optical verification at edge for resource constrained IoT devices," *INTERNET OF THINGS,* vol. 28, 2024, doi: 10.1016/j.iot.2024.101346.

[28] H. D. Kuang, KX; Wang, QX; Ye, W; Qu, HH; Li, J, "Deep meta-learning approach for regional parking occupancy prediction considering heterogeneous and real-time information," *ADVANCED ENGINEERING INFORMATICS,* vol. 64, 2025, doi: 10.1016/j.aei.2024.102969.

[29] M. S. Babic, B; Hluchy, L; Baiamonte, G; Cali, M, "Modeling Parking Occupancy Using Algorithm of 3D Visibility Network," *IEEE ACCESS,* vol. 13, 2025, doi: 10.1109/ACCESS.2025.3562796.

[30] G. Z. Chen, S; Weng, WY; Yang, WJ, "Residual spatial-temporal graph convolutional neural network for on-street parking availability prediction," *INTERNATIONAL JOURNAL OF SENSOR NETWORKS,* vol. 43, 2023, doi: 10.1504/IJSNET.2023.135840.

[31] E. B. Magsino, JMC; Puno, A; Ong, S; Siapco, C; Vibal, J, "Determining Commercial Parking Vacancies Employing Multiple WiFiRSSI Fingerprinting Method," *JOURNAL OF SENSOR AND ACTUATOR NETWORKS,* vol. 12, no. 2, 2023, doi: 10.3390/jsan12020022.

[32] W. Z. Shao, Y; Xiao, PF; Qin, KK; Rahaman, MS; Chan, JF; Guo, B; Song, AY; Salim, FD, "Transferrable contextual feature clusters for parking occupancy prediction," *PERVASIVE AND MOBILE COMPUTING,* vol. 97, 2024, doi: 10.1016/j.pmcj.2023.101831.

[33] Y. Zhao, "Embracing Large Language Models in Traffic Flow Forecasting," *arXiv preprint arXiv:2412.12201,* 2024. [Online]. Available: https://arxiv.org/abs/2412.12201.

[34] N. B. Thakur, E; Jain, R; Acharya, B; Hu, YC, "Deep learning-based parking occupancy detection framework using ResNet and VGG-16," *MULTIMEDIA TOOLS AND APPLICATIONS,* 2023, doi: 10.1007/s11042-023-15654-w.

[35] X. Zhang, "Enhancing Predictive Models for On-Street Parking Occupancy: Integrating Adaptive GCN and GRU with Household Categories and POI Factors," *Mathematics,* vol. 12, no. 18, p. 2823, 2024. [Online]. Available: https://www.mdpi.com/2227-7390/12/18/2823.

[36] C. Y. Huang, Y; Wei, LN, "SENSOR NETWORK SOLUTIONS FOR AIRCRAFT ROUTE SCHEDULING AND PARKING ALLOCATION WITH LOCALIZATION AND SYNCHRONIZATION," *SCALABLE COMPUTING-PRACTICE AND EXPERIENCE,* vol. 25, no. 1, 2024, doi: 10.12694/scpe.v25i1.2391.