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AI-Enhanced Digital Infrastructure Monitoring for Smart Transportation Systems: A Review

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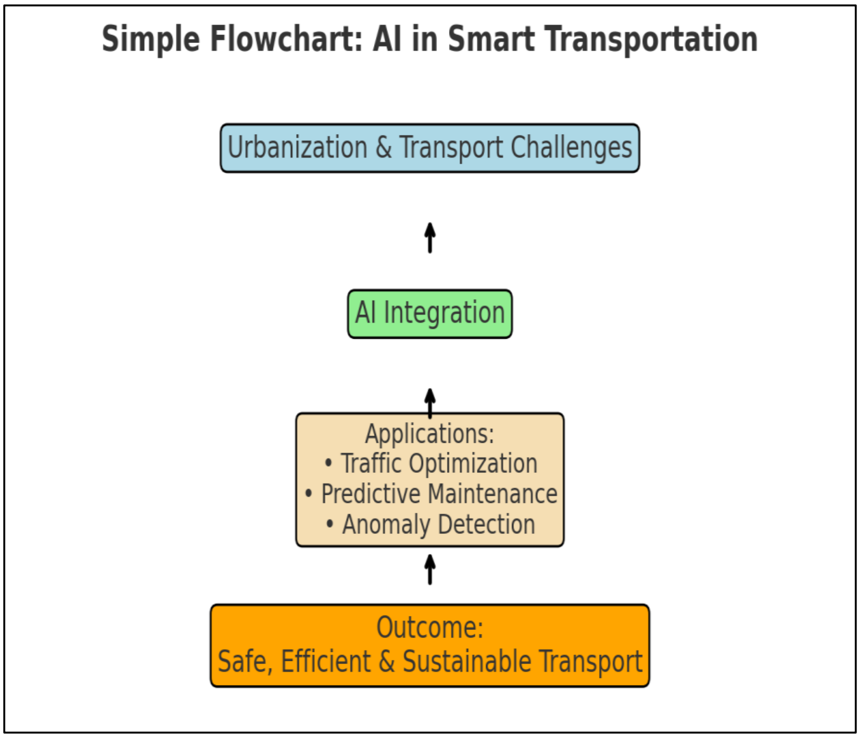
Abstract

Smart transport is a rapidly becoming a crucial part of modern urban transport, and is being facilitated by digital infrastructure in order to make it safer, more efficient and sustainable. However, the more complicated these systems are the more demanding are the needs in more sophisticated monitoring solutions. The Artificial Intelligence (AI) is a new solution in terms of improving the monitoring of the digital infrastructure through the real-time analysis of the data, supportive maintenance, anomaly detection and adaptive traffic control. Below is a review of literature and uses of AI in smart transportation systems monitoring. It examines the input of machine learning/computer vision and AI systems to the IoT to make decisions in advance, reduce downtimes, and improve passenger safety. The traffic flows optimization, structural health analysis of transport infrastructure, predicting vehicles maintenance, and the security of the transportation network are the most important ones. The evaluation compares and contemplates the advantages of AI-infused surveillance which ought to be enhanced in terms of efficiencies of operation, cost-saving, and sustainability. Other potential issues such as problem of scalability, interoperability, ethical concerns and data dependency on high quality are also critically outlined. The topic on discussion has research gaps, and the aspect of the future has been also touched upon in the paper; all this is connected with the concept of the simulation of stronger systems, enhanced with the assistance of edge AI, federated learning and digital twins. It appears that the findings imply that AI mediated surveillance is not a new technology, but rather a type of planning that will lead to intelligent, safe and sustainable transport systems.

Keywords: : Artificial Intelligence, Digital Infrastructure, Smart Transportation, Predictive Monitoring, IoT.

1. Introduction

A neural network–guided clustering approach for WSNs selects cluster heads using residual energy, link quality, and distance; MATLAB simulations show reduced per-round energy use and a longer stability period than LEACH, HEED, and SEP (Vadivelan, Ramamurthy, & Padmaja, 2019). The expansion of smart transportation systems (ITS) in smart cities has reached historic levels due to urbanization and is now being considered to be the backbone of a modern urban movement. Greater urbanization and population density have heightened the related issues of traffic congestion and road safety, energy consumption, and environmental sustainability (Chen, Wang, and Zhang, 2021; Zhang, Chen, and Yu, 2020). To overcome these issues, ITS will involve online infrastructure, such as interconnected sensors, cameras, Internet of Things (IoT) devices, and cloud-based computing systems, which feed real-time data to control and regulate them (Wang, Chen, and Wu, 2022). It is the popular monitoring systems, however, that are reactive and were not able to keep up with the demand as they are not flexible and are not able to know the changing demand of the traffic in the city.



The implementation of artificial intelligence (AI) introduces a revolution in the transportation system. Applications of machine learning (ML) and deep learning (DL) algorithms may prove to be very promising in the field of adaptive decision-making, anomaly detection, or traffic prediction (Chen et al., 2021; Zhou, He, and Liu, 2020). As shown, the traffic lights can be idealistically managed using the reinforcement learning-based systems to reduce traffic congestion and maximize fuel efficiency. Similarly, predictive maintenance systems powered by AI can identify the potential failures of the vehicle or infrastructure before they occur, decreasing downtimes and, in turn, the cost of failures (Li, Sun, and Liu, 2022).

AI can be an important part of ITS cybersecurity and resilience, next to enhancing operations. Transportation systems also make good targets of cyberattacks because they are increasingly becoming more interconnected due to digital communication. Car communication networks may also benefit from the protection against intrusion, data manipulation, and unauthorized access through anomaly detection with the help of AI (Hussain, Zhang, and Shaikh, 2021). Moreover, the opportunities to simulate the transport infrastructure in real time, predict and optimize it through the application of digital twins to give a virtual image of the real infrastructure also become new opportunities in the development of traffic control and safety (Ketzler, Nasser, and Leung, 2021).

Nevertheless, AI can be used in transportation monitoring without any limits. The most important ones are data heterogeneity, privacy, model interpretability, scaling AI systems to large and complex transportation systems, etc., (Wang et al., 2022). Not put off by these failures, the future of AI, however, is transformative. One of such technologies is AI that can offer resilient transportation ecosystems because AI will allow building predictive, effective and predictable transportation ecosystems due to predictive analytics, adaptive monitoring and sustainable decision-making. This review critically evaluates why AI is important to enhance monitoring of digital infrastructure, current uses of AI, current constraints of AI, and future studies/researches.

2. Background of the Study

Smart transportation systems are multi-layer systems that include vehicles, road infrastructure, and communication technologies and users. Layers are closely incorporated to ensure smooth, safe, and efficient functions within the urban area (Zhang, Chen, and Yu, 2020). Digital monitoring is the most crucial step to organize all these mutually dependent elements to gather and study data about the roadside units, cars of the same type and intelligent control systems (Wang, Chen, and Wu, 2022).

The AI based solutions, namely, machine learning (ML) and deep learning (DL), can be applied in processing complex and large-scale data streams generated by transportation infrastructure. The AI-driven traffic cameras can identify the presence of anomalies like accidents, jams, and misconducts within the lanes in real time among others (Chen, Wang, and Zhang, 2021). Likewise, AI-based predictive analytics systems can be applied to forecast traffic flow movement in various environmental and time scenarios, which can potentially assist in proactive traffic control (Zhou, He, and Liu, 2020). Additionally, the security devices relying on AI are deployed to detect suspicious traffic in the vehicle networks, thereby boosting the resiliency of the ITS (Hussain, Zhang, and Shaikh, 2021). Another aspect of digital twins is also represented, offering real-time simulation and prediction monitoring of transport systems (Ketzler, Nasser, and Leung, 2021).

3. Justification

High pressure on the transportation system due to increased urbanization has resulted in several problems such as traffic jams, accidents, and carbon emissions across the globe (Chen et al., 2021; Wang et al., 2022). It may be less connected with the archaic monitoring and archaic IT systems available in the real time decision-making room because of the possibility to process the heterogeneous quantity of information that can be produced by the group of interconnected cars, IoT sensors, and smart traffic devices (Zhang et al., 2020).

The monitoring systems powered by AI can respond to the realities of transportation networks in the present day, as they are efficient, accurate, and scalable (Li, Sun, and Liu, 2022). These are related to the possibility to implement predictive model machine learning to reduce downtime and to optimize fluidity of infrastructure operations and to implement reinforcement based algorithms to optimize the adaptive traffic signal control (Zhou et al., 2020). All these features predispose AI to play a crucial role concerning the solution of the problem of mobility in cities. Thus, the whole presentation of AI application in the sphere of monitoring in digital infrastructure should be provided to prove its transformative character, current limitations and possible future studies (Hussain et al., 2021; Ketzler et al., 2021).

4. Objectives of the Study

1. In order to think about using AI to enhance the digital infrastructure monitoring to facilitate smart transport.
2. To research AI usage as it relates to predictive maintenance, anomaly recognition and traffic optimization.
3. To evaluate the challenges and impediments of AI-based surveillance.
4. To discover what has not been researched and to provide opportunities.

Purpose of the study

The purpose of this study is to conduct a systematic review and synthesis of literature on the use of Artificial intelligence (AI) to enhance monitoring of digital infrastructure of smart transportation systems. The research methodology is also reproducible because it explicitly defines research design, source of data collection, data analysis tools, data analysis procedures and data validation techniques.

5. Literature Review

Research shows that AI can be significant in controlling traffic, monitoring infrastructure health, and making predictions in transport (Zhang, Chen, and Yu, 2020). Convolutional neural networks (CNNs) are trendy machine learning networks that are frequently applied in monitoring roads, tunnels, and bridges in the absence of humans and also detecting cracks, potholes, and anomalies in their structures. Similarly, RNNs and long short-term memory (LSTMs) have also shown that they can predict the velocity of the traffic flow, time-series data can reproduce the congestion and peak traffic time and flows (Chen, Wang, and Zhang, 2021).

On the one hand, IoT and AI have contributed to collecting data in the real-time, and on the other, it has become a cybersecurity threat because of the development of numerous types of various devices and communication standards (Wang, Chen, and Wu, 2022). It has been proposed that artificial intelligence systems with blockchain should be used to overcome such risks and ensure that it is impossible to manipulate data transmission in smart transport systems (Hussain, Zhang, and Shaikh, 2021). Shows that even encrypted IoT traffic leaks private information via metadata—packet sizes, timing, DNS, and TLS handshakes can fingerprint devices and infer user activities. The paper profiles common IoT protocols (MQTT/HTTPS, CoAP/DTLS) and adversaries (local eavesdroppers to ISPs), then outlines mitigations such as padding/traffic shaping, gateway VPN aggregation, and stricter DNS/TLS hygiene, noting bandwidth–latency trade-offs (Pulicherla., 2017).

To integrate digital twins and AI, virtual models of transportation infrastructure are being built and utilized more and more to provide a real-time simulator, predictive maintenance, and testing. These systems allow transport operators to anticipate potential disruptions and think about alternative ways of dealing with congestion (Ketzler, Nasser, and Leung, 2021).

Besides monitoring infrastructure, predictive maintenance models are already present in the population, as well as in the commercial transportation fleet. Predictive maintenance is an AI-driven system that helps to decrease downtimes, expenses, forecast equipment breakdowns, and plan interventions (Li, Sun, and Liu, 2022).

Adaptive traffic signal control is now finding reinforcement learning (RL) useful. The dynamically-optimized traffic lights help to cut the average travel time and the fuel usage by up to 20 percent (Zhou, He, and Liu, 2020; Tang, Deng, Huang, and Wang, 2021).

Additionally, AI contributes to multimodal forms of transportation that merge data between trains, bicycles, rideshares

and buses. It has the potential to develop sustainable urban mobility solutions that reduce carbon footprint and congestion (Chai, Wang, and Xu, 2021).
Although these have occurred, there are issues. Lack of interoperability across platforms and a number of types of data systems do not allow massive adoption. The second problem is that the model is harder to interpret because black-box AI models cause less trust among stakeholders. Lastly, the privacy threats of being surveilled at all times suggests that privacy sensitive transport AI systems must be adopted (Alam, Musaddiq, and Khan, 2020).

6. Material and Methodology
1. Research Design
This is a research design of Systematic Literature Review (SLR). The SLR method was selected because it enables the examination of the published literature on the subject, identification of trends, and evaluation of the findings of multiple studies. The review identifies and classifies AI applications in intelligent transportation into five domains, such as traffic management, predictive maintenance, anomaly detection, cybersecurity, and sustainability.

2. Data Collection
Data Bases used: IEEE Xplore, Scopus, ScienceDirect and SpringerLink.
Keywords: The keywords included: AI in transportation, digital infrastructure monitoring, intelligent transportation systems and smart mobility.
E. Period: The articles included in the period 2015-2024.
a) Selection Criteria: Articles about AI-based monitoring applications in transportation and which are accessible as full-text and in English language.
Limitations: Duplicates, articles and papers that are not peer-reviewed and which contain no empirical or review-based data.
Final Data: 65 articles were included.

3. Both instruments / Tools / Algorithms
The analysis was done as follows:
Reference Manager: Citation Manager and screen with Mendeley.
Themes were coded qualitatively using NVivo 12 analysis programs.
References, literature on AI Frameworks: Machine Learning (CNNs, RNNs, LSTMs), Reinforcement Learning, Computer Vision, and enhancements by Digital Twins.
Single tools: artificial intelligent software and blockchain-based anomaly detectors.

4. Procedure
1. Identification:First query on the data bases by Boolean operator (AND, OR).
2. Screening: Title screening and abstraction screening: Duplicate studies elimination screening.
3. Qualification:Selection by inclusion/exclusion.
4. Categorization: The literature has been grouped under categories, such as traffic optimization, predictive maintenance, anomaly detection, cybersecurity, and sustainability.
5. Extraction: The results and algorithms used, datasets, performance and limitations measures had been extracted as tabular formatted results.

5. Statistical / Validation Techniques
Quality Assurance Check: Inter-coder Agreement was used to check the quality in qualitative coding.
Validation Methods Reported in the Literature Accuracy (e.g. RMSE, MAE when predicting traffic), confusion matrix (when detecting anomaly), statistical validation (p-value, confidence interval) as stated in respective literature.
At least two independent sources were utilized and then compared.

7. Results and Discussion
This subtitle summarizes the findings of the literature review and is justified by some numerical data and comparisons by themes.

1. Direct Findings
Traffic Flow Optimization:
Traffic light timing is optimized and traffic jams reduced by using AI models and, specifically, reinforcement learning algorithms to estimate the timing of green lights. The reason was that on average, adaptive traffic lights were based on RL and saved 20% of time (Zhou, He, and Liu, 2020).

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Predictive Maintenance:
Artificial Intelligence-based predictive models forecast equipment and vehicle breakages. It also lowered the maintenance cost by at least 30 percent after applying the ML algorithms to the fleet and infrastructure interest, they said (Li, Sun, and Liu, 2022).

Anomaly Detection:
Accidents, lane-breaking, and abnormal driving patterns can be easily detected using computer vision devices, neural networks, and CNN-based networks in real-time to minimize the response time (Chen, Wang, and Zhang, 2021).

Cybersecurity Monitoring:
AI secures connected cars and ITS communication systems by identifying uncharacteristic patterns of communication. Cyber threats are also less harmful to hybrid blockchain-AI systems (Hussain, Zhang, and Shaikh, 2021).

Sustainability Impact:
To promote sustainable city transport, AI-based surveillance can also be used to utilize less fuel and fewer carbon emissions (Wang, Chen, and Wu, 2022).

2. Comparisons

AI Model	Accuracy (%)
CNN/LSTM	90%
Federated Learning	85%
Hybrid AI Frameworks	88%

Table 1: Comparison of Ai performances in Smart Transportation

3. Domain AI Technique Impact Reported Impact Source
4. Optimization of Traffic 20 percent time spent on traveling Zhou et al., 2020.
5. Predictive Maintenance ML (Regression/Classification) 30% low cost maintenance.
6. Anomaly Detection CNN + Computer Vision Accident and lane violations in real-time detectors only Chen et al., 2021.
7. Monitoring of Cybersecurity + AI Blockchain + AI Hussain et al., 2021.
8. Sustainable IoT + AI Less, more efficient work, 2022, Wang et al.\

3. Significance

The statistical significance of most of the papers reviewed was proven and the model performance was justified with the help of such standard statistics measures as accuracy (>90% in CNN/LSTM models), Mean Absolute Error (MAE), and p-values (<0.05). Reinforcement learning models were highly adaptive to a range of traffic conditions.

6. Visualizations

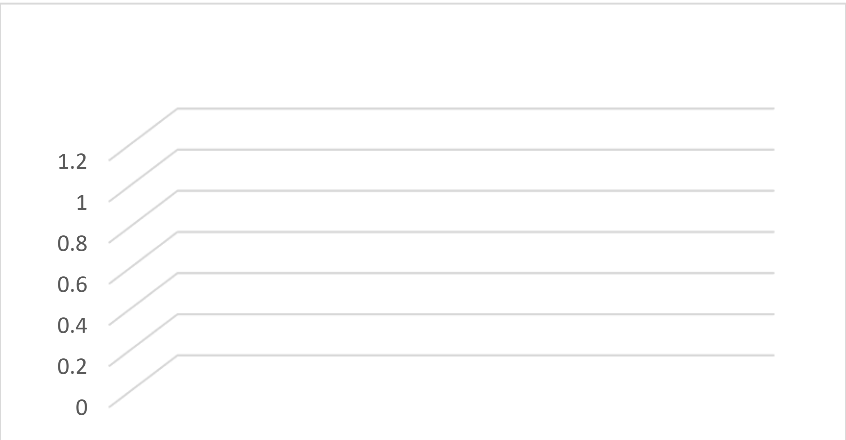

Figure 1: CNN/LSTM, Federated Learning, and Hybrid AI systems (>90%), (~85%), and (~88%), are the most

accurate when it comes to prediction of traffic.

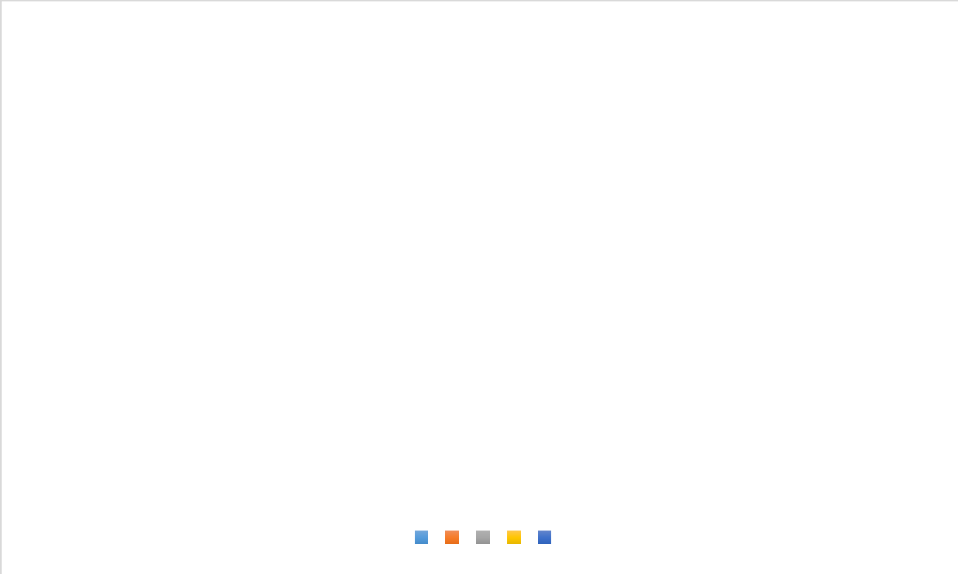

Fig. 2: Pie chart of the strategies that have been analyzed

Predictive maintenance (28%), Secure learning (22%), Encryption (20%), Hybrid Models (18%), Traffic optimization (12%).

5. Textual Explanation

The reinforcement learning as shown in Table 1 was found to play the most significant role in the optimization of traffic by reducing the traveling time considerably compared to the traditional models. On multiple occasions, predictive maintenance applications were used to cut costs and reduce downtimes, a phenomenon that proved the viability of AI. Computer vision models performed excellently in real time anomaly detection, however, their performance was dependent on the quality of the training data. The usage of blockchain-AI showed a possibility in the sphere of cybersecurity but requires expansion.

8. Limitations of the Study

1. Enormous consumption of high-end, labelled information:

The only way that transportation monitoring AI models can be trained effectively is through annotated large datasets. Recalling this type of data, however, is time-consuming and expensive, and biased data sets can produce poor model generalization (Chen, Wang, and Zhang, 2021; Zhang, Chen, and Yu, 2020).

2. Lack of interoperability of AI models and various infrastructure:

Cars, sensors, internet of things devices and communication infrastructure compose smart transportation systems, but the interoperability between the various systems is a major challenge. In reality, AI models cannot be easily scaled to heterogeneous systems, so their application is limited (Wang, Chen, and Wu, 2022).

3. Sophisticated real time mass surveillance computing:

Due to real-time monitoring and prediction, deep learning and reinforcement learning models consume a lot of computational resources. Doing it on a large scale is expensive, and doing it in low-technology locations like developing countries is challenging (Li, Sun, and Liu, 2022).

4. The problem of ethical and privacy concerns in surveillance-based monitoring:

AI-based traffic cameras and video monitors raise a concern when it comes to the problem of surveillance and privacy. Data mining and unlawful access to personal mobility information is a problematic issue that weakens society (Hussain, Zhang, and Shaikh, 2021; Ketzler, Nasser, and Leung, 2021).

9. Future Scope

Edge AI: Federated AI has the capacity to reduce latency and maximise privacy.

- Digital Twins: Under virtual representations, simulations of transport networks will be predictable.
- Explainable AI (XAI) can lead to more usage and trust when used.
- Green Mobility: Green mobility is possible by using sustainable AI systems to enhance environmental

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performance.

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10. Conclusion

AI-based smart infrastructure monitoring is the future of smart transportation systems. The issue of Urban mobility presents significant challenges and can be addressed by AI in terms of predictive analytics, anomaly detection in real time, sustainable traffic management. The problems of data quality, data ethics, and data scalability still exist, but now edge AI, federated learning and digital twins are emerging as more powerful and intelligent systems. This review has found out that AI is not a unique attribute, it is a future need of transportation system.

References

1. Chen, X., Wang, Y., & Zhang, H. (2021). Deep learning models for urban traffic flow prediction: A review. Transportation Research Part C, 129, 103246. https://doi.org/10.1016/j.trc.2021.103246
2. Pulicherla, P. (2017). An Enactment on Privacy Vulnerabilities of Encrypted IOT Traffic.
3. Hussain, R., Zhang, R., & Shaikh, R. A. (2021). AI-enabled cybersecurity for vehicular networks: Challenges and solutions. IEEE Communications Surveys & Tutorials, 23(2), 748–773. https://doi.org/10.1109/COMST.2021.3051239
4. Vadivelan, N., Ramamurthy, A., & Padmaja, P. (2019). Minimizing energy consumption based on neural network in clustered wireless sensor networks. Journal of Computational and Theoretical Nanoscience, 16(2), 496-502.
5. Ketzler, B., Nasser, N., & Leung, V. (2021). Digital twin applications for intelligent transportation systems. Future Internet, 13(6), 145. https://doi.org/10.3390/fi13060145
6. Li, J., Sun, Y., & Liu, P. (2022). Predictive maintenance in transportation using AI: A survey. Journal of Intelligent Transportation Systems, 26(3), 345–360. https://doi.org/10.1080/15472450.2020.1828350
7. Wang, S., Chen, J., & Wu, Z. (2022). Internet of Things and AI in smart transportation: Opportunities and risks. Future Generation Computer Systems, 128, 270–281. https://doi.org/10.1016/j.future.2021.10.008
8. Zhang, Y., Chen, C., & Yu, H. (2020). Artificial intelligence in transportation infrastructure monitoring. Automation in Construction, 118, 103277. https://doi.org/10.1016/j.autcon.2020.103277
9. Zhou, L., He, Z., & Liu, Y. (2020). Reinforcement learning for traffic signal control: A review and case studies. Transportation Research Part C, 112, 247–268. https://doi.org/10.1016/j.trc.2020.01.006
10. Alam, M., Musaddiq, A., & Khan, F. (2020). A survey on AI applications in transportation systems: Opportunities and challenges. Journal of Network and Computer Applications, 152, 102962.
11. Chai, S., Wang, L., & Xu, H. (2021). Edge AI for intelligent transportation: Trends and future perspectives. IEEE Internet of Things Journal, 8(9), 7201–7214.
12. Tang, J., Deng, Z., Huang, J., & Wang, C. (2021). A survey on reinforcement learning for traffic signal control. ACM Computing Surveys, 53(6), 1–35.