

Machine Learning in Intelligent Transportation: A Systematic Review

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Abstract. In recent years, machine learning technology, with its powerful data-driven capability, has shown a broad application prospect in intelligent transportation. This paper adopts a systematic literature review approach to comprehensively analyze the application of machine learning in intelligent transportation systems, including such key areas as traffic congestion management, traffic safety enhancement, public transportation resource optimization, and environmental pollution control. It is found that advanced algorithms represented by Neural Network and Graph Neural Network have made breakthroughs in spatio-temporal prediction of traffic flow, accident risk assessment, and public transport scheduling optimization. Machine learning technology promotes the intelligent transportation system to realize the transformation from theoretical innovation to practice, which not only significantly improves the operational efficiency of the existing transportation infrastructure but also provides a new paradigm for solving urban transportation management problems.

Keywords: Intelligent Transportation System, Machine Learning, Urban Transportation, Review.

1. Introduction

With the acceleration of urbanization, the number of vehicles has been growing exponentially. The resulting contradiction between traffic supply and demand has become a major bottleneck restricting the sustainable development of cities. Traffic congestion, traffic accidents, and vehicle emissions are becoming more and more prominent, seriously affecting the sustainable development of cities. City managers have taken many measures, but practice shows that it is neither sound nor reasonable to rely solely on increasing road supply to meet the growing traffic demand. According to Downs Law, every 10% increase in road supply will induce 8.5% new traffic in the short term. Coupled with the limited land resources in the city and the rigid constraints of the *Standard for Urban Comprehensive Transport System Planning*, the expansion of the road network faces significant bottlenecks.

In the face of increasingly severe road load pressure, city managers not only need to implement more efficient traffic management programs and more reasonable traffic resource allocation policies, but also need to explore innovative solution paths. In recent years, the rapid development of the Internet of Things (IoT) and Intelligent Transportation Systems (ITS) has provided new ideas and solutions for solving urban transportation problems. This not only significantly reduces the additional consumption of energy [1] but also effectively reduces the frequency of urban traffic accidents and improves the overall safety of urban transportation systems. At present, ITS has been widely used in the world, and China has also established a relatively complete one.

Machine learning technology, as an important support in the field of intelligent transportation, is reshaping the mode of urban traffic management with its wide application. Advanced algorithms such as neural networks, deep learning, KNN, and Naive Bayes have demonstrated excellent performance in the fields of urban traffic flow prediction, transportation system reliability assessment, traffic congestion management, and automated driving, which have attracted extensive attention from the industry. The innovative solutions proposed by scholars have achieved remarkable results. For example, the Hybrid Time-varying Graph Neural Network (HySTGNN) proposed by Dai et al. [2] reduces the 15-minute traffic flow prediction error to 6.3% in the PeMS benchmark test through the dynamic weather event mapping construction method. The multi-graph neural network for traffic flow prediction incorporating traffic accidents (MTPP) framework developed by Ye's team [3] (KDD

2023) realizes an increase of 87.4% for the average monthly accident warning accuracy of the key monitored road sections after the engineering deployment in the Hangzhou City Traffic Brain. Chen et al. [4] innovatively integrated the Teaching-Learning-based Optimization (TLBO) and Hybrid Neural Network (ANN-RNN) architectures to construct a multi-objective optimization model, which systematically incorporates the key parameters of traffic modal interaction cost, energy efficiency, and environmental externalities, significantly improving the ability of adaptive regulation and control of the urban road network.

These technological breakthroughs mark the paradigm shift of intelligent transportation research from theoretical innovation to engineering application, which provides a new path to crack the Downs-Thomson Paradox by improving the operational efficiency of the existing road network instead of simply expanding the road capacity. In order to summarize previous research results, provide references for subsequent researches, and offer reference for city managers, this paper summarizes the application and research progress of the existing machine learning methods in the field of urban transportation, and discusses different machine learning methods in solving the current problems by combing literature from Web of Science, ScienceDirect, IEEE, CNKI and other databases. It further looks forward to the future development direction of machine learning applications.

2. Status of Urban Transportation Development

In the face of the continuous expansion of urban space and population concentration, the traditional transportation system gradually shows its limitations in response to the increasingly complex travel demand and resource constraints. In order to solve this problem, the current multi-modal transportation system has developed rapidly, promoting the urban transportation system to present multi-dimensional innovation [5]. This is manifested in the enhancement of the quality and efficiency of the traditional public transportation system, the synergy between shared mobility and individual transportation, the maturation of automated driving technology, and the intelligent and intensive construction of integrated hubs such as seamless metro-bus interchange centers. Through rational allocation and collaborative scheduling of different transportation modes, urban transportation managers are focusing on systematically enhancing travel efficiency, alleviating congestion, and promoting the transformation and upgrading of urban transportation in the direction of low-carbon intelligence.

Although the application of multi-modal transportation systems and intelligent transportation technologies has improved the effectiveness to a certain extent, it still faces significant challenges in the actual development process.

- (1) The effectiveness of traffic congestion management is limited. With the continuous progress of urbanization, the population and motor vehicle ownership continue to rise, bringing more carrying pressure to the road network. Especially during peak commuting hours, congestion has become the norm on major urban roads and key nodes, severely restricting travel efficiency and quality of life. Despite the continuous promotion of road capacity expansion and public transportation capacity enhancement, traditional traffic management methods are difficult to effectively respond to the challenges of diversified travel demand and complex traffic flow.
- (2) Traffic safety risks remain prominent. The growth of urban traffic volume and a high-density road network environment multiply the pressure of accident prevention and control, and the accident rate on urban roads remains high. On the one hand, the proliferation of shared mobility services and the mixed traffic involving diverse participants have exacerbated conflicts, with the tension between motorized and non-motorized vehicles being particularly pronounced. On the other hand, the deficiencies in infrastructure planning and the lagging of traffic regulations have further amplified the systemic safety risks.

- (3) A structural imbalance exists between supply and demand for public transportation. During critical hours, such as peak commuting hours, there is a significant spatial and temporal mismatch between capacity supply and travel demand, leading to overloading of core routes and forcing residents in underserved areas to turn to individual motorized travel. This tidal supply-demand contradiction, combined with deficiencies in network coverage, creates a vicious cycle of transportation mode switching.
- (4) The effectiveness of transportation pollution control is lagging. As the main source of mobile pollution in cities, motor vehicles emit exhaust gases containing a large number of harmful substances, such as carbon dioxide, nitrogen oxides, and particulate matter, which not only exacerbate the deterioration of air quality in cities but also pose a great threat to the health of residents. Although some cities have implemented environmental policies such as traffic restrictions and the introduction of electric vehicles, the problem of traffic pollution has not yet been fundamentally solved.

ITS is another important part of the modern urban transportation system. Considering the efficiency bottleneck encountered by the traditional traffic management method, ITS has become a strategic choice to crack the urban traffic management dilemma. By integrating machine learning algorithms into traffic signal control strategies, ITS can significantly improve intersection efficiency [6]. In addition, with the extensive link between cloud platform and IoT, ITS can also collect real-time urban road and environmental data to realize continuous detection and tracking of vehicle conditions [7]. On this basis, ITS is able to predict the trend of traffic flow, identify potential traffic bottlenecks and congestion points in advance, and dynamically adjust traffic signals to achieve more flexible traffic management. Furthermore, ITS can provide drivers with real-time navigation and route planning suggestions to help them avoid congested areas and improve travel efficiency.

3. Evolution of Machine Learning

During the iterative evolution of the smart city transportation system, machine learning has reconstructed the traditional transportation governance mode with its unique data-driven paradigm. From the analysis of disciplinary attributes, machine learning is essentially a cross-disciplinary system integrating statistical inference, optimization theory, computational complexity analysis, and convex optimization methods. Its core paradigm is to build an algorithmic architecture with autonomous evolution capability. With key technologies such as feature space mapping, hyperparameter dynamic optimization, and gradient optimization of loss function, the system is able to analyze potential laws from massive multimodal traffic data, break through the traditional experience-dependent management mode, and then complete the closed loop of intelligent decision-making from dynamic path planning to accident risk prediction.

The technological evolution of machine learning can be divided into four well-characterized historical stages.

The period from the mid-1950s to the mid-1960s was the initial development phase of artificial intelligence research, marking the establishment of the foundational paradigm of the field. With symbolism as the core path, research in this phase focused on constructing intelligent models anchored on rule-based reasoning, aiming to achieve a breakthrough in the autonomous cognitive ability of machine systems. In 1950, Alan Turing proposed the Turing Test, which constructed a standard for evaluating machine intelligence. In 1955, A. Newell and H. Simon proposed the Logic Theorist program, which was the first to enable machines to automatically prove mathematical theorems, being recognized as the first practical example of artificial intelligence research. The introduction of General Problem Solving in 1957 expanded the application of symbolic systems in the field of complex problems. In 1959, the checkers program designed by A. M. Samuel verified the machine's ability to learn autonomously. The technological breakthroughs in this phase are of dual historical significance. In the theoretical dimension, the Turing test (1950) established the evaluation system of intelligent systems. In the methodological dimension, the paradigm divide between

supervised and unsupervised learning emerged. Although limited by the computational power and data size at that time, it set the stage for the subsequent theoretical debate between connectionism and behaviorism.

The second period of machine learning evolution, from the mid-1960s to the mid-1970s, marked a strategic shift in the research paradigm from data-driven to knowledge engineering. The core features are reflected in the fact that researchers constructed knowledge representation systems through symbolic logic systems, attempted to realize cross-domain transfer learning, and focused on developing conceptual cognitive frameworks based on expert systems. This phase is essentially the conceptualization of a machine to simulate the human learning process through artificial induction and formalization of rules. In 1962, Hubel and Wiesel revealed the local receptive fields of neurons with direction-selective mechanisms through a study of the cat visual cortex, which provided the theoretical basis for the later biological modeling of Convolutional Neural Networks (CNNs). In 1967, the K-Nearest Neighbor (KNN) proposed by Thomas Cover realized unimodal pattern recognition for the first time. Meanwhile, the structural learning system of Patrick Winston and the rule-based reasoning framework of Frederick Hayes-Roth have made progress in the conceptual abstraction level, but the limitations of their single-task learning and logical generalization defects have made it difficult to realize engineering applications. These fundamental bottlenecks made this phase a hard time in the evolution of machine learning development.

The third phase of machine learning is from the mid-1970s to the end of the 1980s, marked the revival and transformation of the research paradigm. The core breakthroughs in this period are reflected in the fact that the research focus shifted from artificial rule encoding to autonomous knowledge discovery. The leap from single-concept recognition to multi-concept association learning was realized. During this period, the idea of decision tree algorithms began to sprout, which simulates human hierarchical conceptual cognition through tree structures. The idea of connectionism continued to develop, laying the foundation for the subsequent proposal of BP algorithms and the rise of deep learning. In the field of reinforcement learning, the establishment of Markov Decision Process (MDP) frameworks provided mathematical foundations for policy optimization in dynamic environments and triggered a discussion on how to learn optimal policies by interacting with environments. Meanwhile, expert systems have made breakthroughs in engineering practice, with the successful applications of MYCIN (a medical expert system) [8] and DENDRAL (an expert system in chemistry) [9] demonstrating the potential of knowledge engineering in modeling human decision-making processes.

The fourth phase of machine learning, from the 1980s to 2012, marks the massive expansion of technology applications and the deepening of interdisciplinary integration. With the improvement of computer arithmetic power and breakthroughs in data acquisition technology, machine learning technology has expanded from single-concept to multi-concept. Learning methods and systems integrating psychology, neurophysiology, mathematics, automation, and computer science have been applied in various fields. In 1982, the Hopfield neural network was proposed to express the associative memory patterns of an organism in a physical sense in an intuitive way. In 1986, Rumelhart, Hinton and Williams [10] succeeded in establishing the most basic of the neural network algorithms, the BP neural network algorithm, which constantly adjusts the weights and biases of the network by using the back propagation algorithm during the training process to minimize the error between the predicted and actual values. In 1995, Freund and Schapire [11] improved the Boosting algorithm and proposed the AdaBoost algorithm, which optimizes the algorithm by adjusting the weight allocation mechanism and the iterative training process. In the same year, Leo Breiman and Adele Cutler [12] proposed the Random Forest algorithm, which combines the bootstrap resampling method and decision tree algorithm to enhance the prediction and classification performance. In 2006, along with the rapid development of computer hardware technology, Geoffrey Hinton and Ruslan Salakhutdinov [13] proposed a deep learning model, which opened the wave of deep learning in academia and industry. In 2012, AlexNet surpassed the traditional methods in the ImageNet

competition with an accuracy rate of 10.8%, marking the formal entry of machine learning into a new era of data-driven co-evolution with representation learning.

In recent years, machine learning has become one of the research hotspots as new algorithms and systems continue to emerge. More and more machine learning methods have been applied to real-world scenarios, bringing significant innovations and breakthroughs to several fields. It is foreseeable that machine learning will play an even more important role in promoting the development of transportation safety in the future.

4. Applications of Machine Learning in Typical Urban Transportation Problems

With the acceleration of urbanization, traffic congestion, frequent accidents, uneven distribution of public transportation resources, and environmental pollution are becoming more and more prominent. Traditional solutions are facing efficiency bottlenecks. In this way, machine learning, with its powerful data modeling and prediction capabilities, provides new ideas for solving these complex problems.

4.1 Traffic Congestion Management

Traffic flow prediction, as a key technology to manage urban traffic congestion in ITS, provides accurate technical support for road network flow regulation by constructing dynamic decision-making models through multi-source data fusion and deep learning algorithms. The current research focuses on the field of short-term prediction, and the main technical paths can be summarized into the following three categories.

First, in terms of a hybrid prediction framework based on signal decomposition-reconstruction, Dai et al. [14] innovatively constructed a coupled model of Optimized Variational Mode Decomposition (OVMD) and Long-Short-Term Memory network (LSTM), optimized the VMD parameters through an enhanced bat algorithm, and used a bi-directional LSTM (L-BILSTM) to capture the traffic flow temporal features, which was carried out in the urban Changsha city of China for validation. The results show that this method significantly improves the prediction accuracy compared with the traditional model, especially the MAE was reduced by about 13% and the RMSE by about 17%. Zhao et al. [15] further introduced Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Permutation Entropy (PE) to construct a signal reorganization mechanism, which combined with a novel meta-heuristic optimization algorithm that integrates quantum computing ideas and multiple optimization strategies and parameters of the Deep Extremum Learning Machine (DELM). The mechanism was then validated by using the data of checkpoints on a mountainous scenic highway, and the results showed that it demonstrated greater accuracy improvement in multiple evaluation metrics, e.g., RMSE, MAE, and MAPE. Furthermore, in terms of spatio-temporal feature-oriented neural network architecture innovation, Wang et al. [16] proposed a traffic flow prediction model based on Dynamic Graph Convolutional Network (DTM-GCN). The spatio-temporal dependence of the traffic network and the input-output layer are optimized through the synergy of the dynamic topology generation module and the MK time series prediction module. The adaptability and prediction accuracy were finally validated on the Los Angeles and PeMS07 datasets. Again, in terms of hybrid modeling methods based on distribution optimization, Wu et al. [17] broke through the traditional Gaussian distribution assumption and proposed a new error-distribution-free kernel extreme learning machine to better cope with complex traffic flow data.

In addition, Hammoumi et al. [18] used machine learning to predict traffic congestion in Casablanca, Morocco, with real-time data from the Waze navigation platform. The results showed that the Random Forest model performed the best with a prediction accuracy of 96%. Kashifi et al. [19], on the other hand, focused on the application of machine learning to transportation travel mode choice, and compared the performance of five commonly used machine learning models, including

logistic regression, random forest, decision tree, multilayer perceptron, and LightGBDT, in the task of travel mode prediction by using the data from the National Travel Survey of the Netherlands. It was found that the LightGBDT model performed the best in predicting travel mode choice, especially under the oversampling strategy, with an overall accuracy of 89.6%, which was much higher than other models.

4.2 Traffic Safety Enhancement

In recent years, with the significant increase in the complexity of urban traffic flow, traffic safety problems have become increasingly serious. Therefore, it is necessary to continuously explore more efficient intelligent modeling methods to improve the accuracy and generalization ability of accident prediction and risk identification.

Gao et al. [20] innovatively proposed a graph neural network method integrating Graph Attention Mechanism (GAT) and Gate Recurrent Unit (GRU) with a four-parameter Zero-Inflated Tweedie distribution parser, which successfully solved the problem of zero-accident roadway feature annihilation and overfitting in high-risk areas. Validation based on real traffic data in London shows that the point estimation error was reduced by 34.6%, while the uncertainty quantification index was improved by more than 47%, which is significantly better than the traditional spatio-temporal prediction model. For the trajectory anomaly detection problem, Qiu et al. [21] proposed a new vehicle trajectory anomaly detection method, AMDDBN. The framework incorporates three modules of self-encoder feature extraction, weighted martensitic distance, and Dynamic Bayesian Network (DBN) time-series modeling. The method achieved excellent results on the local dataset from Wuhan City's urban expressway and the HighD dataset from German highway, with an average accuracy of 93.35%, which is better than the existing mainstream detection methods. In the field of driving risk prediction, Xie et al. [22] proposed a real-time driving risk prediction method based on a self-attention mechanism-bidirectional long-and-short-term memory network. The model achieves four-level risk dynamic classification through multi-source data fusion and a triple sliding time window optimization mechanism.

For special transportation safety, Chai et al. [23] proposed the "SF-T0.25" machine learning model based on more than 600,000 U.S. hazardous materials transportation accident data, which is a multi-model mechanism for predicting the time of accidents, weather conditions, and instantaneous speed of vehicles in hazardous materials transportation. The model uses Stacking to fuse base models such as Random Forest and Extra Trees, achieving 96.28% accuracy in the task of joint prediction of spatio-temporal attributes of accidents, with the Jaccard coefficient higher than 0.97, which is significantly better than the other comparative models. In the area of intelligent control optimization, Ma et al. [24] proposed a following driving style indicator based on a generalized asymmetric behavioral model and combined it with an interpretable machine learning approach to assess its impact on traffic conflict risk. Their radar-visual fusion trajectory database has provided a high-quality benchmark for microscopic driving behavior research. Hou et al. [25] designed the Gated-Transformer-MMD migration framework to achieve an 11.9% improvement in F1 value in the cross-region traffic conflict prediction task through a domain-invariant feature learning strategy, effectively breaking through the bottleneck of model geographic adaptation.

4.3 Improvement of Uneven Distribution of Public Transportation Resources

As big data-enabled transportation digital transformation continues to advance, dynamic optimization algorithms based on machine learning are reshaping the paradigm of public transportation resource allocation. Their application scope has been extended from macro road network planning to the micro level of operation and control.

In operation simulation optimization, Delhoum et al. [26] proposed a microscopic public transportation simulation framework based on RT regression tree. Combined with the probability distribution method, the framework used the regression tree model for travel time prediction, setting a new quantitative criterion for the assessment of public transportation reliability. In the study of

spatial evolution of car-sharing systems, Ma et al. [27] fused CatBoost gradient boosting model and SHAP interpretable analysis to study the development patterns of Car-Sharing Stations (CSSs). Multidimensional time series clustering was first performed using a dynamic time regularization algorithm, after which a CatBoost classification model was constructed to predict the development pattern. Key impacts of urban infrastructure and land use on the distribution of car-sharing stations were also quantitatively revealed through the SHAP interpretability framework. Aiming at the multi-modal transportation coordination problem, Liu et al. [28] combined extreme gradient boosting and Shapley additive interpretation to experimentally validate on shared travel data in Shanghai, providing a new scheme for the optimization of urban traffic management and multi-modal travel system. For demand forecasting, Ayman et al. [29] proposed a method based on neural architecture and feature search for predicting ridership on public transportation routes. Adaptive optimization of the parameters of the passenger flow prediction model for public transport routes can be achieved through neural architecture search, avoiding the labor intensity of traditional manual adjustment. As for bus operation cost control, Amicosante et al. [30] systematically compared the performance of six machine learning models, such as KNN, SVR, MLP, etc., and identified the key factors affecting the cost through feature selection and SHAP analysis, which provides an effective support for bus management and policy formulation. In terms of real-time monitoring techniques, Makara et al. [31] proposed an incremental learning-based public traffic congestion detection method, which utilizes a long and short-term memory network to capture the long-term temporal variation patterns of bus travel speeds and applies an incremental learning strategy to achieve real-time traffic congestion detection. Model validation using traffic data from Pécs, the fifth largest city in Hungary, showed a prediction accuracy of 82.37%. Aiming at the arrival time prediction challenge, Panovski et al. [32] innovatively modeled traffic data as 2D images and combined it with convolutional neural networks to predict the arrival time of buses at each station, which was also compared with traditional machine learning methods. The experimental results show that the proposed method outperforms the traditional method in terms of prediction accuracy and computational efficiency, with an accuracy improvement of up to 18%.

4.4 Environmental Pollution Control

Carbon emissions and air pollution caused by urban transportation are becoming a key constraint to sustainable development. Researchers are integrating machine learning and multi-source data modeling to reveal the spatial and temporal evolution of pollution emissions and the driving mechanism.

In the field of carbon emission prediction, Ji et al. [33] used machine learning and deep learning algorithms such as ANN, SVM, DL, etc., to predict the future trend of urban transportation carbon emission and energy consumption based on the data of China's transportation industry from 2009-2022. Two types of mathematical regression models, linear regression and exponential regression, were used for comparative analysis. It was found that the annual growth rate of CO₂ is about 3.66%, and the annual growth rate of energy demand reaches 3.8%. The model predicts that the total emissions will grow to more than 3.5 times those of 2022 by 2050. Wu et al. [34] systematically evaluated the nonlinear effects and threshold characteristics of urban form factors on carbon emissions from urban transportation based on data from 282 prefecture-level cities in China using a gradient boosting decision tree model. Characteristic importance analysis shows that urban form variables occupy 31.32% of the explanatory power in predicting transportation carbon emissions, of which "total boundary length", "number of urban centers", "shape index", and so on have significant effects. Some variables have an obvious tipping point and turning effect. Hou et al. [35] constructed an interpretable machine learning model to quantitatively analyze the city-scale drivers of PM_{2.5} based on multi-source data from 297 cities in China from 2000-2021. The study combined the TPE algorithm to optimize the model performance and used SHAP values to explain the influence weights of each variable. The results show that population density, science and technology expenditures, and industrial emissions are the most significant influences, and the model prediction accuracy reaches

96.44%. In terms of pollutant source assessment, Mobasshir et al. [36] evaluated the performance of three types of vehicles, namely hybrid, diesel, and biodiesel, on six pollutants, CO₂, NO_x, PM, SO₂, CO, and UBHC, based on real-vehicle multi-condition experiments and quantified the environmental impact level through a hybrid machine learning method of AHP, EDAS, and K-means. The results show that hybrid vehicles have the lowest pollutant emissions, and biodiesel vehicles have the worst. The study reveals nonlinear differences in the contribution of different power technologies to urban air pollution and provides actionable recommendations for hierarchical management. Using Oslo, Norway as a case study, Cao [37] systematically analyzed the composite mechanism of urban traffic and meteorological conditions on air pollution based on hour-by-hour traffic, PM_{2.5} and NO_x concentrations, and meteorological data for the whole year of 2019. The study constructed two time series models and compared them with traditional machine learning methods. It was found that the traditional statistical model outperforms the machine learning model in terms of air pollution prediction accuracy, especially after the introduction of interaction terms and lag effects.

5. Conclusion and Prospect

This paper systematically reviews the research progress and application results of machine learning technology in the field of intelligent transportation, highlighting its practical effects and development potential in traffic flow prediction, safety risk assessment, public transportation resource optimization, and environmental pollution control. Previous studies show that machine learning can significantly improve the operational efficiency and safety level of transportation systems. However, such studies still face many challenges, such as the insufficient generalization ability of models in complex scenarios, data privacy and ethical risks in practical applications, and limitations in the interpretability and transparency of models. Future research should focus on the robustness and reliability of models in real traffic environments and work on developing a more concise and interpretable algorithmic framework to enhance their operability in practical decision making. It is foreseeable that further exploration of the above directions will promote the in-depth integration of machine learning technology and urban traffic management, and ultimately promote the more efficient, safer, and more sustainable development.

References

- [1] The Role and Optimization Path of Intelligent Transportation Systems in Smart City Construction.
- [2] B.-A. Dai, B.-L. Ye & L. Li, A novel hybrid time-varying graph neural network for traffic flow forecasting, 2024. 6. 17, arXiv: arXiv:2401.10155. doi: 10.48550/arXiv.2401.10155.
- [3] Y. Ye, Y. Xiao, Y. Zhou, S. Li, Y. Zang & Y. Zhang, Dynamic multi-graph neural network for traffic flow prediction incorporating traffic accidents, *Expert Systems with Applications*, vol.234, pp. 121101, 2023.12, doi: 10.1016/j.eswa.2023.121101.
- [4] G. Chen & J. W. Zhang, Intelligent transportation systems: Machine learning approaches for urban mobility in smart cities, *Sustainable Cities and Society*, vol.107, pp.105369, 2024.7, doi: 10.1016/j.scs.2024.105369.
- [5] New Directions for Urban Traffic Governance: Implementation Paths and Challenges of Sustainable Multimodal Travel Strategies
- [6] The Role and Optimization Path of Intelligent Transportation Systems in Smart City Construction
- [7] Key Technologies and Applications of Intelligent Vehicle-Road Coordination System
- [8] W. V. Melle, MYCIN: a knowledge-based consultation program for infectious disease diagnosis
- [9] B. G. Buchanan & E. A. Feigenbaum, *Dendral and Meta-Dendral*.
- [10] D. E. Rumelhart, G. E. Hinton & R. J. Williams, Learning Internal Representations by Error Propagation, *Readings in Cognitive Science*, Elsevier, 1988, pp.399–421. doi: 10.1016/B978-1-4832-1446-7.50035-2.

- [11] Y. Freund & R. E. Schapire, A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting, *Journal of Computer and System Sciences*, vol.55(1), pp.119–139, 1997.8, doi: 10.1006/jcss.1997.1504.
- [12] Research on Random Forest Algorithm Optimization
- [13] Z. R. W. Yong-bin, Research on Machine Learning with Algorithm and Development.
- [14] G. Dai, J. Tang & W. Luo, Short-term traffic flow prediction: An ensemble machine learning approach, *Alexandria Engineering Journal*, vol.74, pp.467–480, 2023.7, doi: 10.1016/j.aej.2023.05.015.
- [15] K. Zhao, D. Guo, M. Sun, C. Zhao, H. Shuai and C. Shao, Short-term traffic flow prediction based on hybrid decomposition optimization and deep extreme learning machine, *Physica A: Statistical Mechanics and its Applications*, vol.647, pp.129870, 2024.8, doi: 10.1016/j.physa.2024.129870.
- [16] X. Wang, Y. Shang & G. Li, DTM-GCN: A traffic flow prediction model based on dynamic graph convolutional network, *Multimed Tools Appl*, vol. 83(41), pp.89545–89561, 2024.2, doi: 10.1007/s11042-024-18348-z.
- [17] K. Wu, C. Xu, J. Yan, F. Wang, Z. Lin & T. Zhou, Error-distribution-free kernel extreme learning machine for traffic flow forecasting, *Engineering Applications of Artificial Intelligence*, vol.123, pp.106411, 2023.8, doi: 10.1016/j.engappai.2023.106411.
- [18] L. Hammoumi, S. Farah, M. Benayad, M. Maanan & H. Rhinane, Leveraging machine learning to predict traffic jams: Case study of Casablanca, Morocco, *Journal of Urban Management*, pp.S2226585625000172, 2025.3, doi: 10.1016/j.jum.2025.02.004.
- [19] M. Tamim Kashifi, A. Jamal, M. Samim Kashefi, M. Almoshaogeh & S. Masiur Rahman, Predicting the travel mode choice with interpretable machine learning techniques: A comparative study, *Travel Behaviour and Society*, vol.29, pp.279–296, 2022.10, doi: 10.1016/j.tbs.2022.07.003.
- [20] X. Gao et al., Uncertainty-aware probabilistic graph neural networks for road-level traffic crash prediction, *Accident Analysis & Prevention*, vol.208, pp.107801, 2024.12, doi: 10.1016/j.aap.2024.107801.
- [21] M. Qiu, S. Mao, J. Zhu & Y. Yang, Spatiotemporal multi-feature fusion vehicle trajectory anomaly detection for intelligent transportation: An improved method combining autoencoders and dynamic Bayesian networks, *Accident Analysis & Prevention*, vol.211, pp.107911, 2025.3, doi: 10.1016/j.aap.2024.107911.
- [22] Z. Xie, Y. Ma, Z. Zhang & S. Chen, Real-time driving risk prediction using a self-attention-based bidirectional long short-term memory network based on multi-source data, *Accident Analysis & Prevention*, vol.204, pp.107647, 2024.9, doi: 10.1016/j.aap.2024.107647.
- [23] H. Chai, K. Dong, Y. Liang, Z. Han & R. He, Machine learning-based accidents analysis and risk early warning of hazardous materials transportation, *Journal of Loss Prevention in the Process Industries*, vol.95, pp.105594, 2025.6, doi: 10.1016/j.jlp.2025.105594.
- [24] X. Ma et al., Assessing the impact of car-following driving style on traffic conflict risk using asymmetric behavior model and explainable machine learning, *Accident Analysis & Prevention*, vol.211, pp.107904, 2025.3, doi: 10.1016/j.aap.2024.107904.
- [25] Q. Hou, Y. Yang, J. Liang, X. Huo & J. Leng, A deep transfer learning approach for Real-Time traffic conflict prediction with trajectory data, *Accident Analysis & Prevention*, vol.214, pp.107966, 2025.5, doi: 10.1016/j.aap.2025.107966.
- [26] Y. Delhoum, O. Cardin, M. Nouiri & M. Harzallah, A microscopic public transportation simulation framework based on machine learning, *Journal of Public Transportation*, vol.26, pp.100103, 2024, doi: 10.1016/j.jpubtr.2024.100103.
- [27] Y. Ma, R. Miao, Z. Chen, B. Zhang & L. Bao, An interpretable analytic framework of the relationship between carsharing station development patterns and built environment for sustainable urban transportation, *Journal of Cleaner Production*, vol.377, pp.134445, 2022.12, doi: 10.1016/j.jclepro.2022.134445.
- [28] X. Liu, Q. Ye, Y. Li, K. Yang & X. Shao, Investigating relationships between ridesourcing and public transit using big data analysis and nonlinear machine learning: A case study of Shanghai, China, *Transportation Research Part A: Policy and Practice*, vol.192, pp.104339, 2025.2, doi: 10.1016/j.tra.2024.104339.

- [29] A. Ayman, J. Martinez, P. Pugliese, A. Dubey & A. Laszka, Neural Architecture and Feature Search for Predicting the Ridership of Public Transportation Routes, 2022 IEEE International Conference on Smart Computing (SMARTCOMP), Helsinki, Finland: IEEE, 2022.6, pp. 56–61. doi: 10.1109/SMARTCOMP55677.2022.00023.
- [30] A. Amicosante, A. Avenali, T. D’Alfonso, M. Giagnorio, A. Manno and G. Matteucci, Predicting costs of local public bus transport services through machine learning methods, *Expert Systems with Applications*, vol.260, pp.125396, 2025.1, doi: 10.1016/j.eswa.2024.125396.
- [31] L. A. Makara, P. Maric & A. Pekar, Public transport congestion detection using incremental learning, *Pervasive and Mobile Computing*, vol.91, pp.101769, 2023.4, doi: 10.1016/j.pmcj.2023.101769.
- [32] D. Panovski & T. Zaharia, Public Transportation Prediction with Convolutional Neural Networks, *Intelligent Transport Systems. From Research and Development to the Market Uptake*, vol.310, A. L. Martins, J. C. Ferreira & A. Kocian, (ed.), *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering*, vol. 310., Cham: Springer International Publishing, 2020, pp.150–161. doi: 10.1007/978-3-030-38822-5_10.
- [33] T. Ji, K. Li, Q. Sun & Z. Duan, Urban transport emission prediction analysis through machine learning and deep learning techniques, *Transportation Research Part D: Transport and Environment*, vol.135, pp.104389, 2024.10, doi: 10.1016/j.trd.2024.104389.
- [34] J. Wu & C. Li, Illustrating the nonlinear effects of urban form factors on transportation carbon emissions based on gradient boosting decision trees, *Science of The Total Environment*, vol.929, pp.172547, 2024.6, doi: 10.1016/j.scitotenv.2024.172547.
- [35] Y. Hou, Q. Wang & T. Tan, Evaluating drivers of PM2.5 air pollution at urban scales using interpretable machine learning, *Waste Management*, vol.192, pp.114–124, 2025.1, doi: 10.1016/j.wasman.2024.11.025.
- [36] M. Mobasshir et al., Analyzing vehicle emissions using a hybrid machine learning approach using weighted average based k-means clustering for sustainable transportation decision-making, *Green Technologies and Sustainability*, vol.3(3), pp.100163, 2025.7, doi: 10.1016/j.grets.2024.100163.
- [37] C. Cao, How to better predict the effect of urban traffic and weather on air pollution? Norwegian evidence from machine learning approaches, *Journal of Economic Behavior & Organization*, vol.221, pp.544–569, 2024.5, doi: 10.1016/j.jebo.2024.03.018.