Proceedings of CONF-APMM 2025 Symposium: Simulation and Theory of Differential-Integral Equation in Applied Physics
DOI: 10.54254/2753-8818/2025.DL27110

Exploring Deep Learning Applications in Traffic Flow Prediction

Huayi Guo[1,2]

[1]*Reading Academy, Nanjing University of Information Science and Technology, Nanjing, China*
[2]*School of Data Science, University of Reading, Reading, UK*
202283710066@nuist.edu.cn

Abstract. Traffic flow prediction plays an important role in intelligent transportation systems, supporting efficient traffic management and scientific decision-making. With the rapid advancement of deep learning, various advanced models have sprung up, aiming to capture the nonlinear, high-dimensional and dynamic evolution of traffic data. This paper systematically reviews three representative methods: autoencoder-based models, recurrent neural networks (RNNs), and graph neural networks (GNNs). With its stack-optimized structure, Autoencoder has demonstrated its capability in feature extraction, noise reduction and efficient representation learning, thereby improving prediction robustness and computational efficiency. RNNs and their variants (including LSTM and GRU) excel at portraying the temporal dependence of traffic sequences, while hybrid models that incorporate external data or optimize algorithms further enhance accuracy and adaptability. In recent years, GNN methods have emerged to specialize in spatial dependencies caused by complex road network structures. By combining GCNs with temporal models and enhanced learning, these methods have achieved remarkable results in capturing spatio-temporal correlations and long-term predictions. Overall, the integrated evolution of AE, RNN and GNN models explains the leap-forward development from feature compression, temporal modeling to spatio-temporal integrated learning. Despite the significant advantages, challenges remain in multimodal data fusion, computing efficiency and real-time deployment, which points out a promising direction for future research.

Keywords: Traffic Flow Prediction, Autoencoder (AE), Recurrent Neural Network (RNN), Graph Neural Network (GNN), Spatiotemporal Modeling.

1. Introduction

Traffic flow prediction has become an essential component of intelligent transportation systems, offering critical support for real-time traffic management, route planning and congestion management. Accurate and reliable predictions enable traffic management departments to take precautions and dynamically adjust signal timing while improving road safety. However, traffic flow data is inherently nonlinear, random and spatio-temporal correlation, making prediction work challenging. Traditional statistical methods such as ARIMA and Kalman filtering, as well as machine learning methods such as SVR, KNN and random forests, although they have made little

DOI: 10.54254/2753-8818/2025.DL27110

achievements in time series modeling, they often fail to capture complex nonlinear patterns and spatial interactions, so forecasting capabilities in large-scale urban road networks are stretched.

With the advent of deep learning, more advanced models have emerged to meet these challenges. Autoencoders provide effective feature extraction and dimensionality reduction, offering robustness against noise and improving representation learning for traffic data. Recurrent neural networks are widely adopted for capturing long-term time series dependencies, while RNN-based hybrid methods improve prediction accuracy by integrating external data and optimization strategies. More recently, graph neural networks have attracted attention for its unique ability to model the complex spatial dependence of road networks. When paired with time series modules or reinforcement learning strategies, GNN-based methods add benefits to spatio-temporal modeling capabilities and long-term prediction reliability.

This paper comprehensively reviews the traffic flow prediction methods based on AE, RNN and GNN, systematically analyzes their theoretical basis, typical models and experimental results, and points out the advantages and disadvantages of each method pointedly. In addition, this survey also discussed current challenges, including multimodal data fusion, computational efficiency improvements, and real-time transportation system deployment. Finally, the survey proposed future research directions from a strategic perspective, aiming to bridge the methodological gap and promote accurate and efficient traffic flow prediction models to a higher level.

2. Traffic flow prediction

2.1. AE-based traffic flow prediction

As a typical representative of unsupervised learning, Autoencoder realizes efficient feature extraction and reconstruction of traffic flow data through the encoder-decoder architecture. In traffic flow prediction, its main advantage lies in its ability to learn potential low-dimensional representations without teaching, thereby demonstrating superior performance in denoising, nonlinear modeling and feature compression. In recent years, AE-based prediction methods have been widely explored, among which stacked autoencoders and structurally optimized deep autoencoder models have demonstrated extremely high prediction accuracy and robustness in different studies.

For example, Jin et al. proposed a traffic flow prediction framework based on the combination of multi-layered autoencoder unsupervised pre-training and supervised fine-tuning [1]. This method can gradually extract deep abstract features from traffic flow data, and through practical verification, its performance far exceeds traditional regression models and shallow neural networks. In particular, it demonstrates greater robustness when dealing with random fluctuations and abnormal data. Another study took a different approach and proposed an improved AE framework from the perspective of structural optimization and computational efficiency [2]. By systematically tuning the configuration of encoder and decoder layers, activation functions, and regularization techniques, the model not only outperforms the baseline model in terms of RMSE and MAE indicators, but also showed remarkable progress in training time and computing resource consumption.

Overall, these two research directions have respectively highlighted the potential of autoencoders in deep feature learning and robustness, as well as structural optimization and efficiency improvement. They jointly confirm that AEs can easily cope with the high-dimensional and nonlinear characteristics of traffic flow data, and opens up a broad road to meet the dual needs of traffic prediction accuracy and real-time.

DOI: 10.54254/2753-8818/2025.DL27110

2.2. RNN-based traffic flow prediction

Traffic flow prediction is a typical time time-series problem, and recurrent neural networks and their variants have been widely applied in this field. With its hidden states, RNN are capable of capturing tempora correlations in sequential data, but its training process is often hampered by problems such as gradient disappearance and gradient explosion. Long Short-Term Memory networks and Gated Recurrent Units are improved versions of RNN that introduce gating mechanisms that allow long-term dependencies to be effectively preserved. Because of this, they have shown strong applicability and robustness in traffic flow prediction.

At the basic application level, Du et al. confirms the effectiveness of LSTM in the field of traffic prediction [3]. They built an LSTM network to model traffic flow time series, and the results showed that the model can maintain high accuracy in long-series predictions. In the experiment, the loss value of the LSTM model on the test set is about 0.6089, and the prediction accuracy rate reaches 80.03%. Its generalization ability is evident [3]. This research not only sets a benchmark for subsequent RNN-based models, but also demonstrates the feasibility and superiority of LSTM in traffic flow prediction.

In order to expand application scenarios, Azad et al. took a different approach and integrated LSTM with external data sources, and proposed a dual-layered stacked LSTM prediction framework [4]. They used traffic scenarios in Dhaka, Bangladesh-including signalized intersections, unsignalized intersections and free-flow road sections-and used real-time and historical traffic data from Google Maps to make one to three step predictions. The results show that the average prediction error fluctuates between 8.25% and 14.09%, with the prediction accuracy of free-flow sections ranking first [4]. This research not only confirms the robustness of stacked LSTMs in complex transportation environments, but also demonstrates the huge potential of multi-source data fusion through external platforms, especially providing new ideas for traffic prediction and management in developing countries.

In the field of improvement and fusion, Tian et al. found another way and proposed a hybrid prediction model combining Deep Extreme Learning Machine and Grey Wolf Optimizer [5]. This method not only avoids the local optimal trap effectively, but also improves the prediction accuracy by leaps and bounds by providing optimal initial weights for DELM through GWO. Based on the measured data of the M25 motorway near Heathrow Airport in the United Kingdom, the prediction error of GWO-DELM model is greatly reduced compared with traditional methods, and the MAPE index is reduced to 3%-5%, which is nearly 50% higher than that of LSTM model. This research confirms the feasibility of optimization algorithms and deep learning complementing each other, especially for intelligent transportation systems that pursue high accuracy and real-time performance at the same time.

Overall, RNN and its variants have shown significant advantages in the field of traffic flow prediction, effectively capturing temporal dependencies while maintaining high accuracy across diverse scenarios. From fundamental LSTM applications, to extended frameworks that integrate external data sources, to hybrid models that integrate optimization algorithms, the development of RNN-related technologies has demonstrated the broad prospects of deep learning in promoting traffic prediction.

2.3. GNN-based traffic flow prediction

Traffic flow prediction is further complicated by spatial dependence caused by the complex topology of road networks. Traditional time-series methods and machine learning approaches achieve certain effectiveness in temporal modeling, but they often fail to accurately capture spatial correlations, thereby limiting prediction accuracy. In order to break through this shackle, researchers have taken a different approach, introducing Graph Neural Networks to characterize the road network topology, supplemented by time series modeling technology, and a two-pronged approach to improve prediction performance.

In terms of fundamental applications, Jiang et al. have taken a different approach and proposed a method to integrate rapid traffic flow statistics with Graph Convolutional Networks [6]. In the preprocessing stage, they collected vehicle images through trigger sensors, used ResNet34 to classify them, and used target detection algorithms to achieve efficient traffic flow statistics.In the prediction process, the research team ingeniously introduced a GCN model equipped with a moving horizon mechanism. Compared with traditional models, this scheme can dynamically absorb the latest traffic data in each round of training, thereby More accurately capture the dynamic spatio-temporal characteristics of traffic flow. Experimental results based on the public data set of PeMS04 show that this method is superior, with an average RMSE reduced by about 2.1% and MAE reduced by about 2.3% [6]. Compared with SVR, LSTM, and GRU, its spatio-temporal modeling capabilities are superior; in terms of real-time and prediction accuracy, it outperforms STGCN and STSGCN. There are two innovations in this research: first, it creates an efficient traffic data collection and cleaning method to ensure input quality; second, it introduces a moving horizon mechanism to strengthen GCN's dynamic modeling capabilities. These results indicate that methods relying solely on spatial or temporal modeling face inherent limitations, whereas combining GNNs with RNNs enables more effective spatiotemporal correlation capture, thereby enhancing both prediction accuracy and practical value.

In terms of spatio-temporal joint modeling, Yuan et al. proposed the ST-GNN-GRU model, which combines a spatial graph neural network with a time-series gated loop unit for short-term traffic flow prediction [7]. Specifically, the method first uses a graph convolution structure to capture the spatial dependence relationship between roads and monitoring stations in the traffic network, then uses GRU to model time-series dynamic characteristics, and finally generates prediction results through the fully connected layer. Experiments on the METR-LA dataset show that using RMSE, MAE and MAPE as evaluation indicators, compared with a single GCN, GRU or S-GNN model, ST-GNN-GRU achieves significant reductions in errors in multi-step prediction tasks (5, 10, 15 and 30 minutes), demonstrating greater robustness and generalization capabilities. These results confirm that methods that rely solely on spatial or temporal modeling have inherent shortcomings. Only by combining GNN and RNN can we more effectively capture spatio-temporal correlation, thus balancing prediction accuracy and practical value.

Regarding improvements and integration, ST-RL Net advanced traffic flow prediction by combining spatiotemporal feature modeling with deep reinforcement learning strategies The model employed graph structures to capture spatial dependencies among monitoring sites while using a temporal sequence encoder to extract dynamic patterns from historical traffic flow [8]. The prediction introduce a strategy optimization mechanism based on reinforcement learning, using prediction accuracy and stability as reward signals, guiding the network to easily balance short-term and long-term error control in multi-step prediction tasks. This design effectively alleviates the problem of error accumulation that deep-learning models accumulate in long-term prediction. Empirical results from multiple real-life traffic datasets show that ST-RLNet is particularly skilled in long-range prediction tasks, and its performance far exceeds the benchmark model that uses only supervised learning. Taking the 30-minute to 1-hour forecast as an example, this model not only significantly reduces the RMSE and MAE indicators, but also strives for excellence in trend fitting and fluctuation capture. Compared with classic spatio-temporal convolution models such as STGCN and STSGCN, ST-RLNet has shown extraordinary adaptability to sudden changes in traffic patterns during holidays and peak periods. This improvement is mainly attributed to the ability of reinforcement learning to adapt to dynamic decision-making and policy updates, allowing it to draw inferences from one example in road networks of different sizes and types, and its generalization ability is outstanding.

Overall, GNN-based traffic flow prediction research has experienced an evolution from purely modeling spatial dependence, to combining recurrent neural networks to achieve spatio-temporal joint modeling, and then to integrated optimization through reinforcement learning. The GNN method effectively overcomes the shortcomings of traditional time series and machine learning models in capturing spatial correlations, making it particularly handy in complex road networks and real-time intelligent traffic scenarios. However, it still faces challenges in multimodal data fusion, computational efficiency improvement, and deployment in resource-constrained environments, which are promising directions for future research.

3. Conclusion

Models based on Autoencoder perform well in extracting low-dimensional features, eliminating noise interference, and enhancing feature robustness, thereby significantly improving the reliability of prediction. Recurrent Neural Networks and its variants excel at capturing temporal dependencies, while hybrid frameworks further expand their application boundaries by integrating external data and optimization strategies. Graph Neural Network-related methods represent the latest technological development trend. They can accurately depict spatial correlations in complex road networks. When combined with time modules or reinforcement learning, these methods can greatly improve the accuracy and long-term stability of spatio-temporal prediction.

Despite these advances, several challenges persist. Existing models generally face problems such as insufficient scalability, insufficient multimodal data processing, and high computing costs, which makes their deployment in real-time scenarios difficult. Therefore, future research should focus on developing lightweight adaptive architectures, integrating heterogeneous data sources, and improving model interpretability, thereby offering better support for decision-making in intelligent transportation systems.

References

[1] Jin, Y., Xu, W., Wang, P., & Yan, J. (2018, August). SAE Network: A deep learning method for traffic flow prediction. IEEE Xplore.
[2] Yang, H.-F., Dillon, T. S., & Chen, Y.-P. P. (2017). Optimized structure of the traffic flow forecasting model with a deep learning approach. IEEE Transactions on Neural Networks and Learning Systems, 28(10), 2371–2381.
[3] Du, Y. (2024, November). Research on traffic flow analysis based on LSTM algorithm. In 2024 5th International Conference on Artificial Intelligence and Computer Engineering (ICAICE) (pp. 512–515).
[4] Azad, A. K., & Islam, M. (2021, December). Traffic flow prediction model using Google Map and LSTM deep learning. In 2023 IEEE 8th International Conference on Intelligent Transportation Engineering (ICITE).
[5] Tian, Z., & He, D. (2022, April). Short-term traffic flow prediction based on GMO-DELM. In 2022 3rd International Conference on Geology, Mapping and Remote Sensing (ICGMRS) (pp. 260–264).
[6] Jiang, D., Hou, Q., Liu, X., & Gao, S. (2023, October). Traffic flow prediction method based on fast statistics of traffic flow and graph convolutional network. In 2023 IEEE 8th International Conference on Intelligent Transportation Engineering (ICITE) (pp. 54–59).
[7] Yuan, L., Fang, W., Xiao, H., Xiao, J., Shi, Y., & Yang, Y. (2022, December). Short-term traffic flow prediction by graph deep learning with spatial temporal modeling. In 2022 2nd International Conference on Electronic Information Technology and Smart Agriculture (ICEITSA) (pp. 172–177).

DOI: 10.54254/2753-8818/2025.DL27110

[8] He, L., Shi, S., Zhang, D., & Luo, W. (2025, July). ST-RLNet: Spatio-temporal representation learning for multi-step traffic flow prediction. Neurocomputing, 652, 131020.