

# Deep Learning's Current and Future Applications in Predicting Vehicle Traffic Flow

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**Abstract.** With the acceleration of urbanization and the continuous growth of traffic flow, accurate prediction of highway traffic flow has become a key demand for optimizing traffic management and alleviating congestion. Traditional prediction methods are often inefficient in dealing with complex traffic patterns, while deep learning technology brings new solutions for traffic flow prediction with its powerful feature learning and pattern recognition capabilities. This paper reviews deep learning applications' current state and future trends in highway traffic flow prediction. It introduces deep learning technology and its advantages in traffic flow prediction. The paper then analyzes the specific applications of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants in data processing, feature extraction, and prediction performance. The challenges currently faced, such as data preprocessing and the capture of long-term dependencies, are also discussed, along with proposed solutions. Finally, the paper looks forward to the future development of deep learning in the field of traffic flow prediction, highlighting its importance in improving traffic management efficiency.

**Keywords:** Deep learning, highway traffic flow prediction, traffic flow dynamic analysis, real-time traffic prediction, traffic flow optimization.

## 1. Introduction

In recent years, the acceleration of urbanization, dense population, and rapid growth of motor vehicles have brought great pressure to the road traffic system. In this context, accurate prediction of highway traffic flow is very important for optimizing traffic management, alleviating congestion, and improving traffic efficiency. Traditional traffic flow prediction methods, such as time series analysis and machine learning models, often struggle to capture complex traffic patterns and dynamic changes. With the rapid development of big data and artificial intelligence technology, deep learning provides new possibilities to solve this challenge. The rapid development of deep learning technology has significantly affected various fields, of which traffic flow prediction is a prominent application area. Accurate traffic flow prediction is essential for optimizing traffic management, reducing congestion and improving overall traffic efficiency. As urban areas continue to expand and traffic becomes more complex, the need for advanced predictive models has never been greater. Accurate traffic flow prediction can help traffic authorities better plan and deploy resources to improve road efficiency as well as reduce carbon emissions, and ultimately improve the overall sustainability of the city's traffic.

With the development of artificial intelligence technology, deep learning has become a powerful tool to solve these challenges. Deep learning models have demonstrated their ability to learn complex patterns and features from large-scale data, effectively learning from traffic sensor data to capture spatial and temporal dependencies that traditional methods might ignore. For example, Zhang et al. demonstrated that deep learning models can automatically identify complex traffic patterns without the need for explicit feature design [1]. Similarly, Xu et al. confirmed that the traffic flow prediction model based on deep learning can make use of a large number of sensor data to significantly improve the prediction accuracy [2]. In addition, Katambire et al. proposed a traffic flow prediction model based on LSTM, which can effectively capture the long-term dependence relationship in time series data [3]. These advances highlight the transformative potential of deep learning in traffic management.

Despite these advances, challenges remain when applying deep learning to traffic flow predicting. Alhussen points out that missing data and equipment failures are major obstacles that require further research [4]. In addition, improving the model's ability to generalize across different cities and traffic conditions is also an area that needs ongoing research. Addressing these challenges will require continued innovation and refinement of deep learning techniques as well as the integration of new approaches such as transfer learning and model fusion.

Based on the current status of deep learning in highway traffic predicting, this paper gives a comprehensive overview of the current status of deep learning in traffic flow predicting, and discusses the existing and emerging models. This article will explore the advantages and limitations of various deep learning techniques and discuss recent advances in the field, such as deep learning-based methods for dynamic traffic signal control and the incorporation of physical information into predictive models. In addition, this paper will also delve into the key developments and applications of deep learning in traffic flow predicting, identify existing challenges, and outline future research directions. By highlighting recent advances and pointing out areas for improvement, this paper aims to contribute to ongoing efforts to enhance traffic management through advanced predictive modeling.

## 2. Correlation Theories

Deep learning is a machine learning technique that learns and recognizes complex patterns by using multiple layers of neural networks. Key features of deep learning include the ability to learn features automatically, without the need for manual design of features, which allows deep learning to tackle more complex problems. Deep learning can also be trained on large amounts of data for better performance. In many fields, such as computer vision, natural language processing, deep learning technology has made breakthroughs. Compared with traditional machine learning, deep learning also has unique advantages in the field of highway traffic flow prediction. For example, deep learning can use a large amount of historical traffic data for training, so as to obtain more accurate prediction results [5]. Deep learning models can also perform efficient parallel computation on GPUs, enabling them to quickly process large amounts of traffic data [6]. Deep learning has shown strong performance in the field of highway traffic flow prediction, thanks to its automatic feature learning capabilities, big data training capabilities, and efficient parallel computing capabilities. These advantages make the application of deep learning in traffic flow prediction promising.

The main models for deep information include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and their variants such as Long Short-Term Memory networks (LSTM) and Gated Recurrent Units (GRUs), as well as Variational Autoencoders (VAE) and deep reinforcement learning, each with its own applicable scenarios and advantages. Convolutional Neural Network (CNN) is a deep learning model specifically designed to process two-dimensional image data. Its main feature is that it can automatically extract the local features of the image and combine these features into higher level features. CNN is good at processing spatial data and can effectively extract the correlation between different sections in the traffic network. A Recurrent Neural Network (RNN) is a deep learning model capable of processing sequence data, memorizing previous input information to better understand the current input. Variants of RNN include Long Short-Term Memory networks (LSTMs) and Gated Recurrent Units (GRUs), which are better able to capture long-term dependencies. [7] [8] Variational Autoencoder (VAE) is a generative deep learning model that learns the potential distribution of data and generates new samples similar to the training data. VAE can be used for anomaly detection and missing data completion [9]. In the practical application of data processing, deep learning can automatically learn complex data features through end-to-end learning, effectively solving many shortcomings and drawbacks of traditional methods [5][6]. In the processing of large-scale data, deep learning models can better utilize the potential information in the data and improve the prediction accuracy and generalization ability [10]. In addition, deep learning can apply the knowledge learned from one city to other cities through transfer learning and other technologies to improve the generalization ability of the model [11]. It can be seen that the advantage

of deep learning technology in the field of highway traffic flow prediction lies in its strong feature extraction and nonlinear modeling capabilities, which can more accurately capture complex traffic flow patterns, thereby improving the accuracy and robustness of short-term traffic flow prediction. Deep learning models can also leverage large amounts of historical data for end-to-end automatic learning without too much manual feature engineering, thus greatly improving the scalability and adaptability of prediction systems.

### 3. Typical Methods and Applications

#### 3.1. The State of Road Traffic Flow Forecasting Technologies at the Moment

With the accelerating process of urbanisation and the increasing complexity of urban traffic systems, highway traffic flow prediction technology is widely used in traffic management and control. Highway traffic flow prediction technology can help traffic management departments to optimise traffic signal control, ease traffic congestion and provide the operational efficiency of urban transport systems. This chapter summarizes the existing traffic flow prediction methods, including traditional statistical methods and modern deep learning-based prediction models. The goal is to examine the advantages and disadvantages of these models and methods and to discuss possible future development paths.

Early traffic flow prediction methods were mainly based on statistical models, such as ARIMA (Autoregressive Integral Sliding Average Model), Kalman Wave, and Support Vector Machine (SVM). These traditional models are relatively simple in structure and do not require a large amount of training data to achieve prediction, but the traditional models perform poorly in different scenarios and complex traffic patterns, and the long-term prediction performance is weak to meet the modern traffic system. Deep learning prediction techniques have become more popular in recent years, providing new solutions for traffic flow prediction. Prediction models based on deep learning differ from traditional approaches in terms of their ability to model nonlinear networks, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Graph Neural Networks (GNN), which are able to handle complex nonlinear data relationships. Deep learning models have the ability to automatically capture these complex relationships through hierarchical features. This increases the models' predictive power significantly. In addition to single prediction models, there are also hybrid models based on convolution and looping, e.g., CONV-LSTM, which has the advantage of capturing not only temporal and spatial features in the traffic flow at the same time, but also dependencies in the time series, and thus it is able to capture the data more accurately. CONV-LSTM has a wide range of applications, and it is able to be used in the fields of natural disaster prediction and intelligent traffic signal control.

#### 3.2. Application of Deep Learning in Traffic Flow Prediction

##### 3.2.1. TSE models integrating physical information Ddeep learning (PIDL) techniques with computational maps

In the context of the rapid development of artificial intelligence, smart connected cars and intelligent transport systems, traffic state estimation (TSE) plays a pivotal role in the prediction of urban traffic. TSE models can help transport departments to formulate rational transport policies, monitor urban traffic conditions, and provide drivers with accurate traffic information to help them find the best path. However, the existing model-driven and data-driven approaches are limited by the quality and quantity of data. Therefore, the researcher combines PIDL with TSE model.

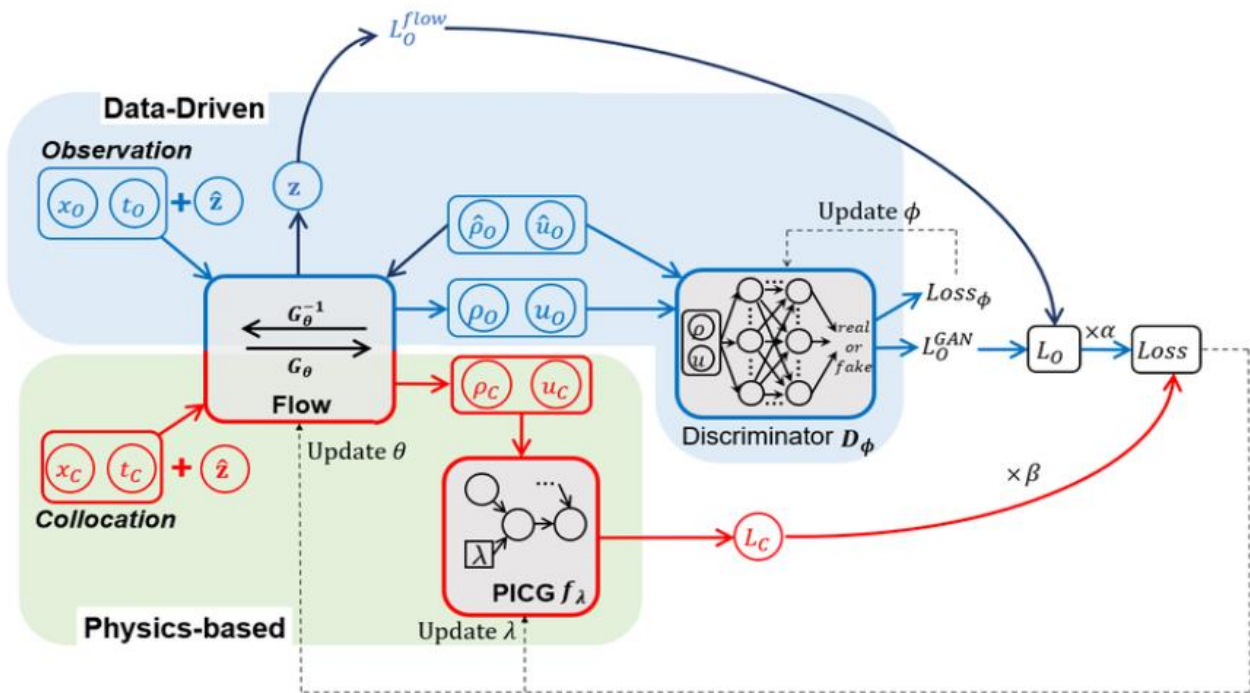


**Fig. 1** Specific structure of the TSE model[22]

An innovative TSE hybrid framework that combines physically-based and data-driven models to handle complex system prediction issues, such as traffic flow prediction, is shown in Fig. 1. The two components of the new model are Physics-Based and Data-Driven. The physics-based portion of the model employs physical information to perform point matching and loss calculations, while the data-driven half uses actual observational data from traffic models for prediction and optimization. Ultimately, traffic conditions may be precisely approximated by summing the losses from the physics-based and data-driven components. This model has the benefit of using PIDL, which improves the generalization capacity and dependability of deep learning models by using the innate traffic flow patterns from traffic flow models as prior knowledge. The experimental findings show that PIDL can accomplish accurate traffic state estimation and outperforms conventional prediction models in the presence of sparse data from loop detectors and observed vehicles.

Furthermore, it is possible to view the PIDL method for traffic state estimate as a standard illustration of the integration of model-driven and data-driven methodologies, offering perspectives for its potential use in various domains. By investigating and implementing this strategy, a better understanding of the benefits and drawbacks of data-driven and model-driven techniques, as well as their functions in traffic status prediction, may be gained.

### 3.2.2. TSE models integrating physical information deep learning (PIDL) techniques with computational maps

A deep learning-assisted approach based on traffic flow dependencies and dynamics (TD2-DL) was developed to predict high-resolution traffic speed propagation across the network by explicitly integrating temporal-spatial flow dependencies, traffic flow dynamics, and deep learning techniques in order to accurately predict future traffic speed distributions and their propagation across the network. In particular, based on the anticipated time domain and traffic delays, the study first creates a graph-theoretic-based method that adaptively finds local temporal-spatial traffic dependencies between each road and its neighboring roads. After that, they use v-CTM to mathematically characterize the traffic speed propagation on each route depending on the initial and boundary circumstances of the traffic.

After that, they used a Long Short-Term Memory (LSTM) model to forecast the boundary conditions while accounting for the historical data anticipated by the v-CTM and the temporal-spatial traffic relationships. In order to increase the accuracy of traffic speed prediction, they included a feed-forward neural network (FNN) and utilized the extended Kalman filter (EKF) to fuse the traffic speeds predicted by the v-CTM and LSTM models with the field traffic data.

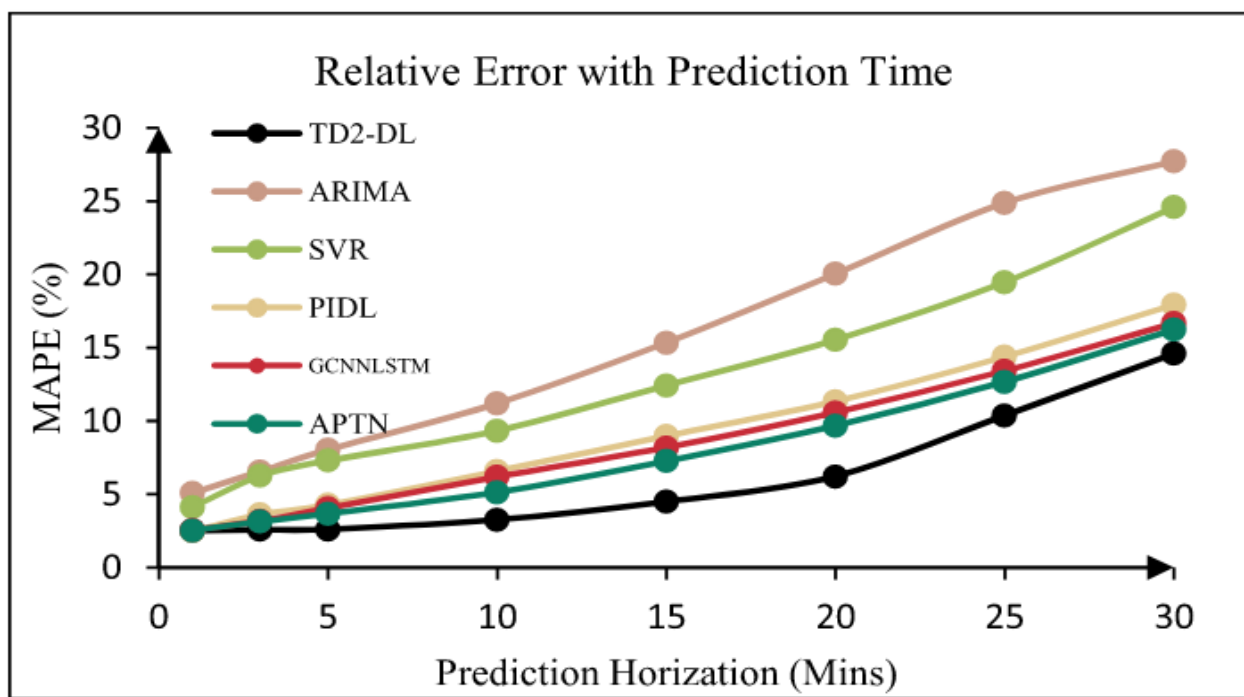


**Fig. 2** TD2-DL comparison with alternative methodological models[14]

To reduce data requirements and processing strain, TD2-DL combines a physical traffic model (v-CTM) with a Long Short-Term Memory (LSTM) model. It then applies a graph-theoretic technique to discover local temporal and spatial relationships for each road segment.错误!未找到引用源。 In order to guarantee predictions that are both theoretically sound and responsive to real-time data, this is able to leverage both physical modeling and deep learning.

### 3.2.3. Performance evaluation and application of novel models

This section compares the TD2-DL approach with conventional models to illustrate its benefits. Traditional time series analysis techniques (ARIMA), fundamental machine learning techniques (SVR), deep learning models (GRU), and physically informative neural networks (PIDL) are some of the benchmark techniques that were chosen. The results of forecasting network-level traffic speeds using every tested strategy for the following 30 minutes are shown in Fig. 2 The outcomes demonstrate the TD2-DL approach's distinct advantage over the recently created PIDL method and its great superiority over ARIMA and SVR [14]. The performance of the traditional model in terms of prediction accuracy is displayed in the upper panel of Fig. 3 The root mean square error (RMSE) is displayed in the right-hand panel, while the mean absolute percentage error (MAPE) is displayed on the left for various prediction time horizons. It is evident that when the prediction time grows (0 to 30 minutes), both MAPE and RMSE steadily increase, suggesting that the prediction error also gradually increases. In contrast, the TD2-DL model's performance is depicted in the lower panel of Fig. 3, wherein an increase in error is observed with an increase in prediction time. However, this increase is more gradual than that of the model in the top panel.

In summary, Fig. 3's content compares the trends in the two error measures, MAPE and RMSE, to illustrate how well the two models perform over varying prediction time spans. The TD2-DL variant appears to have a more stable performance. Overall, when the prediction range is set between 10 and 20 minutes, the TD2-DL technique performs better than all other methods in this comparison.

Additionally, this work aims to demonstrate the superior performance of deep learning techniques over ARIMA and SVR, including PIDL, CNN-LSTM, APTN, and TD2-DL. Thus, it can be said that traffic flow prediction models based on deep learning have greater benefits than conventional prediction models.

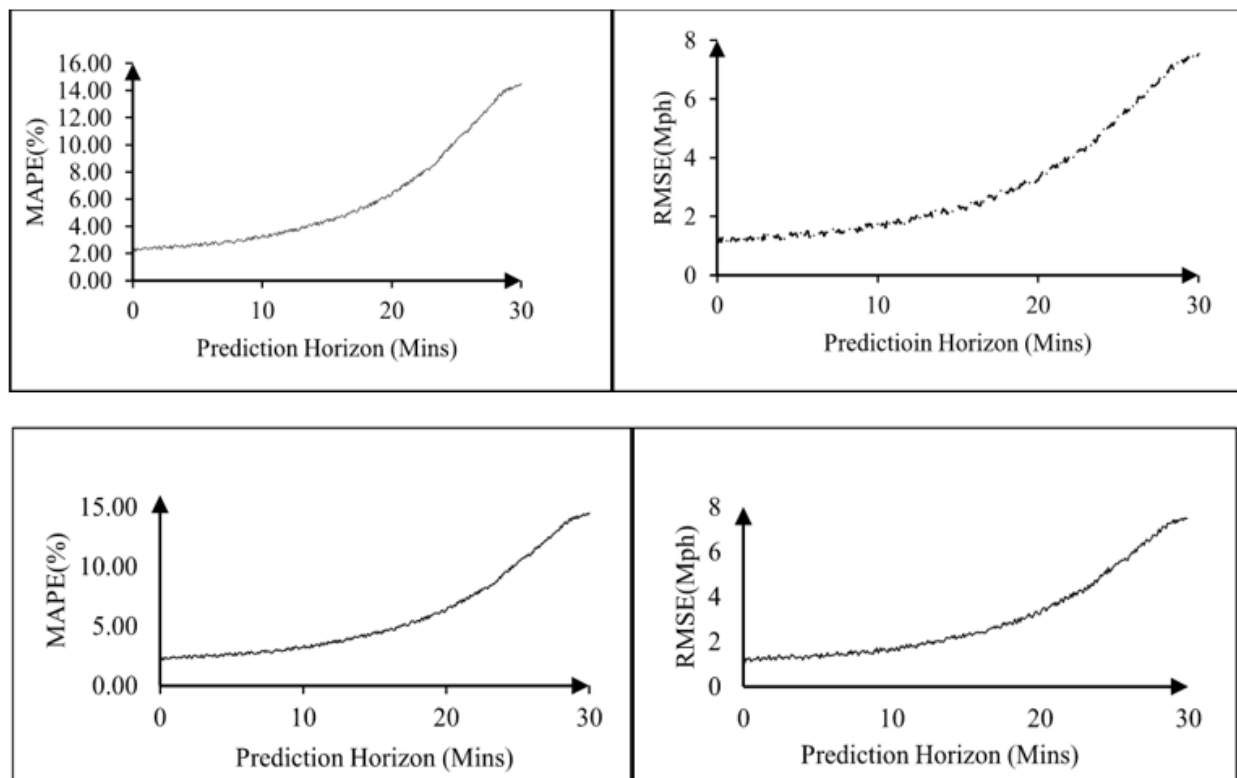


**Fig. 3** The average performance of TD2-DL is displayed on the bottom graph, while the top graph displays the prediction range vs average prediction accuracy.[14]

## 4. Challenge

### 4.1. Data Missing and Noise Problems

During highway traffic flow forecasting, the quality of data is very important. Among them, the filling method of missing data is a key step. For example, using linear interpolation to fill in missing values based on trends in existing data.

By calculating the mean, the central trend of the data can be obtained, which provides the basis for subsequent analysis. Missing data filling can ensure data integrity. Data preparation [15] can make the data input to the deep learning model more accurate and effective, thus improving the accuracy and reliability of the prediction and providing strong support for traffic planning and management.

### 4.2. Face the Problem of Capturing Long-Term Dependencies

LSTM can effectively remember long-term information through its unique gating mechanism, such as capturing the long-term impact of cyclical factors such as holidays on traffic flow [16]. The GRU simplifies the structure and reduces the computational cost while maintaining the performance. For example, in a city's traffic flow forecast, LSTM was used to successfully predict long-term traffic changes due to major activities.

There are multiple challenges when using LSTM or GRU for traffic flow forecasting, and obtaining and processing high-quality, long-term historical traffic data is a major challenge, especially data that includes periodic events. Second, model training and optimization are time consuming and resource intensive, and hyperparameter tuning is critical to performance. In addition,

models need to have good generalization ability to deal with previously unseen data and anomalies while maintaining the accuracy of predictions. High-performance computer resources may be needed if models are to provide predictions rapidly in a constrained amount of time for real-time prediction. Although long-term dependencies are intended to be captured by LSTM, it might be difficult to preserve long-term memory while remaining responsive to short-term changes.

In this study, a better adaptation to various data features can be obtained by varying the structural parameters of the model, such as the number of layers and neurons. At the same time, the algorithm is optimized. The adaptive learning rate, regularization and other methods are adopted in this paper to prevent overfitting and improve the generalization ability of the model. Specifically, through the optimization algorithm, the prediction accuracy of traffic flow in a certain area is improved by 10%, providing more accurate decision-making basis for the traffic management department.

### 4.3. Difficulty in Improving Model Generalization Ability

#### 4.3.1. Cross-City data interaction

Traffic flow data of different cities have certain commonalities and differences. Through interactive analysis, more general rules and characteristics can be dug out. The morning rush hour congestion mode of city A may have reference value for city B [17].

The difficulties are reflected in the fact that data format, collection frequency and quality of cross-city data interaction in traffic flow analysis may be different in different cities, leading to complicated data integration and pre-processing. Unique factors such as traffic mode, infrastructure and population distribution of each city make cross-city data interaction analysis need more refined consideration and adjustment. Even protecting the privacy and security of cities and ensuring compliance in data interactions is a challenge. Finally, cross-city data interaction requires efficient information sharing and collaboration mechanisms.

#### 4.3.2. Model fusion and transfer learning

Model fusion can synthesize the advantages of multiple models and improve the stability of prediction. Transfer learning can apply a model trained in one city to other cities, reducing the training cost and time of new models. However, research on short-term traffic flow prediction is mainly based on a single type of traffic flow under pure high-pressure environment [18], which has certain limitations. In order to predict short-term traffic flow more comprehensively and accurately, it is necessary to consider more complex environmental factors and traffic flow types to improve the generalization ability and practicability of the model.

## 5. Future Direction

In the field of highway traffic flow forecasting, there are still many challenges and broad future research directions.

In terms of technology development trends, more efficient deep learning algorithms will emerge in the future, and new neural network architectures may appear 错误!未找到引用源。, further improving the performance and efficiency of the model. At the same time, the deep integration of big data and cloud computing will make it more convenient and faster to process massive traffic data 错误!未找到引用源。, providing strong support for accurate prediction.

In the application field expansion, cross-domain data fusion and collaborative prediction will become mainstream. For example, weather data and social activity data are combined with traffic data 错误!未找到引用源。 to make a more comprehensive forecast. Real-time traffic management and intelligent navigation services will also be further optimized to provide travelers with more personalized and accurate route planning.

By improving traffic operation efficiency and service quality, the capacity of urban roads will be greatly improved. Reducing traffic accident rates and travel costs can make people's travel safer and more economical. For example, efficient traffic flow forecasting can adjust signal timing in advance,

reducing congestion-related accidents while reducing vehicle fuel consumption and traveler time costs.

In short, the future development of deep learning in traffic flow forecasting is exciting and will bring profound changes to urban transportation.

## 6. Conclusion

This paper focuses on highway traffic flow forecasting and points out the current challenges such as data loss and noise, difficulty in capturing long-term dependence relationships, and the need to improve model generalization ability. At the same time, the current problems and future research directions are clarified, including the development of deep learning in traffic flow prediction. The application status of typical methods in this field and the improvement of depth methods based on typical methods are also described.

Through the study of highway traffic flow forecasting, it is deeply realized that solving the existing challenges is very important to improve the accuracy of forecasting. The depth method improves the prediction effect to some extent, but there is still room for improvement.

Looking forward to the future development, the most important thing is that the technology studied can supplement the gaps in the literature of deep learning in the field of traffic flow prediction, integrate deep learning methods with traditional methods, and create new methods that are more suitable for predicting traffic flow. On the basis of this study, more effective data processing methods can be further explored in the future to deal with missing and noise problems. At the same time, in terms of capturing long-term dependency, the algorithm keeps innovating, improving the generalization ability of the model, and better adapting to the demand of traffic flow prediction under different scenarios. Finally, deep learning technology will continue to bring new breakthroughs and developments to traffic flow forecasting.

## Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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