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Research Article

The Application of Virtual Reality Technology on Intelligent Traffic Construction and Decision Support in Smart Cities

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The core of smart city is to build intelligent transportation system.. An intelligent transportation system can analyze the traffic data with time and space characteristics in the city and acquire rich and valuable knowledge, and it is of great significance to realize intelligent traffic scheduling and urban planning. This article specifically introduces the extensive application of urban transportation infrastructure data in the construction and development of smart cities. This article first explains the related concepts of big data and intelligent transportation systems and uses big data to illustrate the operation of intelligent transportation systems in the construction of smart cities. Based on the machine learning and deep learning method, this paper is aimed at the passenger flow and traffic flow in the smart city transportation system. This paper deeply excavates the time, space, and other hidden features. In this paper, the traffic volume of the random sections in the city is predicted by using the graph convolutional neural network (GCNN) model, and the data are compared with the other five models (VAR, FNN, GCGRU, STGCN, and DGCNN). The experimental results show that compared with the other 4 models, the GCNN model has an increase of 8% to 10% accuracy and 15% fault tolerance. In forecasting morning and evening peak traffic flow, the accuracy of the GCNN model is higher than that of other models, and its trend is basically consistent with the actual traffic volume, the predicted results can reflect the actual traffic flow data well. Aimed at the application of intelligent transportation in an intelligent city, this paper proposes a machine learning prediction model based on big data, and this is of great significance for studying the mechanical learning of such problems. Therefore, the research of this paper has a good implementation prospect and academic value.

1. Introduction

With the rapid development of social economy, the process of industrialization and urbanization has been continuously promoted, people's living standards continue to rise, all kinds of means of transportation are becoming more and more popular, the popularity of domestic cars is constantly improving, the supply of urban infrastructure is in short supply, the limited traffic resources cannot meet the growing traffic needs, and the contradictions between people and vehicles, vehicles and roads, and roads and people are increasingly obvious; the imbalance of traffic structure leads to the limitation of urban sustainable development. At present, various cities have appeared to have traffic congestion; traffic congestion is spreading from the first-level cities to the second- and third-level cities, gradually affecting the travel safety and living standards of most people. For this contradiction, it is not an efficient way to increase the number of traffic channels by relying on traditional methods. Only an efficient transportation system can truly solve a series of problems such as traffic safety, vehicle supervision, traffic congestion, and traffic flow supervision caused by road vehicle conflicts. Intelligent transportation involves the full application of information technology. On the basis of communication and electronic traffic management technology, a set of complete coverage, accurate results, and efficient operation management system is established. An intelligent transportation system can effectively utilize the existing traffic resources, improve the operating efficiency and safety factor of the entire transportation system, and reduce congestion and environmental pollution [1, 2]. Therefore, in facing the future, intelligent transportation should be a necessary choice to strengthen urban traffic construction. The core of an efficient transportation system is intelligent, so how to build and improve the intelligent transportation system has become an urgent problem. A good road environment can give users a clear and pleasant feeling, thereby increasing the fun of the journey, eliminating fatigue, and reducing traffic accidents.

The research on an intelligent transportation system abroad mainly includes the intersection of transportation planning, information technology, traffic information technology, and so on; the theory of the intelligent transportation system is applied to guide the construction of the urban transportation system. Sedjelmaci et al. proposed an intelligent transportation system evaluation index system, using big data to comprehensively evaluate six kinds of indicators, including traffic structure, traffic information service, traffic efficiency, traffic safety, energy saving and emission reduction, and social inclusion. The traffic big data includes license plate recognition (LPR), GPS, and automatic vehicle location (AVL), and smartphone data provide a more scientific theoretical basis for the evaluation of these indicators. But they did not provide specific data to support [3]. Hanapi et al. have designed a public transport charging proposal system. By analyzing the subway card data, it can predict the future travel mode of the public, so as to guide the travel time, ticket purchase method, and other information, so as to save the capital and time cost. However, they only aimed to improve public transport and could not fully cover road traffic [4]. Tourani proposed a decision support model for urban traffic planning based on traffic big data, which is divided into three stages: the location data of taxi passengers entering and leaving, the definition of alternative public transport routes, and the comparison of alternative schemes to scientifically calculate the public transport lines that the government should increase [5].

Based on the research of the intelligent transportation industry in our city, this paper analyzes and summarizes the benefits and risks of smart city management capability big data crash research method circulation. Through the improvement of the city's intelligent transportation system, improve the city's traffic quality, promote urban economic development, and accelerate the construction of smart cities.

2. Big Data Application of the Intelligent Transportation System in a Smart City

2.1. Role of Intelligent Transportation in a Smart City

2.1.1. Definition of a Smart City. A smart city is the product of the new generation of information technology revolution and knowledge economy. It is based on the Internet and the Internet of things, combined with the telecommunications network, broadcasting network, and broadband network. A smart city will further promote the development and construction of the basic information system and implementation information system and form a network-based, information-based, intelligent, and modern city. A smart city is characterized by highly integrated information integration and deep integration of information application; it is to use communication and information media to detect and integrate key information of the central city system. Wisdom responds to various needs such as life, environmental protection, public security, and urban services [6–8]. A smart city pays more attention to intelligent discovery and problem solving and has stronger innovation and development ability. The road model is mainly used to describe the geometric characteristics of the road, the lane division, the width of the isolation belt and the shoulder, the type of the road surface, and the location of fixed traffic signs.

2.1.2. Definition of Intelligent Transportation. An intelligent transportation system (ITS) is an efficient, accurate, and integrated real-time traffic management system developed on the basis of traditional road facilities; by studying the basic theoretical model, the advanced information technology and sensor technology are effectively integrated; and information technology, electronic control technology, and mechanical system technology are the development direction of modern transportation systems and have become the development direction of modern transportation systems, the best way to solve traffic problems in modern society. It includes all existing vehicles. By collecting, processing, analyzing, providing, and using traffic information, the transformation from traffic system construction to traffic management is an important part of China's high-tech industry.

2.1.3. Connection between a Smart City and Intelligent Transportation. The development of intelligent transportation conforms to the inner needs of the construction of smart cities. On the one hand, traffic congestion and traffic pollution are the main "urban diseases." Through the effective integration of high and new technologies, intelligent transportation can reduce road congestion and road accidents and indirectly reduce vehicle exhaust emissions, which is an important and effective means to control urban traffic diseases. On the other hand, due to the demand development based on intelligent transportation, governments at all levels and transportation departments have implemented calculation application of cloud. Application of Internet of things and other advanced technologies in daily traffic management operation [9, 10]. Obviously, the development of intelligent transportation will inevitably drive the development of emerging industries such as the mobile Internet to better meet the needs of smart city construction.

Intelligent transportation accelerates the construction of smart cities. The development of smart transportation has promoted the development of smart public transportation, smart parking, and information services. It has improved people's living standards and embodies the characteristics of smart cities. Therefore, intelligent transportation plays an important role in the construction of smart cities and can promote the construction of smart cities. The rapid development of the intelligent transportation industry has contributed to the construction of smart cities.

The construction of smart cities provides huge opportunities for the development of smart transportation. Improving the efficiency of smart city construction has laid a good foundation for the development of smart transportation. At the same time, the modernization of other smart city systems will also accelerate the pace of smart transportation construction [11].

2.1.4. Application of Big Data in Intelligent Transportation

(1) Big Data Classification in Traffic Management. The situation of road traffic management is becoming more and more serious. The management design is wide and the number of participants is large. Various behaviors and traffic management methods produce a lot of basic data. Road is the carrier of traffic flow. The true description of road network topology and road geometric conditions and the establishment of a reasonable and scalable road traffic network data structure are the basis for traffic flow simulation. From the perspective of operators, the main traffic data mainly includes the following basic data types:

(1) Dynamic traffic information collection data, for example, data collected through road monitoring, intersection flow collection, etc. As far as the city is concerned, the daily traffic behavior of nearly 600000 motor vehicles will be uploaded to the monitoring system and data acquisition equipment to generate astronomical basic road traffic data. These traffic behaviors are widely distributed in urban, suburban, and county traffic arteries

(2) Static traffic management statistics, for example, basic parking management data. In this regard, the main elements of transportation especially include the following aspects: first, the location of a parking lot, the internal regional planning of a parking lot, the classification of parking lot nature, and the number of parking spaces and second, the parking state of the vehicle, the specific parking time of the vehicle, etc. [12]. In addition, there are a series of data about parking management, such as administrator status, time charge, or one-time charge

(3) Basic data of driving management service, such as the number of motor vehicles and the number of drivers. There are millions of motor vehicle drivers in this city; a large amount of basic data is generated in every connection related to the driver, including driving license application, renewal, verification, and cancellation. Similarly, the registration, annual inspection, scrapping, and other related procedures of more than 600000 vehicles will also generate huge basic data. The sum of the two data has reached the level of 10 million

(4) Traffic management data summary, for example, traffic violation data processing, off-site road traffic violation data processing, road accident data processing, road traffic basic data processing, and traffic illegal behavior data processing. In recent years, the number of traffic violations is positively correlated with the development speed of traffic participants. Among them, each traffic violation involves at least one traffic participant, motor vehicle or nonmotor vehicle, and one or more families. In the process of handling traffic and accident infringement, a large number of basic data have also been generated [13, 14]

(5) Auxiliary data of road traffic management. Just like the component of the regional traffic management department, it includes the number of traffic police, the number of assistants, traffic, and civilized traffic counselor data. In the case of further subdivision, it can be specific to the basic situation of these traffic controllers, personality characteristics, specific preferences, attendance status, administrative effect, and other quantitative indicators. In addition, with the support of traffic management, basic data such as road network structure and traffic monitoring, traffic signs and points, and basic data such as flow collectors are also provided

(6) Road traffic management information. This paper mainly deals with the relevant units and aspects that directly affect traffic management. For example, the police patrol, public security, and other parts share defense data, such as multifleet and hazardous chemical operation data, for example, the peak period of pedestrian and vehicle flow in the market, the time of school and holiday, as well as the number of students and details of traffic violation fines collected by banks [15].

(2) Benefits of Big Data in Intelligent Transportation. Big data is not only a social phenomenon but also a scientific and technological achievement, which is the inevitable result of the historical development trend of information science and technology and knowledge economy. The availability of mining, power transmission, and large-scale data technology and the corresponding technical processing methods are technical means for massive data collection and processing, as well as a large amount of structured, semistructured, and unstructured data sets by systematically using nontraditional existing hardware and software tools, to obtain survey results and analysis. Big data technology mainly includes data extraction technology, data maintenance technology, calculation and processing technology, data research technology, and result display technology [16, 17]. At the same time, in the application of large-scale data technology, it mainly involves data sorting and merging, data storage, data mining, and other multilevel and all-round content. Big data technology has become the infrastructure guarantee of big data and its implementation, so it plays an important role.

Based on the above theoretical basis, the benefits brought by big data injection into public management decision-making can be divided into the following benefits:

(1) Improve traffic operation efficiency

Because big data is real-time, distributed, efficient and predictive, it improves the effectiveness of emergency traffic management. Managers can call real-time data from the big data background at any time. The distribution of big data solves the problem of cross regional management and has unique advantages in information integration and combination [18]. Big data improves the command, dispatch, and guidance ability of traffic managers in an all-round way and improves the response and processing efficiency of traffic violations.

(2) Improve traffic safety

Big data can improve traffic safety. On the macro level, by improving the data processing capacity of the traffic safety system, it can provide road accident early warning and efficient emergency decision-making assistance for managers and avoid traffic accidents as far as possible. On the micro level, the comprehensive safety performance monitoring of vehicles and drivers is carried out. The monitoring contents include the real-time relationship between the vehicle and the complex traffic environment during driving, and whether the driver may drive drunk or fatigue.

(3) Enhance the decision-making ability of the government

A large amount of data can improve the scientific nature of government decision-making and governance capabilities. Scientific decision-making mainly benefits from the coexistence of new and traditional data sources, through some accurate, detailed, and fast updated data. Traffic decision-makers can find the information flow that cannot be detected in the past and hidden development patterns and relationships. Rich data provide a window for observing the real social operation and support the decision-making based on evidence of the government.

(4) Improving the Environment and Saving Energy

Big data can improve the environment and save energy. On the one hand, big data can be used for effective environmental monitoring. Big data is comprehensive, detailed, and rapidly updated data, which has advantages in monitoring and forecasting traffic emissions. At the same time, it can also associate environmental data and establish a data platform for the exchange and sharing of traffic big data and environmental data, so as to carry out causal analysis. On the other hand, by improving the traffic operation efficiency and shortening the congestion time, the emission of vehicle pollutants is indirectly reduced [19].

2.2. Traffic Flow Prediction Model Based on Machine Learning. A traffic prediction task is the basis of its stable operation. Accurate and reliable traffic prediction results can assist active and dynamic traffic control. In recent years, prediction methods based on deep learning have received considerable attention [20]. Some research attempts to use deep repetitive neural networks (RNN) and vaccine neural networks (CNN) to predict traffic flow. However, these methods are not suitable for data points with irregular graph relations [21]. Because a traffic network can be represented by graph, a graph convolution neural network (GCNN) naturally becomes a very suitable choice in this scenario. Research shows that GCNN with a deep structure is very effective in short-term traffic prediction. The basic model of GCNN is shown below.

(1) Graph Convolution Neural Network

The graph convolution neural network uses $M = (v, \varepsilon, w)$ to express a directed graph, where v represents all the P vertex sets in the graph, ε represents the set of all edges in the directed graph, and w represents the weight matrix corresponding to M. The signal values of all vertices in the graph are expressed as a vector $a \in \mathrm{RP}$, where AI is the signal value at the i-th vertex. The Laplacian matrix of a digraph is expressed as $\mathrm{l} = D - W$, and the corresponding feature decomposition can be expressed as $\mathrm{l} = \mathrm{u}\,\Lambda\,\mathrm{ut}$. When D is the diagnosis matrix, the value of the i-th element of the graph is equal to the number of times of the i-th rotation in the graph, that is, $DiI = \sum jwij$. U is an orthogonal matrix. The Fourier transform of vector a can be expressed as $\widehat{A} = U^T A$. Therefore, the graph convolution operation of signals A_1 and A_2 in the Fourier domain can be expressed as follows:

$$A_1 * MA_n = U\left(\left(U^T A_1\right) \cdot \left(U^T A_2\right)\right), \tag{1}$$

A signal is convoluted by g_θ and can be expressed as

$$y = g_\theta(L)A = g_\theta\left(U \wedge U^T\right)A = U g_\theta(\wedge) U^T A. \tag{2}$$

In order to realize K localization and reduce computational complexity, formula (2) can be further expressed as follows:

$$y = U g_\theta(\wedge) U^T A = U\left(\sum_{k=0}^{k-1} \theta_k \wedge^k\right) U^T A = \sum_{k=0}^{k-1} \theta_k L^k A, \tag{3}$$

where parameter $\theta \in R^K$ is the vector of the polynomial Fourier coefficients. The convolution operation makes the distance $\mathrm{DG}\,(I, J)$ between nodes I and j limited to K hops. At that time, $d_g(i, j) \geq K$ and $L_{i,j}^K = 0$. Therefore, convolution operation on the spectral domain of k-order polynomial expressed as the Laplacian matrix can realize k-localization [22, 23].

Assuming that each vertex contains CIN features, the signal values of the P nodes in graph M can be represented by a matrix with the size of $\mathrm{CIN} * P$. When the matrix is used as the input of a graph convolution layer, the convolution operation with tensor of size (CIN, cout, K) as a convolution kernel can be expressed as follows:

$$y_j = \sum_{ie[1,c_{\text{in}}],ke[1,K]} \theta_{ijk} \quad K^k x_i, \quad j = 1, 2, \cdots, c_{\text{out}}, \tag{4}$$

Among them, c_{in} and c_{out} represent the size of the input and output characteristic graph of the graph neural network, respectively.

(2) Figure signal processing

In the graph signal processing area, the signal forms a function at the top of the weighted graph. The main challenge in this area is to learn graph structures from data. The chart read must have a substantial explanation and be useful for analysis. Given a set of V nodes and a set of corresponding labels on these nodes, the graph structure is learned by estimating the matrix L. the nonzero mode defines the connectivity at both ends of the graph.

Given a p-dimensional random graph signal x and its N observations $x_1, \cdots x_N$, its sampling covariance is $Q = 1/N \sum_{i=1}^{N} x_i x_i^T$. A graph structure learning problem is often transformed into a matrix optimization problem, and an effective solution is found. According to the maximum likelihood estimation of L,

$$\min_{I \geq 0; L_{ij} \leq 0, \forall i \neq j} - \log \det (L) + \operatorname{tr}(\mathrm{QL}). \tag{5}$$

Minimizing tr (QL) is equivalent to improving the average smoothness. The logarithmic function det, as the obstacle of the minimum eigenvalue of L, is used to enforce the semidefinite constraint. Symbolic constraints can be handled using Lagrange multipliers [24, 25].

3. Simulation Experiment

3.1. Environment Configuration. For road planning and design in a three-dimensional virtual city, due to the need to test and compare different design schemes, it will involve modifying the number of lanes, road width, and other attributes. As shown in Table 1, it includes the system configuration required by the experimental platform, such as CPU, memory, hard disk, and other hardware information. The model algorithm is programmed with the Java language and operates on a computer with the Windows 10 operating system.

3.2. Experimental Data Collection. In this paper, we collect the traffic data in the morning and evening of the same road section in the city. The data collection time is the first three days of the experimental simulation, and the data sampling medium is 5 minutes. This paper randomly selects 6 sensor tracking data from the urban transportation department. From the morning peak time (7:00-10:00) and the evening peak time (17:00-20:00), each sensor collects and outputs the traffic data every 5 minutes and adds the daily weather data.

Table 1: System configuration.

Configuration	Software and hardware
CPU	Intel Core i5
Frequency	2.5 GHz
RAM	8 G
Hard disk	256 G
Operating system	Windows 10
Program development environment	Visual Studio 2015

3.3. Experimental Evaluation Index. In the process of designing roads, this article through intuitive understanding of the surrounding environment of the road is conducive to a more comprehensive consideration of the relationship between the road and the environment and the impact on traffic safety. In order to verify the appropriateness and accuracy of the prediction model, we should use performance evaluation indicators to evaluate the prediction model. Commonly used performance evaluation indicators are mean square error (MSE), average absolute percentage error (MAE), and average absolute percentage error (MAPE). In this paper, MAE and MAPE are used as the evaluation indexes of the prediction results. The average absolute error (MAE) can directly reflect the difference between the actual value and the predicted value; the average relative error (MAPE) is an error in the actual value, which is a dimensionless value that can reflect the level of error and the measured value reliability.

$$\mathrm{MSE} = \frac{1}{N} \sqrt{\sum_{i=1}^{N} (y_i - y\wedge)^2}, \tag{6}$$

$$\mathrm{MAE} = \frac{1}{N} \sum_{i=1}^{N} y_i - \hat{y}, \tag{7}$$

$$\mathrm{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_1 - \hat{y}_1}{y_1} \right| \times 100\%, \tag{8}$$

where y_i is the actual traffic volume at time i, $\hat{y}_i$ is the expected traffic volume over a period of time i, and N is the total number of individuals of the predicted value. Four other models are selected for performance comparison: VAR, FNN, GCGRU, and STGCN.

4. Statistics and Comparison of Experimental Results

4.1. Prediction Accuracy of Each Model. In this paper, five models (VAR, FNN, GCGRU, STGCN, and DGCNN) were run for 15 times, and the average prediction error was obtained to obtain the accuracy of each model in the traffic flow prediction. In the way of using virtual urban traffic to simulate actual urban traffic, it can be observed in a realistic three-dimensional urban traffic scene with various control methods from viewpoints, and various scenes can be

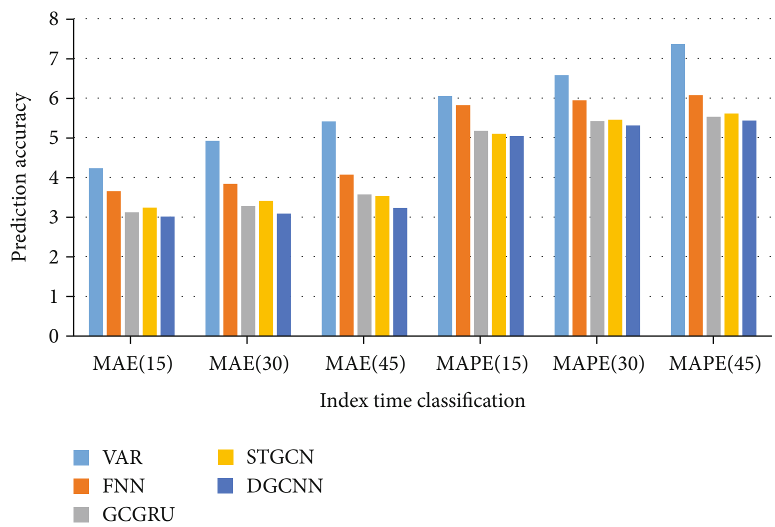

Figure 1: Accuracy of model prediction.

generated through changes to ultimately establish an effective city. Traffic control and management provide an effective basis.

As shown in Figure 1, the GCNN model presented in this paper achieves the lowest RMSE and MAE in traffic prediction accuracy on both datasets, which is better than all other comparison models. It can be clearly seen from the forecast results that the traditional linear prediction method VAR is the worst because it cannot deal with the variability of traffic data. Compared with the other three deep learning models, GCNN also performs better, with an average prediction error of 8%-10%. The traffic mode and spatial dependence of urban road network are dynamic. By ignoring the dynamic change of the road network spatial dependence, the prediction error of the other three models is large.

4.2. Prediction Fault Tolerance of Each Model. Due to sensor failure or traffic accidents on some road sections, local anomalies may exist in real-time traffic samples. In order to test the fault tolerance ability of the model in extreme environment, this paper randomly selects the designated road section to destroy some historical observations.

As shown in Figure 2, the DGCNN model shows higher fault tolerance, with an average prediction error reduction of 10%-25% compared with the two most advanced models based on graph CNN. Even if the failure rate of all road sections reaches 90%, DGCNN still shows strong prediction ability. The DGCNN model can detect the change of spatial dependence hidden in the "polluted" traffic samples and adjust the perceptual domain of graph convolution operation. With the increase in the training period, DGCNN achieves the lowest verification error compared with GCNN and STGCN, which shows the training effect. The reason is that the dynamic Laplace matrix estimator increases the performance and flexibility of the prediction model to capture the influence of various factors in the road network. In the urban traffic simulation system, the road network model is not only a simple geometric figure, but more importantly, it should be able to play the role of a traffic simulation carrier. Through effective data organization, the road network model must actively and efficiently reflect its dynamics. The effect of entity-vehicle constraints improves the efficiency of simulation operation.

4.3. Comparison of Early Peak Model Prediction. As shown in Figure 3, the prediction effect of the DGCNN model is better than that of the other two models in the morning peak hours of weekdays. The prediction curve is more suitable for the actual traffic flow curve, and its changing trend is basically consistent with the actual traffic flow. Although other models are closer to the actual value at certain two points, their change trend is not consistent with the actual value, indicating that DGCNN can effectively reduce the adverse effects of accidental errors.

4.4. Comparison of Late Peak Model Prediction. As shown in Figure 4, the predicted value of the DGCNN model differs very little from the actual value, almost in agreement, while the predicted value of other models always has a certain deviation. Therefore, in this article, due to the selection of the characteristics of the DGCNN algorithm and the optimization of the parameters, the prediction accuracy of the DGCNN model is higher than that of other models. By intuitively understanding the environment around the road, the coordination relationship between the road and the environment and the impact on traffic safety can be considered more comprehensively.

To sum up, through the comparison results of each model, we can know that due to the introduction of more influential factors, such as weather conditions, the feature selection process and parameter optimization process have been improved; the prediction accuracy and error tolerance of the DGNN short-term traffic flow prediction model in the morning and evening hours of the peak working day are better than those of the traditional model.

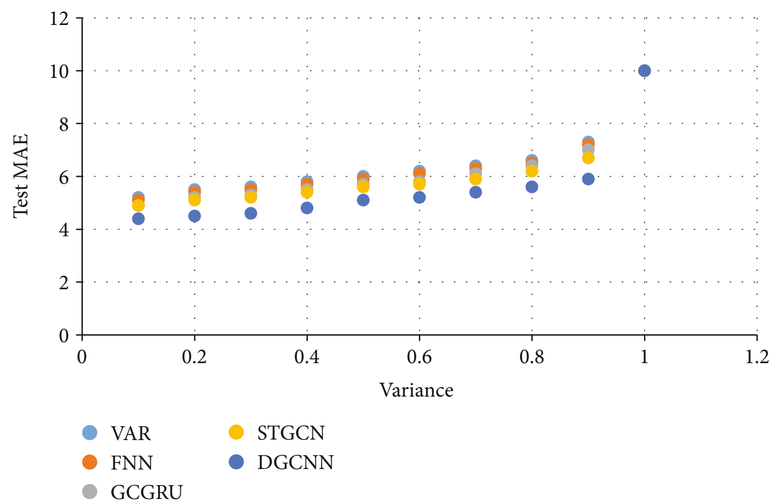

Figure 2: Model fault tolerance comparison.

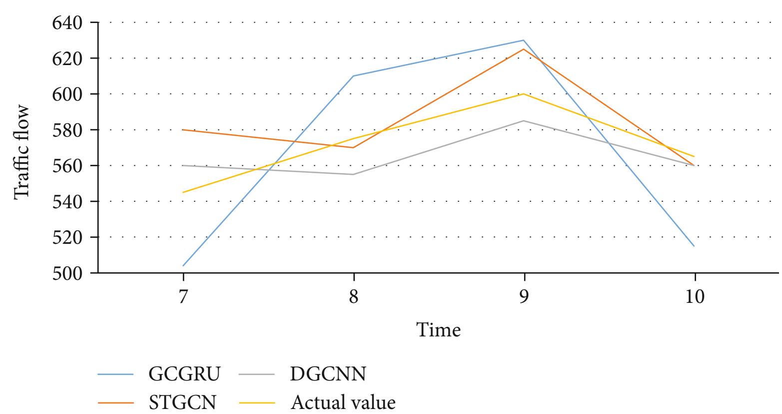

Figure 3: Early peak forecast.

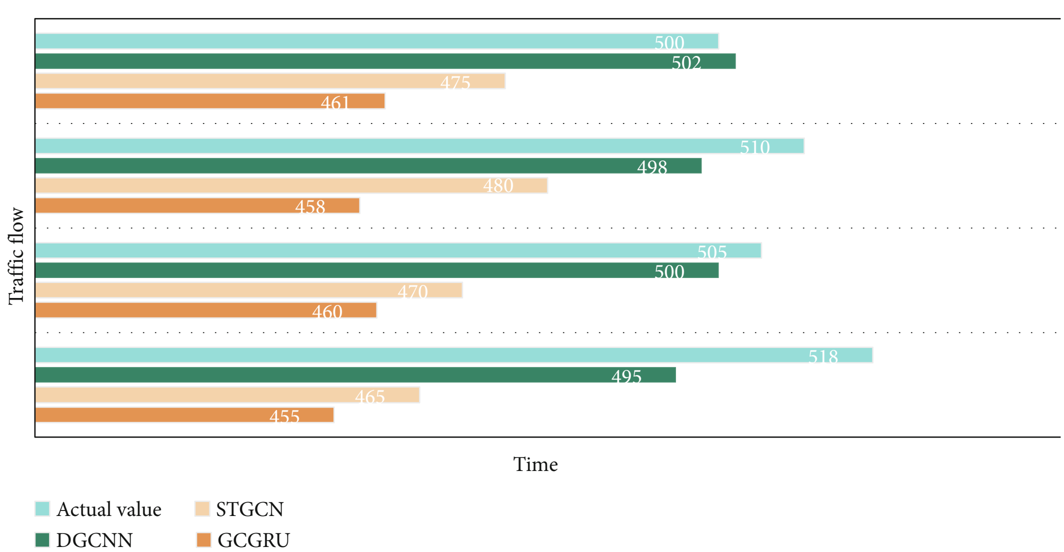

Figure 4: Late peak forecast.

5. Conclusions

With the development of urban economy and the improvement of residents' living standards, the number of urban vehicles in our country is increasing year by year. With the development of urban economy, the contradiction between transportation supply and demand, environmental pollution, and immeasurable economic losses has emerged. After realizing that the traditional traffic management mode cannot solve the modern traffic problems, the governments domestically and internationally began to control public transport since the 1960s. The continuous exploration and innovation of management mode and tools are aimed at creating a travel environment with high efficiency, safety, comfort, energy conservation, and environmental protection for the people. The emergence of big data is widely concerned by people. In the field of transportation, the rapid development of detection technology provides the possibility for efficient and high-quality high-flow data collection, and the continuous improvement of big data analysis ability can transform massive data into public value. With the real-time collection of information of traffic elements such as people, vehicles, and roads, big data has been formed and developed. Big data has been proven to be a favorable tool for urban traffic management in practice.

In this paper, systematic literature review is used to sort out the relevant literature, extract the benefits and risks of big data application in urban intelligent transportation, and summarize and analyze the application of big data in intelligent transportation. In this paper, a machine learning method is applied to urban intelligent transportation scene to solve practical problems, and in the process of solving problems, an innovative model is proposed combining with the characteristics of traffic spatial-temporal data. In this paper, the DGCNN model is used to predict the morning and evening peak traffic flow data and compared with other models. The experimental results show that the DGCNN model has good performance for traffic prediction.

To sum up, we can draw the following conclusions: the intelligent transportation systems were combined, there are many kinds of big data combination modes, and transportation informatization and intellectualization are the fundamental trend of urban transportation system transformation and upgrading in the future; only by effectively integrating the analysis technology of big data with other relevant data of urban management and development can the city be effectively promoted (intelligent transportation construction and development).

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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