

## Retraction

# Retracted: Research on Urban Traffic Industrial Management under Big Data: Taking Traffic Congestion as an Example

### Journal of Advanced Transportation

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] Y. Zhang, S. Yang, and H. Zhang, "Research on Urban Traffic Industrial Management under Big Data: Taking Traffic Congestion as an Example," *Journal of Advanced Transportation*, vol. 2022, Article ID 1615482, 8 pages, 2022.

## Research Article

# Research on Urban Traffic Industrial Management under Big Data: Taking Traffic Congestion as an Example

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This paper establishes a prediction model of traffic flow, where three cycle dependent components are used to model three characteristics of traffic data, respectively. CNN is used to extract spatial features, and the combination of LSTM and attention mechanism is used to dynamically capture the influence of historical period on target period. Finally, the results are obtained by weighted integration of each component. Its prediction result is more accurate, which can provide reference for governance of urban transportation industry under the background of big data.

## 1. Introduction

Road congestion has always been the key problem of traffic industry structure governance [1, 2]. Under smart traffic, predicting road conditions can effectively alleviate the urban traffic pressure and promote the transportation industry to upgrade the construction of an intelligent transportation system, which needs the support of a large amount of data [3, 4]. Only in this way can we ensure the stable operation of intelligent transportation system and bring better traffic experience to users. In the early years, urban traffic relied on manual management, which could only implement manual traffic control according to past data [5]. However, with the increasing number of vehicles, traffic problems can no longer be solved by manual management. The emergence of big data has become the development and application of “timely rain,” which accelerates the collection speed of traffic data and also improves the accuracy and efficiency of data processing. Therefore, applying big data technology to urban smart traffic system is the need of urban transportation development and traffic management [6].

The urban smart traffic management system is still in the initial stage of development in China, and the traffic systems in many cities are moving closer to this direction, gradually

realizing intelligence, abandoning the traditional manual control mode [7], and can better and more scientifically solve the traffic congestion problem. The urban smart traffic system relies on computer artificial intelligence to deal with complex traffic problems, which is a combination of automatic control and computer technology. In the face of real traffic problems, it can obtain the traffic situation in real time and provide data support for traffic management. In addition, in the development of China's urban smart traffic system, the traditional traffic management system has not been completely abandoned, but integrated with it, and on the basis of China's urban development road construction work, the problem of urban traffic has been scientifically dealt with [8]. However, when the system is applied, it needs to be analyzed and calculated based on the massive data of local urban traffic conditions. In order to select the best traffic improvement scheme, we can not only reduce the manpower and material resources consumed by the urban traffic system [9] but also reduce energy consumption through rational planning routes and improve the current and future urban environmental quality in China.

This paper establishes a traffic flow prediction model for traffic congestion prediction of vehicles under big data,

aiming to provide reference for urban traffic industry governance under the background of big data.

## 2. Urban Intelligent Traffic Detection System under Big Data

*2.1. Intelligent Traffic Control.* Intelligent traffic control system relies on integrated management and command and dispatch system to control road traffic conditions. The intelligent traffic control system collects the traffic information from the front devices installed at the intersection and sends the collected information back to the central management system of the control center for comprehensive management, and directly reflects the traffic information on the GIS ground through the integrated information platform of the base GIS. At the same time, traffic controllers control devices through GIS platform to divert road traffic.

It is built around intelligent transportation system (ITS), which integrates advanced information technology, computer processing technology, sensor technology, data communication technology, and electronic automatic control into the traditional transportation system. A real-time, efficient, and accurate comprehensive transportation management system [10] is established by organically combining the environment of pedestrians and vehicles, which can alleviate urban traffic congestion and reduce traffic accidents.

*2.2. Intelligent Traffic Congestion Control.* Traffic congestion is considered as any event which combines low vehicle speed and long queues of these slow-moving cars [11].

The detection of traffic congestion is to detect all kinds of traffic incidents and accidents in a timely, rapid, and comprehensive manner, improve the response time to deal with emergencies, grasp the real situation on the scene in a timely and accurate manner, implement the right measures at the first time, and avoid the occurrence of second incidents. The architecture of the traffic event detection system is shown in Figure 1. Its functions include: real-time monitoring of traffic conditions on accident-prone sections; realize real-time monitoring of traffic condition of main and auxiliary road sections of diverging and merging; realize real-time monitoring of traffic condition of main road. The traffic event detection system combines camera and detection control unit to collect traffic event information through video camera or electromagnetic induction, and transmits the collected traffic event information to the control center in real time through the cable network. In some places that are not conducive to camera installation, the video detector cannot be used for spot placement, and the induction system such as circular coil/geomagnetic infrared can be used.

## 3. Shortcomings and Development of Intelligent Traffic Detection System

The above-mentioned intelligent detection system mainly sends the connected information to the application server through the vehicle, and then the application server forwards

all the information to the cluster, which belongs to the high-frequency track road condition prediction. Therefore, whether it is the traditional statistical method or the single machine learning method, the prediction accuracy of these models is low and the applicability of these models is poor [12].

Forecasting short-term traffic passenger flow is a complex nonlinear problem, which greatly increases the difficulty of passenger flow forecasting because of its characteristics such as nonstationarity, randomness, and sudden change, especially the short-term passenger flow changes too fast and there are too many random influencing factors, resulting in less obvious regularity. Therefore, it is more difficult to predict [13]. Therefore, scholars at home and abroad have also carried out related research. Among all the methods for short-term traffic flow prediction, the neural network model is popular because of its superiority in processing multidimensional data, flexibility of model structure, adaptability to fresh samples, and learning ability.

With the increasing capacity of computer and the iterative upgrade of neural network algorithm, there are more and more research studies on short-term traffic flow prediction by the neural network [14]. Among them, the recurrent neural network (RNN), the convolutional neural network (CNN), and the long and short-term memory network (LSTM) are considered as more appropriate methods to capture the spatiotemporal characteristics of traffic flow [15].

## 4. Prediction Model of Road Condition

With the development of computer technology, target detection technology is widely used in real-time detection of objects, including target location and identification [16]. Real-time target detection is widely used in intelligent transportation. For example, real-time vehicle location and other current vehicle detection methods are mainly divided into two categories [17]: traditional methods based on machine learning and methods based on deep learning. The traditional methods of basic machine learning generally include two links: feature extraction and classification according to features. In addition, support vector machine (SVM) or AdaBoost is used to classify the extracted histogram gradient features or Harr features, while the methods based on deep learning mainly include R-CNN, Fast R-CNN, Faster R-CNN, MaskR-CNN, YOLO, YOLOV2, YOLOV3 SSD. The feature extraction ability of the convolutional neural network is used to extract the vehicle feature information, and then the features are classified by a classifier.

### 4.1. Overview of Neural Network

*4.1.1. Concept and Development.* Artificial neural network refers to a kind of empirical model composed of multiple neurons that can imitate the actions of biological neural units, and similar to biological neural units, one neural unit can not only receive a single stimulus input signal but also receive multiple segments of stimulus input signals at the same time, and the connection between two neurons can

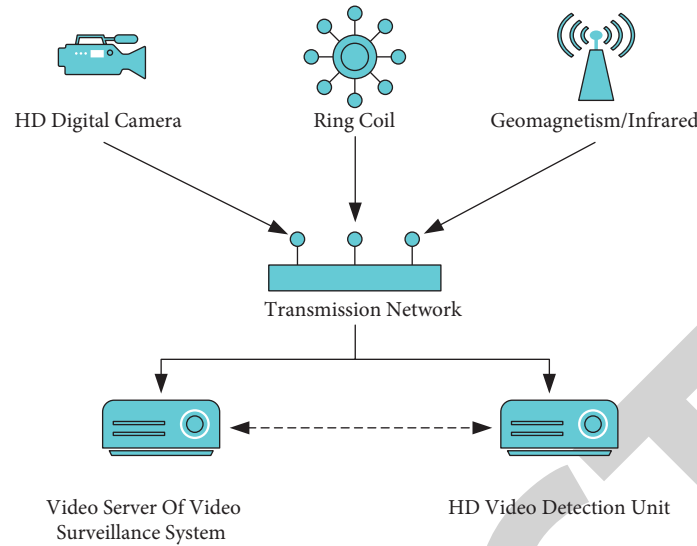


FIGURE 1: Architecture of traffic congestion detection system.

send signals to the output port. Of course, the relationship between input and output is not linear. Therefore, this neural network can be used to simulate all kinds of chaotic signal relationships to realize the original design intention. Through the development of neural network, the neural network model will have more complicated structures and richer parameters with the increase of layers. Therefore, it possesses stronger fitting ability when dealing with major data problems.

**4.1.2. Long and Short-Term Memory Network.** LSTM is a variant of RNN network. The change lies in that it adds memory characteristics on the basis of RNN, which can endow neural network with long-term memory ability and make the model have good applicability to long-term series.

Generally, it is only necessary to set up a four-layer structure to build the LSTM model, as shown in Figure 2.

- (1) Input layer, where one-dimensional time series data is usually input
- (2) LSTM layer, it is also the feature of the LSTM neural network. Three gating units in neurons are the obvious features of LSTM which are different from the traditional circular neural network. They are the input gate forgetting gate and the output gate. Because of the addition of gating units, the problems of gradient disappearance and long-distance dependence have been effectively alleviated.
- (3) Fully connected layer, the role of fully connected layer in the LSTM model is to transform the data from high dimension to low latitude, which increases the complexity of the model while retaining useful information.
- (4) Output layer is mainly responsible for outputting the results of neural network model operation, and there are many prediction scenarios.

The internal structure of LSTM is shown in Figure 3. The gate unit is expanded on the basis of RNN, and the complexity of the hidden layer is improved. The gate unit includes input gate, output gate, memory gate, and forget gate:

- (1) Input gate: filter from input to decide whether to save the information
- (2) Forget gate: determine whether the state information of the current neuron should be discarded
- (3) Output gate: it determines whether the information state of the current neuron should be output
- (4) Memory gate: the new input is filtered to determine which information can be preserved. Through the cooperation of different gate units in the hidden layer, the information is no longer updated indefinitely, but is filtered and removed in an orderly manner, which effectively solves the problem of gradient disappearance and realizes the preservation of long-time series data memory.

Because LSTM introduces the structure of three gates, especially the forget gate that determines whether the current neuron state information should be discarded, LSTM has a better performance than RNN when dealing with time series problems with long intervals and delays. LSTM can control the convergence of gradient during training; thus, the problem of gradient disappearance or explosion can be alleviated. At present, there are two algorithms used to train the LSTM model, namely, back propagation through time (BPTT) and real-time recursive learning algorithm (RTRL). In this paper, the BPTT algorithm is used to build the network model for that it is simpler and clearer in concept, and it can calculate data faster. Except for the prediction of time series data, LSTM has made great achievements in the fields of speech processing machine, image interpretation, handwriting generation, image generation, and so on.

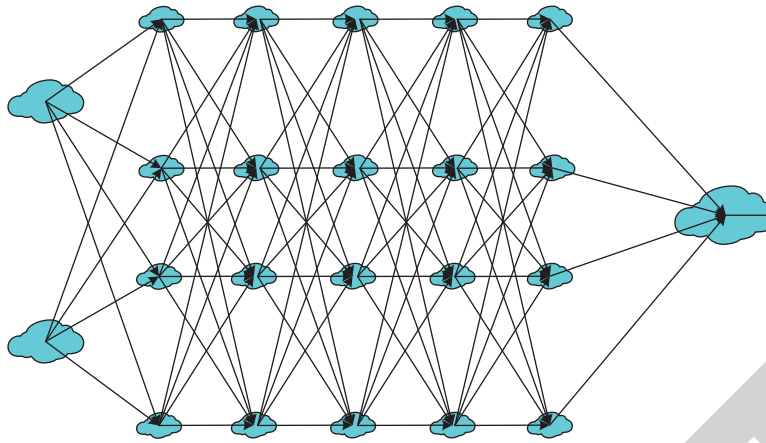


FIGURE 2: Diagram of LSTM structure.

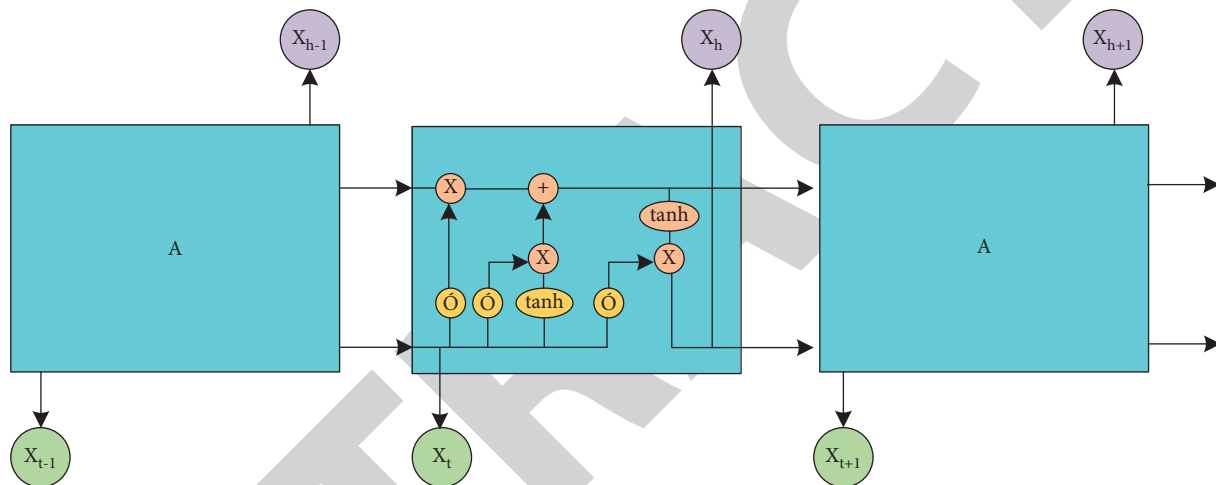


FIGURE 3: Internal structure diagram of LSTM.

**4.1.3. Convolutional Neural Network.** Convolutional neural network is abbreviated as “CNN,” and its network structure generally consists of three parts, namely, convolution layer, pool layer, and fully connected layer for this type of input of pictures. A single convolution layer can realize simple extraction of data features, and more layers of networks can extract more complex features from basic features through iterative training. Multilayer network can extract more deep features from data and improve the effect of the model. CNN has a relatively simple structure and generally takes the BPTT algorithm for training, which makes it a very classic deep neural network model. Convolutional neural network generally consists of input layer, convolution layer, pooling layer, fully connected layer, and output layer, as shown in Figure 4.

The core of CNN lies in convolution layer and pooling layer, which needs to cooperate with other layers to complete the construction of neural network model.

- (1) Input layer: it is the window of data input, and the input of convolutional neural network is a two-dimensional matrix, which is usually a picture.

- (2) Convolution layer is composed of multiple convolution kernels, and the local high-dimensional features of samples are extracted layer by layer through convolution calculation.
- (3) Pooling layer, which realizes downsampling by pooling function, it reduces the dimension of data, improves the computational efficiency of CNN, and at the same time, retains important information in sample data.
- (4) Fully connected layer, which performs full connection operation on related information after convolution and pooling for many times, increasing the complexity of convolutional neural network.
- (5) Output layer is used to calculate the previous sample data and output the calculation result.

Compared with the traditional neural network, the convolutional neural network has the feature of small-scale local convolution weight sharing pooling and dimension reduction. Unlike the feature extracted by the traditional neural network, which is the overall feature, the small-scale

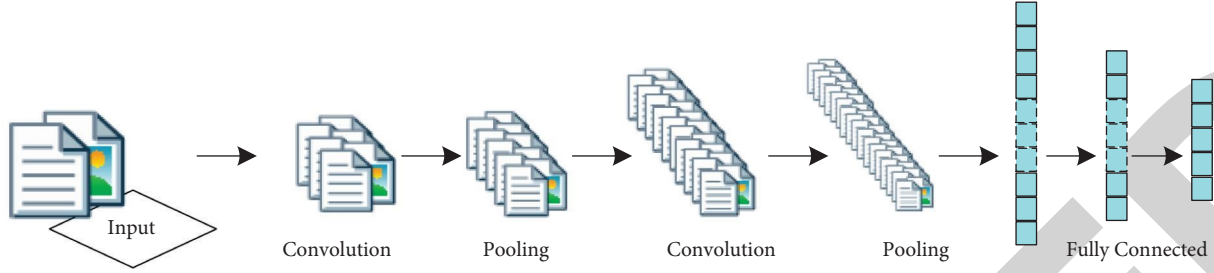


FIGURE 4: CNN network model.

local convolution of the convolutional neural network can be used to convolve the sample matrix data through the convolution kernel in the convolution layer. Each time, only a small part of the matrix data is covered, and then multiple convolution kernels are used to operate so that the high-dimensional local features of the matrix can be obtained, which is more conducive to extracting the local features of the data.

#### 4.2. The Establishment of Prediction Model on Traffic Flow

**4.2.1. Definition of Traffic Flow.** Traffic flow is random, which is a complex problem and will be affected by many factors. In the spatial dimension, for continuous road sections, the traffic situation of the previous road section will affect the traffic situation of the next road section. For example, the traffic jam in the previous road section will affect the traffic flow of the next section. In this paper, the traffic flow data of continuous road sections are used as input, and the idea of forecasting the traffic flow at the end time is studied.

On the road section  $i$ , use total  $n$  periods of traffic flow in the past  $[t - n + 1, t]$  under the upstream and downstream sections  $[i - m, i + m]$  so as to forecast traffic of  $t + 1$  time period.

Make the historical traffic flow in the form of space-time matrix, as shown in formula (1). This spatiotemporal input matrix includes all traffic information of the target road section and adjacent road sections in time and space. Each row in the matrix represents the traffic flow of  $n$  periods in the same section with time interval of  $[t - n + 1, t]$ ; each column represents  $2m + 1$  road section traffic flow on road section range  $[i - m, i + m]$  at a certain moment.

$$X_{i,t} = \begin{bmatrix} x_{i-m,t-n+1} & x_{i-m,t-n+2} & L & x_{i-m,t} \\ M & M & L & M \\ x_{i-1,t-n+1} & x_{i-1,t-n+2} & L & x_{i-1,t} \\ x_{i,t-n+1} & x_{i,t-n+2} & L & x_{i,t} \\ x_{i+1,t-n+1} & x_{i+1,t-n+2} & L & x_{i+1,t} \\ M & M & L & M \\ x_{i+m,t-n+1} & x_{i+m,t-n+2} & L & x_{i+m,t} \end{bmatrix}, \quad (1)$$

where  $x_{i,t}$  represents the traffic flow at section  $i$ , time  $t$ .

$X_{i,t}$  can also be expressed as  $n$  column vectors in chronological order, as shown in formulas (2) and (3):

$$X_{i,t} = [T_{i,1} \ T_{i,2} \ L \ T_{i,t} \ T_{i,n}], \quad (2)$$

$$T_{i,t} = [x_{i-m,t} \ K \ x_{i-1,t} \ x_{i,t} \ x_{i+1,t} \ L \ x_{i+m,t}]^T, \quad (3)$$

where  $T_{i,t}$  is the vector composed of traffic flow of target road section  $i$  and upstream and downstream road section at time  $t$ .

**4.2.2. CNN Model.** The traffic state changes of the upstream and downstream sections are related, and the traffic flows between sections will influence each other. For example, traffic congestion caused by an accident in the upstream section will reduce the traffic flow in the downstream section. In order to reflect the correlation between such traffic sections, CNN can be used to capture its spatial characteristics.

Input the scaled time series into the CNN to learn the spatial characteristics. Input convolution layer  $K$  into  $X_{i,t}$ . The convolution formula is calculated as follows:

$$Y_{i,t}^{(K^*)} = \text{Relu}(W_k * X + b_k), \quad (4)$$

where  $K$  represents the number of convolution layers; the symbol  $*$  represents the convolution operation; ReLU is the activation function;  $W_k$  and  $b_k$  are two sets of parameters in the  $K$ -th convolution layer.

At this time, the spatial features of the three time-dependent features are as follows: short-time dependent component spatial feature  $y_{i,t}$ , daily period-dependent component spatial feature  $y_{i,t}^p$ , and weekly period-dependent component spatial feature  $y_{i,t}^w$ , which are taken as the input of LSTM.

**4.2.3. LSTM Model.** LSTM is used to capture the dependence in time series, and attention mechanism is incorporated to dynamically capture the influence of historical period on target period.

In this paper, the data of the first  $W$  weeks and the first  $P$  days are input, and the traffic data of time period  $[t - q, t + q]$  are extracted from each first  $P$  day and input into the daily cycle component to solve the problem of daily cycle dependence, and the traffic data of time period  $[t - q, t + q]$  is extracted from each first  $W$  week and input into the weekly cycle component to solve the problem of cycle dependence.

LSTM is used to extract time information of different scales as shown in formulas (5) and (6):

$$h_{i,t}^{p,q} = LSTM(y_{i,t}^p, h_{i,t}^{p,q-1}), \quad (5)$$

$$h_{i,t}^{w,q} = LSTM(y_{i,t}^w, h_{i,t}^{w,q-1}), \quad (6)$$

where  $h_{i,t}^{p,q}$  is the representation of section  $i$  in the middle period  $q$  of the  $P$ -th day;  $h_{i,t}^{w,q}$  is the representation of section  $i$  in the middle period  $q$  of the  $w$ -th week;  $y_{i,t}^p$  and  $y_{i,t}^w$  are the spatial features.

At this time, the influence of traffic in different historical periods on the future forecast target is different. Therefore, attention mechanism is introduced to dynamically adjust the influence of different historical periods on the future forecast results.

The importance value  $\alpha_{i,t}^{p,q}$  at different time of day is obtained by comparing the temporal and spatial features  $h_{i,t}$  learned by the short-time component with the hidden state  $h_{i,t}^{p,q}$ . The importance values  $\alpha_{i,t}^{w,q}$  at different times of the week can be obtained similarly. The calculation of significance  $\alpha$  uses the attention mechanism, as shown in formulas (7) and (8):

$$\alpha_{i,t}^{p,q} = \frac{\exp(\text{score}(h_{i,t}^{p,q}, h_{i,t}))}{\sum_{p \in P} \exp(\text{score}(h_{i,t}^{p,q}, h_{i,t}))}, \quad (7)$$

$$\alpha_{i,t}^{w,q} = \frac{\exp(\text{score}(h_{i,t}^{w,q}, h_{i,t}))}{\sum_{w \in W} \exp(\text{score}(h_{i,t}^{w,q}, h_{i,t}))}. \quad (8)$$

The scoring function used in this paper is additive model, such as formulas (9) and (10):

$$\text{score}(h_{i,t}^{p,q}, h_i) = v^{T1} \tanh(W_{H1} h_{i,t}^{p,q} + W_{X1} h_i + b_{X1}), \quad (9)$$

$$\text{score}(h_{i,t}^{w,q}, h_4) = v^{T2} \tanh(W_{H2} h_{i,t}^{w,q} + W_{X2} h_4 + b_{X2}), \quad (10)$$

where  $W_{H1}, W_{X1}, b_{X1}, v^{T1}, W_{H2}, W_{X2}, b_{X2}$ , and  $v^{T2}$  are all parameters learned through training, and  $v^T$  represents the transposition of  $v$ .

The weighted sum of each time interval  $q$  on day  $P$  is expressed as  $h_{i,t}^p$ . The weighted sum  $h_{i,t}^w$  of the corresponding period of the previous  $w$  week is calculated as formulas (11) and (12):

$$h_{i,t}^p = \sum_{q \in Q} \alpha_{i,t}^{p,q} h_{i,t}^{p,q}, \quad (11)$$

$$h_{i,t}^w = \sum_{q \in Q} \alpha_{i,t}^{w,q} h_{i,t}^{w,q}, \quad (12)$$

where  $\alpha_{i,t}^{p,q}$  represents the importance of the time interval  $q$  in the  $P$ -th day;  $\alpha_{i,t}^{w,q}$  represents the importance of the time interval  $q$  in the  $w$ -th week.

Use an LSTM to save these cycle dependency information, and the dynamic dependencies of the daily cycle component and the weekly cycle component of the final output are as follows:

$$\begin{aligned} \mathcal{S}_{i,t}^W &= LSTM(h_{i,t}^p, h_{i,t}^{p-1}), \\ \mathcal{H}_{i,t}^w &= LSTM(h_{i,t}^w, h_{i,t}^{w-1}). \end{aligned} \quad (13)$$

**4.2.4. Combined Model.**  $h_{i,t}^c$  is obtained by weighted fusion of short-term dependence, daily cycle dependence, and weekly cycle dependence, while the time dependence of the predicted road section is retained. The calculation is as shown in formula (14):

$$h_{i,t}^c = W_{\theta 1} \circ \hat{h}_{i,t}^p + W_{\theta 2} \circ \hat{h}_{i,t}^w + W_{\theta 3} \circ h_{i,t}, \quad (14)$$

where  $W_{\theta 1}, W_{\theta 2}, W_{\theta 3}$  are the learned parameters;  $\circ$  is the Hadamard product. Input  $h_{i,t}^c$  to the fully connected layer and activate it with tanh function. The final prediction result is output  $y$ , which is calculated as follows:

$$y = \tanh(W_{\beta} h_{i,t}^c + b_{\beta}), \quad (15)$$

where  $W_{\beta}$  and  $b_{\beta}$  are all parameters learned through training.

The output forecast result of is saved in the file with suffix "pickle," and the predicted traffic flow range is between  $[0, 1]$ . In order to facilitate the analysis, the result data should be played back to the same range of the original data according to the same proportion so that the evaluation index can be calculated later.

## 5. Test Analysis

**5.1. Parameter Setting.** In the establishment of the neural network, parameters in the model should be set. The convolution layer  $K$  of the convolutional neural network is set as 3, the convolution kernel is set as 64 with a size of  $3 \times 3$ , the convolution step is set as 1, and the activation function is ReLU. MAE and RMSE are used for all evaluation indexes. Simulation parameters are shown in Table 1.

**5.2. Analysis of Results.** CNN-LSTM model was used to predict the traffic flow, and the change of the loss function of the model with the increase of training times on working days was studied, as shown in Figure 5. As can be seen from the trend diagram, the loss function of the CNN-LSTM model during weekday training decreases with the increase of the number of training iterations, and rapidly declines in the first 50 iterations, after which the curve gradually flattens out. When the training iteration reaches 600 times, the loss function of CNN-LSTM model is in a stable state.

When the training iteration was 600 times, the loss function of the model on the rest day test set was in a relatively stable state. After 600 training sessions, even if the number of iterations is increased, the loss function does not change significantly but increases the complexity of model calculation and the risk of overfitting. Therefore, the selection of 600 iterations is appropriate, which verifies the rationality of the grid search algorithm.

Figure 6 shows the predicted value curve and real value curve of traffic flow of the CNN-LSTM model in a certain working day time area. It can be seen from the figure that the CNN-LSTM model can accurately predict the change of traffic flow on weekdays, and the predicted value has a good fitting degree with the real value. Compared with the LSTM prediction model, the CNN-LSTM model extracted the

TABLE 1: Simulation parameters.

| Parameters                        | Value                 |
|-----------------------------------|-----------------------|
| Daily and weekly components       | $w=1, P=3,$ and $q=5$ |
| Dimension of hidden layer in LSTM | 128                   |
| Batch                             | 64                    |
| Learning rates                    | 0.001                 |
| Dropout                           | 0.5                   |

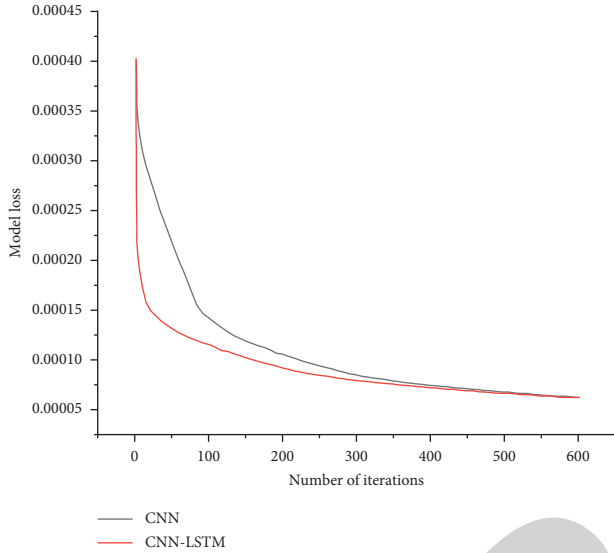


FIGURE 5: Model loss l under 600 iterations.

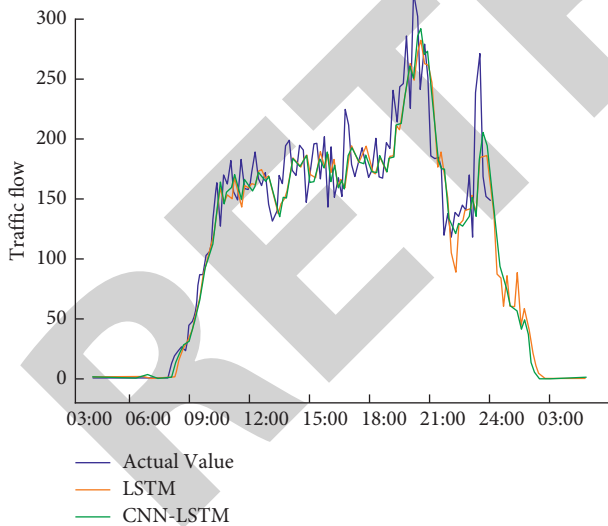


FIGURE 6: Traffic flow prediction under CNN-LSTM model.

TABLE 2: Analysis of experimental results.

| Model                  | Running time (second) | MAE   | RMSE  |
|------------------------|-----------------------|-------|-------|
| LSTM                   | 121.03                | 21.07 | 28.94 |
| CNN                    | 98.71                 | 20.41 | 28.22 |
| LSTM + CNN             | 69.20                 | 18.75 | 24.87 |
| LSTM + CNN + ATTENTION | 45.22                 | 15.61 | 21.52 |

characteristics of passenger flow between stations and predicted the subway passenger flow from the time and space dimensions. The fitting of the model has better accuracy. In addition, the forecast curve of passenger flow on weekends is smoother, which is caused by the randomness of passenger flow on weekends.

The performance results of short-term traffic flow forecast are shown in Table 2. By using different methods to experiment on the same data set, comparing MAE and RMSE of each model, it is found that the model proposed in this paper has the best effect. According to the results in the table, if only CNN is adopted, the model only considers spatial correlation and ignores temporal information, while LSTM only considers temporal correlation and ignores spatial information. Although the CNN + LSTM model extracts time and spatial correlation at the same time, it does not dynamically consider the influence of each historical period on the target period.

From the experimental results, the running time of LSTM + CNN + ATTENTION is smaller than the LSTM and CNN. The smaller the MAE and RMSE index values are, the smaller the model error is and the better the prediction effect is. In contrast, the combined model proposed in this paper based on CNN, LSTM, and attention mechanism is better than the other three models, and its MAE and RMSE values are 15.61 and 21.52, which improves 25.91% and 25.64%, respectively, which shows that this model can accurately predict the traffic flow in different time series, thus effectively reducing traffic jams.

## 6. Conclusion

Traffic flow prediction is one of the key technologies of the intelligent transportation system, which can effectively solve the traffic jam problem. In this paper, three-time characteristic components are used to predict the traffic flow in the future where CNN is used to extract spatial features, LSTM and attention mechanism are used to dynamically extract temporal features, and finally, test of traffic prediction is implemented. The results show that, compared with the other three traffic flow forecasting models, the combined model proposed in this paper based on CNN, LSTM, and attention mechanism has better effect, and its MAE and RMSE values are 15.61 and 21.52, respectively, which shows that this model can accurately forecast traffic flows in different time series, thus effectively reducing traffic jams.

## Data Availability

The dataset can be accessed upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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