Research Article

The Prediction of Multistep Traffic Flow Based on AST-GCN-LSTM

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Aiming at the traffic flow prediction problem of the traffic network, this paper proposes a multistep traffic flow prediction model based on attention-based spatial-temporal-graph neural network-long short-term memory neural network (AST-GCN-LSTM). The model can capture the complex spatial dependence of road nodes on the road network and use LSGC (local spectrogram convolution) to capture spatial correlation features from the K-order local neighbors of the road segment nodes in the road network. It is more accurate to extract the information of neighbor nodes by replacing the single-hop neighborhood matrix with K-order local neighborhoods to expand the receptive field of graph convolution. The high-order neighborhood of road nodes is also fully considered instead of only extracting features from first-order neighbor nodes. In addition, an external attribute enhancement unit is designed to extract external factors (weather, point of interest, time, etc.) that affect traffic flow in order to improve the accuracy of the model’s traffic flow prediction. The experimental results show that when considering the static, dynamic, and static and dynamic combination, the model has excellent performance: RMSE (4.0406, 4.0362, 4.0234), MAE (2.7184, 2.7044, 2.7030), accuracy (0.7132, 0.7190, 0.7223).

1. Introduction

Traffic forecasting is an important field in the research of intelligent transportation [1], and effective traffic flow forecasting can alleviate traffic congestion, travel planning, and traffic management for individual drivers and decision-makers [2, 3]. The complex temporal and spatial correlations between traffic flows will show huge differences affected by external emergencies [4], dynamic factors, and static factors. Ahmed [5] and others proposed an autoregressive integrated moving average model (ARIMA) model that can only deal with nonstationary time series data. It is difficult to explore connections between dynamic data and is no longer suitable for current application scenarios. In addition, though traditional linear methods such as a series of Kalman filtering methods proposed and improved by Stephanedes [6], Xie (2007) [7], Ojeda (2013) [8], Guo [9] have improved the accuracy of traffic prediction in some aspects, its ability to fit nonlinear traffic flow data is still poor, and it increases the prediction time [10–12].

With the development of computer capabilities, typical machine learning methods, such as support vector regression (SVR) [13, 14], k-nearest neighbor algorithm [15, 16] K-NN (K-NearestNeighbor), and decision tree models [17–19], can dig out the essential laws and rich information hidden in traffic flow from massive data [20], and better promote the development process of traffic flow forecasting.

The emergence of deep neural network models has enabled the development of the potential of artificial intelligence in traffic prediction. Although some simple network structures can improve the accuracy of model traffic prediction [21], there are problems such as slow convergence, prone to over-fitting, and prone to error values [22]. Compared with the traditional neural network model, recurrent neural network (RNN) [23], long short-term memory network (LSTM) [24], and gate recurrent unit
(GRU) [25] can effectively use the self-loop system and learn time series features to improve the effectiveness of prediction. Therefore, it is used as a component of each model to predict traffic speed, travel time, traffic flow, etc.

In order to capture the spatial dependencies in the traffic road network, researchers [26] extract spatial features combined with convolutional neural networks (CNN) from two-dimensional spatiotemporal traffic data. The description of the traffic structure using two-dimensional spatiotemporal data is not accurate and does not conform to the complex road network conditions in real life so some scholars [27] have begun to try to convert the structure of the traffic network into images and use CNN to learn the traffic images in order to capture the spatial characteristics. However, there is more or less noise in the images converted by the traffic network structure, and the existence of noise will inevitably cause CNN to capture false relationships. Traditional methods based on CNN cannot essentially deal with the topological structure and physical properties of the traffic network. Recent studies [28, 29] also tried to convert the traffic state data into a three-dimensional (3D) matrix and use 3D convolutional networks to extract characteristics in deeper levels. Researchers [30] learned the traffic network as a graph and extract features from the graph structure of the traffic network using convolution operators based on graphs, which effectively learns the changes in traffic flow under the temporal and spatial attributes and achieves great forecast results.

After considering the dynamic change characteristics of the traffic network, this paper proposes the AST-GCN-LSTM model, which can predict the future traffic state according to historical traffic flow information on roads and external auxiliary information. Since traffic flow is affected by a variety of external factors (actual factors) such as weather, holiday, and time, in this article, we predict the traffic speed in the future based on the traffic speed in the past period of time and the external factors that affect the traffic flow. This is of great significance for realizing dynamic traffic signal optimization, dynamic traffic management planning, and traffic management decision [31].

2. Method

2.1. The Introduction of Basic Algorithms

2.1.1. Graph Neural Network (GCN). The transportation network can be regarded as a graph composed of nodes and edges, so the transportation network as a graph structure has been used for dynamic shortest path routing [32], traffic congestion analysis [33], and dynamic traffic allocation [34].

The most commonly used method for our research on graph networks is to introduce a spectrum frame in the graph structure of the traffic network using convolution operators based on graphs, which effectively learns the changes in traffic flow under the temporal and spatial attributes and achieves great forecast results.

2.1.2. GCN-LSTM Structure. To capture the complex spatial correlation and dynamic time correlation of traffic data in the real world, we have added a long- and short-term memory neural network LSTM. LSTM is an improved recurrent neural network (RNN), and LSTM has better performance than ARIMA when the training time series is long enough [36, 37]. The basic unit of the hidden layer of LSTM is a special cell unit, not a traditional neuron node. It is this special memory unit that enables LSTM to successfully solve the defect of RNN gradient explosion and also capture the temporal correlation of traffic flow. The overall structure of the GCN-LSTM structure is shown in Figure 2. In order to capture the complex spatial correlation and dynamic time correlation of traffic data in the real world, we combine the GCN with LSTM models. The function of the GCN model is to generate a graph of the traffic information of the road segment based on a given graph structure. It learns the representation of the road segment by integrating the characteristics of the local neighborhoods of the node and captures the spatial dependence of these road segments in the road network at each timestamp. Then, these time-varying feature representations are input into the LSTM model to capture the time dependence [38, 39].

2.2. AST-GCN-LSTM Spatiotemporal Graph Convolution Model

2.2.1. Attribute Augmentation Unit. On the basis of the GCN-LSTM traffic flow model introduced in Section 2.1.2, we have added an attribute augmentation unit. As shown in Figure 3, static external attribute features and dynamic external attribute features expand the dimensions of the original traffic feature matrix through attribute augmentation units.

At time $t$, traffic information matrix $X_t$ is extracted from the historical feature matrix $\mathcal{X} = (X_1, \ldots, X_t)$, and $\{L^{t−w}, L\}$ is the set of dynamic attribute features of $w+1$ time windows. In different timestamps, the static attribute feature set of $H$ is always unchanged. $L$ and $H$ are merged to generate an augmented matrix $P$. The problem of multistep traffic flow prediction can be expressed as

$$\hat{y} = f(A, X, P).$$  \hspace{1cm} (1)
Figure 1: K-hop neighbors of graph convolution.

Figure 2: The architecture of the GCN-LSTM model. $i_t$ is the input gate, $o_t$ is the output gate, $f_t$ is the forget gate, and $c_t$ is the input unit state.

Figure 3: The Attribute augmentation unit.
The model learns the complex spatial dependence, dynamic time dependence, and external dependence in traffic data. In this model, the gate structure and hidden state in LSTM are unchanged, but the input is replaced by the graph convolution feature. At time $t$, the input gate, output gate, forget gate, and input unit are defined as formulas (2) to (7):

$$f_t = \sigma(W_f \cdot [g_t(p_t, A), h_{t-1}] + b_f),$$

$$i_t = \sigma(W_i \cdot [g_t(p_t, A), h_{t-1}] + b_i),$$

$$\tilde{c}_t = \tanh(W_c \cdot [g_t(p_t, A), h_{t-1}] + b_c),$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t,$$

$$o_t = \sigma(W_o \cdot [g_t(p_t, A), h_{t-1}] + b_o),$$

$$h_t = o_t \circ \tanh(c_t).$$

The sign “$\circ$” is a matrix multiplication operator, $W_f, W_i, W_c$, and $W_o$ are weight matrices that map the input to the states of three gates and input units, and $b_f, b_i, b_c$, and $b_o$ are four deviation vectors. $s$ is the activation function of the gate, which is usually the sigmoid function. Tanh is the hyperbolic tangent function, and $g_t(\cdot)$ represents the graph convolution operation (Chebyshev polynomial approximation).

2.2.2. Loss Function. In the process of model training, loss is chosen as the training target to optimize the error of multistep prediction and make the prediction result close to the real traffic state. Therefore, the loss function used in multistep traffic prediction AST-GCN-LSTM can be expressed as follows:

$$\text{Loss} = L(y_T, \tilde{y}_T) = \|y_T - \tilde{y}_T\| + \rho L_{\text{reg}}.$$  

$L(\cdot)$ is a function to calculate the error between the predicted $\tilde{y}_T$ value and the true value $y_T$. Here, $L_{\text{reg}}$ represents a regular term avoiding over-fitting of the model, and $\rho$ is a hyperparameter that is learnable in the network.

2.2.3. AST-GCN-LSTM Spatiotemporal Graph Convolution Model. The GCN-LSTM traffic flow model introduced in Section 2.1.2 is combined with the attribute expansion unit in Section 2.2.1. A multistep traffic flow prediction model (AST-GCN-LSTM) that considers external factors is also proposed. This model fully takes the external attribute characteristics that affect the traffic flow into account. Figure 4 shows the overall framework of the model, which is mainly composed of data preprocessing, attribute expansion, and spatiotemporal graph convolutional layers. In the model, we set the number of neural units in all hidden layers to 64, the batch size to 64, the learning rate to 0.001, the order of the Chebyshev polynomial to 3, and the maximum number of training iterations to 3000. The Adam optimizer is used to train the model. The data set is divided into two parts, 80% of the data are used for training, and 20% of the data are used for testing. After dividing the data set into two parts, we generate sequence samples through a time window whose width is $T + T'$.

2.3. Data Set. The traffic speed data set of the real-world road network is used in this article to evaluate the model performance. This public data set contains the taxi trajectory data of every 15 minutes setting on 156 roads from January 1 to January 31, 2015. The data sampling location is Luohu District, Shenzhen, Guangdong Province. The data mainly include the following 4 parts:

1. Adjacency matrix: the data set selects 156 roads, so the size of the adjacency matrix $A$ is $156 \times 156$. The adjacency matrix represents the connectivity between segments. Each row of the matrix represents a road. If there are links connecting nodes $i$ and $j$, then the element in the adjacency matrix $A_{ij} = 1$. If there are no links connecting nodes $i$ and $j$, then the element in the adjacency matrix $A_{ij} = 0$.

2. Feature matrix: the feature matrix size of the data set is $2976 \times 156$. The feature matrix is the speed value of 156 roads in 31 days. Each column represents a road, and each row represents the traffic speed value of 156 roads at a certain time $t$. Speed information is collected every 15 minutes.

3. Static attribute characteristic matrix: the point-of-interest (POI) information on 156 roads is provided in the data set. POI categories include the following nine types: catering, business, shopping, transportation, education, life, medical care, accommodation, and others. When determining the POI category of each road, the POI distribution on each road is calculated first, and then, proportions of the various categories of POIs are calculated. After comparing the proportions of the various categories of POIs, the POI with the largest proportion is used as the static feature of the road. The size of the static attribute feature matrix is $156 \times 1$.

4. Dynamic attribute feature matrix: weather conditions of every 15 minutes in January are provided by the data set, which can be divided into five categories: light rain, heavy rain, cloudy, foggy, and sunny. Time information includes the time of day, weekdays, and weekends. Because they will have a significant impact on the traffic state, this section also takes it into consideration. The size of the three types of external attribute feature matrices is $2976 \times 156$.

2.4. Evaluation Index. Three commonly used traffic forecasting indicators are as follows: mean absolute error (MAE), accuracy, and root mean square error (RMSE) [31] are used to evaluate the performance of the proposed model and the comparison model. The formula is from (9) to (11):
where \( n \) is the total number of test sets and \( y_T \) and \( \hat{y}_T \) represent the true and predicted values of the flow.

### 3. Analysis of Experimental Results

#### 3.1. Analysis of Static Attribute

In order to evaluate the overall performance of our proposed AST-GCN-LSTM model, we compare it with other traditional and common models. These models are as follows:

1. Historical average model (HA): HA models the traffic flow as a seasonal cyclical process and uses the average value of the previous seasons (for example, the flow value of the same time period in the previous days) as the predictive value.

2. Autoregressive integrated moving average model (ARIMA): the autoregressive integrated moving average model (ARIMA) with Kalman filter is widely used in time series forecasting. It predicts the series by fitting time series data.

3. Support vector regression (SVR): linear support vector machine is used to predict the regression task of traffic flow sequence.

4. Diffusion convolution recurrent neural network (DCRNN): diffusion convolution recurrent neural network formulates the diffusion process in graph convolution and uses a two-way random walk to capture the spatial correlation of the traffic flow in graphs. An encoder-decoder is used to capture the temporal correlation of the traffic flow, and the diffusion convolution GCN is combined with the recursive model in prediction.

5. GCN-LSTM: the combination of LSGC and LSTM model using Chebyshev polynomial approximation is introduced in Section 2.1.1.

Among them, HA, ARIMA, and SVR are traditional nonneural network models, DCRNN is a deep learning model that can capture spatial features, and GCN-LSTM is a deep learning model that comprehensively considers the spatial features and dynamic correlation of traffic data.

Table 1 shows the overall prediction performance of the AST-GCN-LSTM model and five representative methods. Three indicators, root mean square error (RMSE), mean...
absolute error (MAE), and accuracy (accuracy) evaluation, are used in the comparison of performances.

According to Table 1, it can be concluded that, from the results of the 15-minute prediction window, compared with the traditional models, HA, ARIMA, and SVR, the RMSE value of the AST-GCN-LSTM model decreases by 3.07%, 44.43%, and 2.95%. Compared with the HA model and the SVR model, the accuracy value is increased by 14.69% and 1.56%, respectively. This shows that HA, ARIMA, and SVR cannot compete with other methods because the data have complex spatiotemporal correlation and high-dimensional features, and nonneural network methods are not suitable for such network-wide prediction tasks. Accounting for external attribute features, the RMSE value of the AST-GCN-LSTM model that takes all external attributes into account is 10.59% and 2.33% lower than that of the DCRNN model and GCN-LSTM model. The value of MAE is lower than that of the DCRNN model and GCN-LSTM model and reduces by 14.73% and 2.42%. According to Table 1, compared with traditional methods and other methods based on deep learning, the model proposed by this article has achieved significant improvements proving the effectiveness of the model.

### Table 1: Performance comparison of different methods.

<table>
<thead>
<tr>
<th>T (min)</th>
<th>Metrics</th>
<th>HA</th>
<th>ARIMA</th>
<th>SVR</th>
<th>DCRNN</th>
<th>GCN-LSTM</th>
<th>AST-GCN-LSTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>RMSE</td>
<td>4.2951</td>
<td>7.2406</td>
<td>4.1455</td>
<td>4.5000</td>
<td>4.1193</td>
<td>4.0234</td>
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<tr>
<td></td>
<td>MAE</td>
<td>2.7815</td>
<td>4.9824</td>
<td>2.6233</td>
<td>3.1700</td>
<td>2.7701</td>
<td>2.7030</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>0.7008</td>
<td>0.4463</td>
<td>0.7112</td>
<td>0.2913</td>
<td>0.7129</td>
<td>0.7223</td>
</tr>
<tr>
<td></td>
<td>MAE</td>
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<td>2.7739</td>
<td>2.7244</td>
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<tr>
<td></td>
<td>Accuracy</td>
<td>0.7008</td>
<td>0.3845</td>
<td>0.7100</td>
<td>0.2970</td>
<td>0.7126</td>
<td>0.7196</td>
</tr>
<tr>
<td>45</td>
<td>RMSE</td>
<td>4.2951</td>
<td>6.7852</td>
<td>4.1885</td>
<td>4.6000</td>
<td>4.1252</td>
<td>4.0587</td>
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<td>MAE</td>
<td>2.7815</td>
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<td>2.7359</td>
<td>3.2700</td>
<td>2.7753</td>
<td>2.7346</td>
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<tr>
<td></td>
<td>Accuracy</td>
<td>0.7008</td>
<td>0.3847</td>
<td>0.7082</td>
<td>0.3021</td>
<td>0.7123</td>
<td>0.7172</td>
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<tr>
<td>60</td>
<td>RMSE</td>
<td>4.2951</td>
<td>6.7708</td>
<td>4.2156</td>
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<td>MAE</td>
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<tr>
<td></td>
<td>Accuracy</td>
<td>0.7008</td>
<td>0.3851</td>
<td>0.7063</td>
<td>0.3069</td>
<td>0.7119</td>
<td>0.7165</td>
</tr>
</tbody>
</table>

3.2. Analysis of the External Attribute. In order to verify the influence of external attribute characteristics in traffic flow prediction, corresponding comparative experiments are done. The experimental settings are divided into four kinds as follows: adding static attribute characteristics only, adding dynamic attribute characteristics only, adding dynamic and static external attribute characteristics at the same time, and not adding external attributes characteristics. The results are shown in Figure 5. Yellow is the result of adding static attribute characteristics. Gray is the result of adding dynamic attribute features. Blue is the result of adding dynamic and static external attributes. The results are shown in Figure 5. Yellow is the result of adding static attribute characteristics. Gray is the result of adding dynamic attribute features. Blue is the result of adding dynamic and static external attributes at the same time.

It can be seen from Figure 5 that when only dynamic attribute features are considered, the value of AST-GCN-LSTM (dynamic) RMSE is 10.31% and 2.02% lower than that of DCRNN and GCN-LSTM models. The value of MAE is lower than that of DCRNN and GCN-LSTM models and reduced by 14.69% and 2.37%. When only static attributes are considered, the value of AST-GCN-LSTM (static) RMSE is reduced by 10.21% and 1.91% compared with DCRNN and GCN-LSTM models, and the value of MAE is reduced by 14.25% and 1.87% compared with DCRNN and GCN-LSTM models. When static factors and dynamic factors are considered at the same time, the RMSE value of the AST-GCN-LSTM model is reduced by 10.59% and 2.33% compared with the DCRNN model and the GCN-LSTM model, and the value of MAE is reduced by 14.73% and 2.42% compared with the DCRNN model and the GCN-LSTM model.

It can be seen from Figure 5 that the model performance when only dynamic attribute features are considered is better than the model performance when only static attribute features are considered. This also indirectly illustrates the importance of considering dynamic external attribute features, and we also observed that when static and dynamic factors are considered at the same time, the performance of the model is optimal.
In summary, considering the external information has a good effect on the prediction of the model under actual conditions.

3.3. Performance in Different Forecast Periods. All tests of this model use 60 minutes as the historical time window, which means four observation data points are used to predict the traffic conditions in the future 15, 30, 45, and 60 minutes ($H = 1, 2, 3, 4$). Figure 6 shows the visualization results of 15-, 30-, 45-, and 60-minute forecast windows. Each graph is the prediction result from January 26, 2015, to January 31, 2015.

It can be seen from Table 2 that when the traffic flow prediction window is 15 minutes, the RMSE value of the AST-GCN-LSTM model is reduced by 10.59% and 2.33% compared with the DCRNN model and the GCN-LSTM

<table>
<thead>
<tr>
<th>T (min)</th>
<th>Metric</th>
<th>DCRNN</th>
<th>GCN-LSTM</th>
<th>AST-GCN-LSTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>RMSE</td>
<td>4.5000</td>
<td>4.1193</td>
<td>4.0234</td>
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<tr>
<td></td>
<td>MAE</td>
<td>3.1700</td>
<td>2.7701</td>
<td>2.7030</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>0.2913</td>
<td>0.7129</td>
<td>0.7223</td>
</tr>
<tr>
<td>30</td>
<td>RMSE</td>
<td>4.5600</td>
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<td>4.0508</td>
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<td>MAE</td>
<td>3.2300</td>
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</tr>
<tr>
<td></td>
<td>Accuracy</td>
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<td>0.7126</td>
<td>0.7196</td>
</tr>
<tr>
<td>45</td>
<td>RMSE</td>
<td>4.6000</td>
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<td>MAE</td>
<td>3.2700</td>
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<td>Accuracy</td>
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<tr>
<td>60</td>
<td>RMSE</td>
<td>4.6400</td>
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<td>MAE</td>
<td>3.3100</td>
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<td></td>
<td>Accuracy</td>
<td>0.3069</td>
<td>0.7119</td>
<td>0.7165</td>
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</table>
Compared with the DCRNN model and the GCN-LSTM model, the value of MAE is reduced by 14.73% and 2.42%. When the traffic flow prediction window is 30 minutes, the RMSE value of the AST-GCN-LSTM model is decreased by 11.17% and 1.70% compared with the DCRNN model and the GCN-LSTM model. The MAE value is decreased by 15.65% and 1.78% compared with the DCRNN model and the GCN-LSTM model. When the traffic flow prediction window is 45 minutes, the RMSE value of the AST-GCN-LSTM model is decreased by 11.77% and 1.61% lower than the DCRNN model and the GCN-LSTM model, and the MAE value is decreased by 16.37% and 1.47% lower than the DCRNN model and the GCN-LSTM model.

When the traffic flow prediction window is 60 minutes, the RMSE value of the AST-GCN-LSTM model is decreased by 12.31% and 1.39% compared with the DCRNN model and the GCN-LSTM model. The MAE value is decreased by 17.21% and 1.47% compared with the DCRNN model and the GCN-LSTM model. The above conclusions show the robustness and stability of our proposed model in long-term prediction.

For different prediction times, the AST-GCN-LSTM model proposed in this paper can predict traffic speed well. The results show that this model can capture the changing trend of traffic speed very well, which also verifies the effectiveness of our model in multistep traffic flow prediction.

Comparing the prediction values of the 15-minute and 60-minute prediction windows, we can see that the prediction effect of the 15-minute window in the short-term prediction is closer to the true value, which also shows that the model can better capture short-term dependence.

In order to test the effectiveness of adding static and dynamic external attribute features, we visualized the model prediction results. Figure 7 shows a comparison of prediction results between models with static external attributes, dynamic external attributes, and models without external attributes.

From the visualization results in Figure 7, it can be found that the deviation between the predicted result of AST-GCN-LSTM and the real speed value is smaller than that of AST-GCN-LSTM (static attribute) and AST-GCN-LSTM (dynamic attribute), which indicates that the diversity of external information can better promote prediction.

### 4. Conclusions

This paper uses the proposed AST-GCN-LSTM model to obtain dynamic attribute features by adding the attribute augmentation unit structure of external factors. After the feature matrix is augmented, the Chebyshev polynomial approximation spectrogram convolution model is used for feature extraction. This model can capture the spatial characteristics of traffic flow from the K-order local neighbors of the vertices in the graph. The K-order local neighborhood can replace the single-hop neighborhood matrix to expand the receptive field of the graph convolution, which can more accurately extract the information of
neighbor nodes. After the information is extracted, the characteristic representation of the information that changes over time is input into the LSTM model to capture the time dependence. By analyzing the performance of the proposed model, including the performance analysis of external attribute characteristics and the performance analysis of different prediction windows, and comparing with different baseline models to verify the effectiveness of the proposed model, it solves the inability of the previous traffic prediction models. The external factors affecting traffic flow are fully considered.

Results show that the AST-GCN-LSTM model can not only fully consider the spatial relationship of road nodes but also capture the time dependence of traffic flow and effectively improve the accuracy of traffic prediction. In addition, the AST-GCN-LSTM model is suitable for both road network traffic flow prediction and mid-term and long-term traffic flow prediction and multistep prediction.

Data Availability

The data set in this article can be obtained by contacting the corresponding author.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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