

Article

Research on Support Vector Regression Short-Time Traffic Flow Prediction Model for Secondary Roads Based on Associated Road Analysis

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Abstract: Short-time traffic flow prediction is essential for intelligent traffic management. By accurately predicting traffic conditions in the near future, it helps to alleviate congestion, improve road efficiency, reduce accidents, and support timely traffic control. Short-time traffic flow exhibits uncertainty and randomness, and this paper proposes an SVR model for short-time traffic flow prediction on non-main and branch roads, using correlations between associated roads to improve accuracy. Association Rule Analysis: First, we use Pearson correlation to identify strongly correlated roads. This step helps in understanding the relationships between different roads and their traffic patterns. SVR Model Construction: Second, based on the identified correlations, we construct an SVR model using traffic data from the target road and its associated roads. The model parameters are optimized using grid search and cross-validation to ensure the best performance. Simulation and Evaluation: Third, we conduct simulation experiments using real traffic data from Xi'an city. The performance of our model is evaluated using metrics such as root mean square error (RMSE), mean absolute error (MAE), and mean relative error (MRE). Simulation experiments show that our model outperforms existing methods. Specifically, our model achieved an RMSE of 11.422, an MAE of 7.017, and an MRE of 0.139. In comparison, other models tested in our study, such as LSTM, Random Forest, and Gradient Boosting Decision Tree (GBDT), had higher error values. For instance, the LSTM model had an RMSE of 14.5, an MAE of 8.2, and an MRE of 0.165; the Random Forest model had an RMSE of 13.8, an MAE of 7.8, and an MRE of 0.152; and the GBDT model had an RMSE of 13.2, an MAE of 7.5, and an MRE of 0.148. These results demonstrate that our proposed SVR model, combined with association rules, is highly effective in predicting short-time traffic flow on non-main and branch roads, which are often overlooked in existing research.

Keywords: intelligent transport; association rules; SVR; short-term traffic flow forecast



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1. Introduction

As the global economy and society continue to advance, China has become a major global automobile-producing and -consuming country. In the past few years, China's automobile ownership has continued to grow at an average annual rate of 30%, bringing tremendous pressure on urban transportation and causing many large- and medium-sized cities to face serious traffic congestion problems. Transportation is a key element for sustainable development and efficient operation of cities. Traffic congestion not only affects the travel efficiency and quality of life of urban residents, but also restricts the

economic development and social progress of cities; therefore, alleviating traffic congestion and improving transportation efficiency have become important challenges for urban development in China. Intelligent transportation systems are excellent in related fields and have become a new way of thinking and a method to solve traffic congestion problems in more and more cities [1]. As one of the core functions of intelligent transportation system, traffic flow prediction is crucial for urban traffic management, which can not only help citizens to understand the road traffic condition in real time, but also guide them to choose the optimal travel routes, so as to effectively alleviate traffic congestion and improve travel efficiency. Therefore, accurate traffic flow prediction is very important. In view of the uncertainty and randomness of short-time traffic flow, establishing an accurate traffic flow prediction model has become a research hotspot in the field of intelligent transportation, which has a far-reaching impact on improving the overall performance of the urban transportation system and the travel experience of residents.

Short-term traffic flow forecasting is a key area of focus within transportation research. In recent years, numerous scholars have achieved advancements in the realm of short-range traffic volume prediction. Zhang et al. [2] addresses the problems of strong random fluctuation of urban traffic flow and the decline of prediction accuracy due to more noise in the data, and proposes a combined model for traffic flow forecasting that utilizes the ensemble empirical modal decomposition and bidirectional gated cyclic cell. Zhao et al. [3] proposed a combined traffic flow prediction model based on short-term traffic flow prediction to enhance the precision of short-term traffic flow forecasting and to solve the problems of short-term traffic flow nonlinearity, i.e., more data noise, and it is more challenging to ascertain the parameters for the long short-term memory (LSTM) network. Pu et al. [4] proposed a CNN-ResNet-LSTM model for urban short-time traffic flow prediction given the influence of traffic flow characteristics and external factors on the results of traffic flow prediction. Zhang [5] fused the neural network model with time series to improve the neural network model's insensitivity to the temporal attributes of traffic flow and enhance the comprehensive predictive performance of the model. Liwei Ouyang et al. [6] proposed a short-term traffic flow prediction algorithm based on the combination of wavelet transform, particle swarm optimization algorithm, and BP neural network characteristics. The new algorithm significantly improved the prediction accuracy of short-term traffic flow and was more suitable for the prediction of short-term traffic flow data with large noise or jagged signal curves. Accurate and timely short-term traffic flow prediction plays an important role in intelligent traffic management and control. Traffic flow prediction has a long history, but it is still a difficult problem because of the highly nonlinear and random nature of complex traffic systems. Danqing Kang et al. [7] used long short-term memory (LSTM) recurrent neural networks to analyze the influence of various input settings on LSTM prediction performance. Bharti Naheliya et al. [8] proposed a bidirectional long short-term memory (Bi-LSTM) model using the Modified Firefly Optimization Algorithm (MFOA) called MFOA-Bi-LSTM.

Short-term traffic flow prediction is crucial for intelligent transportation systems and congestion relief. Therefore, the accurate prediction of real-time traffic conditions becomes more important. Currently, the existing prediction models lack the ability to effectively extract spatiotemporal features and fail to fully consider the influence of nonlinear noise. To address these issues, research [9] proposed an integrated model for short-term traffic flow forecasting utilizing spatiotemporal characteristics. Currently, examining the spatiotemporal attributes of traffic flow has emerged as a focal point in research. Hui Jia et al. [10] proposed a spatiotemporal multifactor fusion graph neural network (STMFGNN), which aims to more comprehensively characterize spatiotemporal features. Precision in traffic flow forecasting is crucial for enhancing traffic management, alleviating traffic jams, and

boosting travel productivity. Deqi Huang et al. [11] proposed the MFSTBiSGAT model. The MFSTBiSGAT model utilizes graph attention networks to extract dynamic spatial features from complex road networks and utilizes bidirectional long short-term memory networks to capture temporal correlations from past and future temporal perspectives. Due to the influence of passenger travel mode and the difficulty of data collection, some traffic flow datasets not only have uneven time distribution but also lack data scale, resulting in inaccurate prediction results. Linlin Zang et al. [12] proposed a method based on transfer learning to predict non-stationary traffic flow with insufficient data in public transportation systems. Traffic conditions in the real world, especially during rush hour, exhibit complex spatiotemporal dynamics and intricate nonlinear relationships. Existing studies tend to ignore traffic flow changes in different periods, locations, and scenarios, resulting in a lack of robustness and accuracy of prediction models across different environments. Siwei Wei et al. [13] introduce a novel approach to address these challenges, namely, a multi-feature spatiotemporal coupled traffic flow prediction model (PE-MFSTC) based on peak-hour embedding. Aiming at the shortcomings of artificial rabbit optimization (ARO) algorithms with low accuracy and slow convergence speed, Haoxu Wang et al. [14] incorporated the idea of sine and cosine algorithm (SCA) into the rabbit optimization algorithm to further enhance the precision of short-term traffic volume forecasting. Combined with the SCA, a new position updating method based on nonlinear sine learning factor, sine cosine ARO (SARO), is proposed. Multi-step highway traffic flow prediction is essential for intelligent transportation systems, and the existing work has made significant progress in this field. However, physical structure, including paths, distances, and node degrees, is critical information in transportation networks and is often overlooked when encoding spatiotemporal dependencies. To overcome the above problems, Guojian Zou et al. [15] proposed a new highway traffic flow prediction multi-task space-time network (MT-STNet), which is composed of an encoder-decoder structure, generative inference system, and multi-task learning.

Based on the summary of the domestic and international research on short-time traffic flow prediction from the current research, the research on short-time traffic flow prediction mainly focuses on highways and trunk routes, while there is very little research on non-trunk roads and feeder routes, which have less traffic flow. Ji Yitong et al. [16] proposed that, in order to facilitate travel of residents and reduce air pollution, it is important to keep the main roads of the city passing vehicles smoothly and quickly, discussing time series prediction models for short-term traffic flow prediction methods. Yalin Wu et al. [17] proposed an innovative congestion prediction method using ship trajectory dynamic big data analysis and multi-scale feature analysis to solve the problem of congestion in the maritime network. Ke Zhao et al. [18] proposed a novel hybrid model (CPQDELM) for short-term traffic flow prediction with the mountainous scenic highway S321k51 dataset as an example. Xinyi He [19] proposed SSA-BiLSTM-BP-Elman integrated model for predicting peak hour traffic flow to solve the problem of congestion on peak road sections. Wen Tian et al. [20] investigated deep learning-based traffic flow prediction method to provide a more accurate basis for sensing the congestion condition of the route network. Zhiyu Wang et al. [21] proposed a novel traffic flow prediction model called anomaly detection probability (ADP) attention bidirectional long and short-term memory (BiLSTM) model, which is used for a comprehensive simulation study of the Shanghai-Chongqing Expressway using the measured traffic flow data. Short-term traffic flow prediction is provided for highway sections.

In addition, short-time traffic flow also shows the characteristics of nonlinear, stochastic, real-time, and spatiotemporal correlation, and the current research is still deficient in the selected indexes [22,23]. Jingyi Lu et al. [24] constructed a short-term traffic flow prediction

model using short-term and short-term memory networks and used variational mode decomposition to solve the mode mixing problem, but the study gave less consideration to the short-term traffic flow indicator system, such as climatic conditions and public transportation status. And no robustness analysis was performed. Ali Reza Sattarzadeh et al. [25] proposed a new hybrid deep learning model based on the attention mechanism, which uses a multilayer hybrid architecture to extract spatiotemporal nonlinear features. However, the effect of climatic conditions on traffic flow is complex, and climatic conditions are not included in the metrics in the study. Kaixin Guo et al. [26] proposed a long-time traffic flow prediction model based on variational modal decomposition (VMD) and autocorrelation mechanism. The model mainly relies on historical traffic flow data and does not consider the influence of external factors such as weather, holidays, and traffic accidents. This may lead to the bias of prediction results in special cases. He-Wei Liu et al. [27] proposed a short-term traffic flow prediction algorithm based on cloud modeling and fuzzy inference system, which is used to solve the problem that the existing research ignores the uncertainty of traffic flow prediction that affects the accuracy and robustness of the model. However, as the number of fuzzy clusters increases, the complexity of the model increases significantly, leading to an increase in training time and computational cost.

Therefore, to improve the prediction accuracy of non-trunk roads and side roads with small traffic flow, this paper proposes a short-time traffic flow prediction model for SVR based on associated roads, using association rules to analyze the data to find the other roads that are strongly related to each road, and using this as the data basis to establish the SVR model, and reconstructs the index system for short-time traffic flow prediction [28–30]. Association rule analysis can help identify other roads that are associated with changes in flow on the target road. The flow data of these related roads can be used as inputs to the SVR model, thus enriching the dataset and improving the generalization ability of the model. With association rule analysis, such correlations can be identified and incorporated into the inputs of the SVR model to improve prediction accuracy. Association rule analysis can reduce the dependence on the parameter selection of the SVR model, thus reducing the sensitivity of the model to parameter selection.

The primary advancements presented in this study include the following: First, this paper not only focuses on the traffic flow of main roads but also studies the non-main roads and branch roads with small traffic flow. Second, the short-time traffic flow also shows the characteristics of nonlinear, random, real-time, and spatiotemporal correlation. This paper expands the short-time traffic flow index system based on current research. Third, a novel SVR-based model for short-term traffic flow prediction is introduced, specifically designed to address the issue of prediction accuracy for minor roads and side streets with lower traffic volumes. Fourth, data analysis is carried out on the real data of the Traffic Police Brigade of Xi'an Public Security Bureau. The model introduced in this study is benchmarked against the reference model across various metrics.

The subsequent sections of this manuscript are outlined as follows: Section 2 describes the association rule–SVR model developed in this paper. Section 3 describes the simulation experiments of the model to confirm the accuracy of the model in this paper through parameter analysis and comparative model analysis. Section 4 summarizes this paper and proposes future research directions that can be considered in this paper.

2. Short-Term Traffic Flow Prediction Model Construction

2.1. Modeling of Urban Associated Roads

In the process of analyzing the traffic flow data and reviewing the relevant literature, we can see that most of the roads between cities have a certain degree of correlation, especially between the main roads, and the connected side roads have a strong correlation.

After the trunk routes reach saturation, the traffic volume of the feeder routes connected to them will gradually increase. Therefore, this chapter first carried out correlation modeling on each road in the city to find out the strong correlation between each road and used this as the basis of the road to carry out the correlation prediction on the short-term traffic flow of the road, to enhance the precision of forecasting short-term traffic patterns on minor roads with low traffic volumes.

2.1.1. Road Association Rule Analysis

The main steps of association rule analysis are as follows:

(1) Data attribute conversion

According to the requirements of the Apriori method on data attributes, the numerical attribute transformation of urban traffic road flow data is carried out to transform the continuous characteristics of data into discrete attributes, and the data are divided according to congestion, and the specific division rules are as shown in Table 1.

Table 1. Conversion rules for road numerical attributes.

Continuous Attributes of Road Data	Discrete Attributes of Road Data
Current traffic volume is more than 30 per cent less than the average value	Smooth roads
Current traffic volume is 10–30 per cent less than the average value	Roads are smoother.
Current traffic volume is 10 per cent above and below average	Roads are more congested.
Current traffic volume 10–30 per cent greater than average	Road congestion
Current traffic volume is more than 30 per cent greater than the average	Heavy road congestion

The table details the specific effects of changes in traffic volume on road conditions by comparing the continuous attribute of the road data (the percentage increase or decrease in traffic volume relative to the mean) with the discrete attribute (the level of congestion on the road). Specifically, when the current traffic volume is significantly lower than the average value (more than 30% or less), the road condition is characterized as smooth with little congestion, which indicates that vehicles can move smoothly. And when traffic volumes are slightly below average (below 10–30%), road conditions are smoother and less congested. When the traffic volume fluctuates around the mean (within $\pm 10\%$), the road begins to show signs of congestion, indicating that the traffic volume is close to or at the regular carrying capacity of the road. Further, when the traffic volume is above the mean (10–30% or more), road congestion increases and vehicle traffic slows down. Finally, when the traffic volume is significantly above average (more than 30%), the road condition becomes heavily congested, indicating that vehicular traffic is greatly affected and emergency measures may be required to alleviate traffic pressure.

(2) Setting association rules

We use the notation D to denote the basic urban road flow dataset used for modeling in this section. In the basic dataset D , the set consisting of all urban road flow data items is denoted as $I = \{i_1, i_2, \dots, i_n\}$. Assuming that the number of items in an item set is k , it is referred to as a k -item set. A frequent item set is a set of certain types of items that occur more often in the dataset D . Assuming that X and Y are both item sets with $X \subset I$ and $Y \subset I$ and that the intersection of X and Y is the empty set, the implication $X \Rightarrow Y$ denotes an association rule among multiple association rules.

(3) Calculate the degree of support

The degree of support measures the frequency of each type of data item for traffic on a road within the set of traffic volume transactions for the entire highway [31]. The

support of a data item set X is denoted as $Support(X)$, which means the ratio of the number of transactions in D that contain X to the total number of transactions in the underlying dataset D , as shown in Equation (1):

$$Support(X) = \frac{count(X)}{count(D)} \quad (1)$$

The support of the association rule $X \Rightarrow Y$ is equal to the support of the item set $X \cup Y$. This relationship can be expressed in Equation (2) as follows:

$$Support(X \Rightarrow Y) = \frac{count(X \cup Y)}{count(X)} \quad (2)$$

If the support exceeds a predetermined minimum minsup, then, it can be considered as a frequent item; conversely, it can be considered as an infrequent item.

(4) Calculate the confidence level

In Apriori algorithm, confidence is used to assess the reliability of association rules. According to the constructed association rule $X \Rightarrow Y$, the confidence measures the probability that, when X occurs, Y will also occur. Specifically, it can be expressed as $confidence(X \Rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)}$. Typically, the minimum confidence threshold required for modeling is found based on the mining of the correlation between urban road flows, denoted as minconf, and an association rule is considered significant only if its confidence exceeds this threshold.

According to the minimum confidence threshold and support threshold set when constructing the model, the goal of finding the road association rules is to discover the strong association rules for roads with support, confidence greater than or equal to the given minimum threshold from the urban road traffic database.

(5) Generate frequent item sets and produce strong association rules

By analyzing the frequent item sets between urban roads, the corresponding association rules can be constructed. Firstly, the largest frequent item set is determined, then all non-empty subsets are filtered from it, and these rules are calculated to determine their confidence level, and finally, a series of strong association rules are derived.

2.1.2. Urban Road Linkage Model Results

To guarantee the optimal effect of urban road correlation results, after many parameter adjustments and related literature research, this paper finally selects the correlation results with 80% support and 90% confidence as the final results of urban road correlation, and the correlation results under different parameters are shown in Table 2:

Table 2. Apriori correlation result table of each parameter.

Degree of Support	Confidence Level	Average Number of Associated Roads
90%	95%	2.6
90%	90%	3.2
85%	95%	3.7
85%	90%	4.1
80%	95%	4.3
80%	90%	7.4
75%	95%	10.9
75%	90%	11.4
70%	95%	17.3
70%	90%	22.1

Explanation of Support and Confidence in Road Association Rules:

(1) Support:

In the context of urban road association rules, support measures the frequency with which a particular combination of roads appears together in the dataset. For example, if a set of roads {Road A, Road B} has a support of 80%, it means that 80% of the transactions (or instances) in the dataset include both Road A and Road B. This indicates a strong correlation between these roads, suggesting that traffic conditions on Road A are likely to affect or be affected by traffic conditions on Road B.

A higher support value indicates a more frequent co-occurrence of the roads in the dataset, which is crucial for identifying significant associations in traffic flow patterns.

(2) Confidence:

Confidence measures the reliability of the association rule. For example, if the association rule {Road A} $\rightarrow$ {Road B} has a confidence of 90%, it means that 90% of the instances where Road A is present, Road B is also present. This indicates a strong directional relationship between Road A and Road B.

A higher confidence value indicates a stronger relationship between the roads, suggesting that traffic conditions on Road A are highly predictive of traffic conditions on Road B. This is particularly useful for predictive modeling and traffic management strategies.

The table shows the average number of roads associated with different levels of support and confidence levels. As the level of support decreases, the number of associated roads gradually increases, suggesting that propositions with a lower level of support may involve a wider range of roads, while at the same level of support, the higher the confidence level, the fewer the number of associated roads, suggesting that the high confidence scenario is more concentrated in terms of the roads affected. In our study, we selected the correlation results with 80% support and 90% confidence as the final results.

2.2. Construction of SVR Short-Time Traffic Flow Prediction Model Based on Associated Roads

2.2.1. Selection of Indicators for Short-Term Traffic Flow Prediction

The indicators used in the current traffic flow prediction module in Xi'an city are only three, i.e., time, location, and traffic flow, resulting in the prediction accuracy not being able to meet the growing demand for traffic prediction, and the accuracy is even more unable to meet the demand for short-term traffic flow prediction. In this way, based on the existing indicator system, this paper through a large number of short-time traffic flow prediction-related literature readings increased the weather factors, and other scholars at home and abroad recognized the greatest impact on the short-time traffic flow indicators; at the same time, the data collection time interval is narrowed to meet the needs of the city's short-term traffic flow prediction, and collated indicators are shown in Table 3.

Table 3. Short-time traffic flow prediction index system in Xi'an.

Index	Formats (Examples)
Time	2022.3.20–15:00
Location	Jiandong Street (East)
Traffic flow	76
Average speed	42 km/h
Holidays or not	Yes/No
Temperature	17.3 °C
Horizontal atmospheric pressure	723.5
Ground relative humidity	54
Course of events	Wind from the northeast
Special weather phenomenon	No/rain/snow/sand/fog
Horizontal visibility	0–10/>10
Total cloud capacity	No apparent cloud/sparse cloud/less cloud/more cloud

After summarizing a large number of studies related to traffic flow prediction, the description of each index and the reasons for selection in this paper are as follows:

(1) Time: In this study, a refined time recording method was used to collect data every 10 min as a time unit. According to the common classification criteria in academia, traffic flow forecasts can be categorized into three types depending on the time unit of data collection: long-term forecasts, medium-term forecasts, and short-term forecasts. Long-term forecasting usually uses days as the unit of traffic counts, and medium-term forecasting uses hours as the unit of measurement, while short-term forecasting focuses on finer time scales and usually collects data on a minute-by-minute basis. This thesis focuses on the field of short-term forecasting and chooses 10 min as the time interval for data collection, aiming to enhance the precision and reliability for enhancing the accuracy of immediate traffic volume predictions in Xi'an by shortening the data collection period.

(2) Location: It is the location of the road where the traffic flow information is collected, and the information for this study comes from the intelligent traffic management system in Xi'an. The data collection devices are deployed in the middle segments of the roadway; therefore, the location metrics in this study focus on roadway segments rather than intersections.

(3) Traffic flow: The database for this study is the traffic flow information from the Xi'an intelligent transportation system. The data collection mechanism used in this system is for monitoring the two-way traffic flow on a road; therefore, the traffic flow data used in this study are the sum of the two-way traffic flow on a specific road during a given time interval. These aggregated data provide a comprehensive view of the traffic flow analysis.

(4) Average speed: In this study, the collection of traffic flow information includes the recording of the average speed of road vehicles during a specified period of time. In the case of experiencing road congestion, the measured traffic flow data may be lower than the flow data when the road is open. In this case, the average speed indicator is particularly important and provides a basis for a comprehensive assessment of road congestion. By analyzing the changes in average speed, we can more accurately determine the actual traffic conditions on the road.

(5) Holidays or not: This study further refines and assigns values to the time indicators. Given that the relevant regulations in Xi'an stipulate that the city's vehicles are not affected by traffic restriction measures during holidays, this usually leads to a significant increase in traffic flow during holidays. To enhance the precision of the immediate traffic flow forecasting model for Xi'an, this study particularly distinguishes the temporal attributes of holidays and divides them as an independent time indicator. Such a treatment helps the model to capture and predict traffic flow changes under special dates more accurately.

(6) Temperatures: Temperature, as a weather factor of general interest, plays an important role in traffic flow prediction. According to the annual traffic flow report of Xi'an and the existing research literature, traffic flow in Xi'an usually decreases significantly under extremely high- or low-temperature conditions. On the contrary, when the temperature is in the appropriate range, the traffic flow will increase. Given this, this study incorporates temperature indicators into the index system for short-term traffic flow prediction in Xi'an to more comprehensively consider the impact of weather factors on traffic flow.

(7) Horizontal atmospheric pressure and ground relative humidity: Several studies in the literature have repeatedly emphasized that barometric pressure and ground humidity have a significant effect on vehicle braking distances, and these changes may indirectly act on the accident rate as well as the operating speed of the road traffic, which may have a chain reaction on the traffic flow. Considering the importance of these factors, this study incorporates barometric pressure and ground humidity as key indicators into the index system for short-term traffic flow prediction in Xi'an city to ensure that the prediction

model can more accurately reflect the potential impacts of these environmental factors on traffic flow.

(8) Course of events and special weather phenomenon: Changes in wind direction and special weather conditions, such as rain and snow, can cause a reduction in the speed of urban vehicles. According to data provided by the Xi'an Intelligent Transportation System, the overall speed of traffic may decrease by about 15–20% under special weather conditions such as rain and snow. This slowdown in speed tends to aggravate the congestion of urban traffic. Therefore, this study incorporates wind direction and special weather conditions as important indicators into the index system for short-term traffic flow prediction in Xi'an to enhance the model's ability to predict traffic flow dynamics.

(9) Horizontal visibility and total cloud capacity: Several studies in the literature have consistently pointed out that horizontal visibility and total cloudiness are the key factors that significantly affect the overall speed of vehicular traffic. In addition, data analysis of the Xi'an intelligent transportation system (XITS) reveals that vehicles generally travel at lower speeds under cloudy weather conditions than in clear, cloudless weather. Therefore, these two indicators are considered important factors affecting traffic flow prediction. Considering their potential exacerbation of urban traffic congestion, this study incorporates horizontal visibility and total cloudiness into the short-term traffic volume forecasting index system of Xi'an to improve the accuracy and practicality of the prediction model.

The above is the indicator system of this paper related to the description and selection of the reasons, and in other literature, there are other related indicators, but this paper did not choose them, and the reason is as follows:

- (1) The peak period and other time-assigned attribute indicators: In this study, the peak period and other attribute indicators have been reflected in the existing time indicator framework of this study. In view of the differences in peak arrival times on different road sections in Xi'an, it is not appropriate to treat them uniformly. Therefore, this study does not single out such specific peak period attribute indicators.
- (2) Whether or not there are schools, shopping malls, and other locations in the vicinity of the assigned attribute indicators: Although some academic literature on schools, shopping malls, and other locations of the attribute indicators has been included in the scope of the road traffic flow prediction, these studies are mainly aimed at long-term traffic flow prediction, and the data cycle is usually in the unit of days or months, which is concerned with the trend of the overall traffic flow changes. Since the attributes of locations such as schools and shopping malls are relatively stable and will not change in the short term, their impact on traffic flow has been reflected in time-related indicators. Therefore, the impact of these location attribute indicators is negligible within the realm of short-term traffic flow prediction research. Based on this, this study does not include such indicators in the index system of short-term traffic flow prediction in Xi'an.

2.2.2. SVR Principle

SVR constitutes a regression technique derived from support vector machines (SVMs), designed to address regression challenges. It builds regression models by finding the best hyperplane in the training dataset [32,33]. As shown in Figure 1, this is equivalent to constructing an interval band of width 2ϵ centered on $f(x)$, and if a training sample falls into this interval band, it is considered to be correctly predicted, and the optimal hyperplane is a plane obtained to maximize the classification interval.

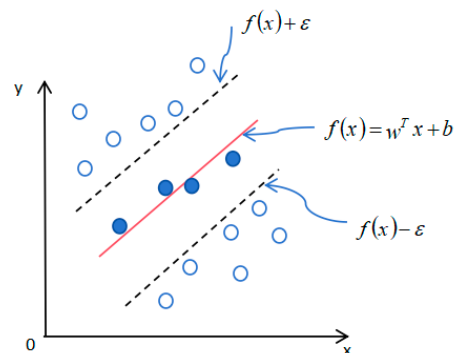


Figure 1. The schematic diagram of the optimal hyperplane.

The data training sample consists of a category of features with a feature vector whose training sample expression is as follows: $D_i = \{x_i, y_i\}$. Here, x_i is used as an input vector to the short-duration traffic flow model, and y_i is used as its category marker. The large interval division hyperplane is obtained along with the corresponding model as follows:

$$f(x) = w_i^T x + b \quad (3)$$

where w is the normal vector to the hyperplane, x denotes the sample value, and b denotes the deviation value. The distance from any point x in the sample space to the hyperplane can be written as follows:

$$\delta_i = \frac{1}{\|w\|} |f(x_i)| \quad (4)$$

Given input data and learning objectives,

$$X = \{X_1, X_2, \dots, X_n\}, Y = \{Y_1, Y_2, \dots, Y_n\}$$

The training process of the model is the process of finding the optimal w and b . Eventually, a set of parameters w and b are obtained to make $f(x)$ closest to y . The problem is transformed into a convex quadratic programming problem, which can be represented as follows:

$$\begin{aligned} \max_{\|w\|} \frac{2}{\|w\|} &\Leftrightarrow \min_{\|w\|} \frac{1}{2} \|w\|^2, \\ \text{s.t. } y_i(w^T x_i + b) &\geq 1, i = 1, 2, \dots, m \end{aligned} \quad (5)$$

It is important not only to maximize the spacing band but also to minimize the loss as a means of determining w and b . Thus, the SVR problem can be formalized as follows:

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m l_\epsilon(f(x_i) - y_i) \quad (6)$$

where C is a regularization constant, and l_ϵ is an ϵ -insensitive loss function as shown in Figure 2.

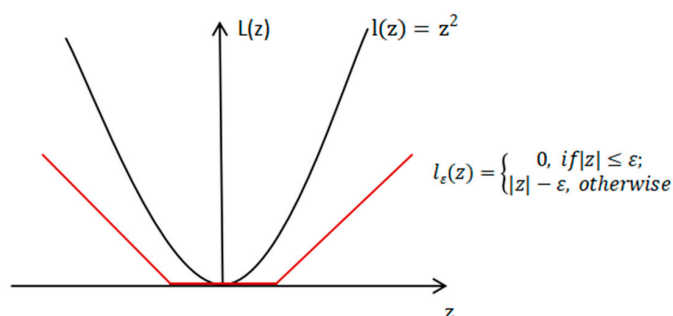


Figure 2. ϵ -insensitive loss function.

Since it is often difficult in real tasks to directly determine the appropriate ε , ensuring that most of the data will fall within the interval bands, and SVR expects all the training data to fall within the interval bands, the relaxation variable ζ is added so that the function's spacing requirements become relaxed, i.e., some samples are allowed to fall outside of the interval bands. As shown in Figure 3:

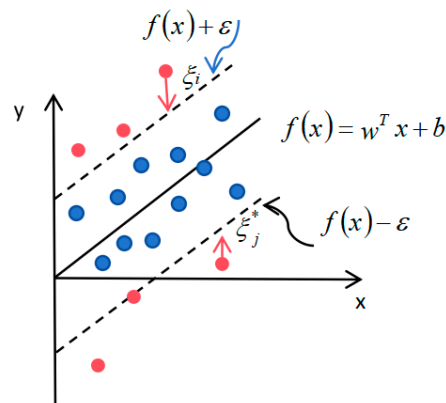


Figure 3. The schematic of SVR with the addition of relaxation variables.

Introducing slack variables ζ_i and ζ_i^* , Equation (6) can be rewritten as follows:

$$\begin{aligned} \min_{w, b, \zeta_i^*} & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m (\zeta_i, \zeta_i^*), \\ \text{s.t.} & f(x_i) - y_i \leq \varepsilon + \zeta_i, \\ & y_i - f(x_i) \leq \varepsilon + \zeta_i^*, \\ & \zeta_i \geq 0, \zeta_i^* \geq 0, i = 1, 2, \dots, m \end{aligned} \quad (7)$$

In order to minimize the objective function, a Lagrangian function is constructed based on the constraints. By introducing the Lagrange multiplier $u_i \geq 0, u_i^* \geq 0, \zeta_i \geq 0, \zeta_i^* \geq 0$, the calculation yields the following:

$$\begin{aligned} L(w, b, \alpha, \alpha^*, \zeta, \zeta^*, \mu, \mu^*) &= \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m (\zeta_i, \zeta_i^*) - \sum_{i=1}^m u_i \zeta_i \\ &- \sum_{i=1}^m u_i^* \zeta_i^* + \sum_{i=1}^m \alpha_i (f(x) - y_i - \varepsilon - \zeta_i) + \sum_{i=1}^m \alpha_i^* (y_i - f(x_i) - \varepsilon - \zeta_i^*) \end{aligned} \quad (8)$$

This can be obtained by substituting (3) and then making the partial derivatives of w , b , and 0:

$$w = \sum_{i=1}^m (\alpha_i^* - \alpha_i) x_i \quad (9)$$

$$0 = \sum_{i=1}^m (\alpha_i^* - \alpha_i) \quad (10)$$

$$C = \alpha_i + \mu_i \quad (11)$$

$$C = \alpha_i^* + \mu_i^* \quad (12)$$

Substituting (9)–(12) into Equation (8) yields the dyadic problem of SVR:

$$\begin{aligned} \max & \sum_{i=1}^m y_i (\alpha_i^* - \alpha_i) - \varepsilon (\alpha_i^* + \alpha_i) - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m (\alpha_i^* - \alpha_i) (\alpha_j^* - \alpha_j) x_i^T x_j, \\ \text{s.t.} & \sum_{i=1}^m (\alpha_i^* - \alpha_i) = 0, \\ & 0 \leq \alpha_i, \alpha_i^* \leq C \end{aligned} \quad (13)$$

The above process is subject to the KKT condition, i.e., requirement:

$$\begin{aligned} \alpha_i(f(x_i) - y_i - \varepsilon - \zeta_i) &= 0, \\ \alpha_i^*(y_i - f(x_i) - \varepsilon - \zeta_i^*) &= 0, \\ \alpha_i\alpha_i^* &= 0, \zeta_i\zeta_i^* = 0, \\ (C - \alpha_i^*)\zeta_i &= 0, (C - \alpha_i)\zeta_i^* = 0 \end{aligned} \quad (14)$$

Finally, the solution of SVR is shaped as $f(x) = \sum_{i=1}^m (\alpha_i^* - \alpha_i)x_i^T x + b$. The samples where $(\alpha_i^* - \alpha_i) \neq 0$ are the support vectors of SVR.

From the KKT condition (14), it follows that, for each sample (x_i, y_i) , $(C - \alpha_i)\zeta_i = 0$ and $\alpha_i(f(x_i) - y_i - \varepsilon - \zeta_i) = 0$. Thus, after obtaining α_i , if $0 < \alpha_i < C$, then $\zeta_i = 0$, and hence,

$$b = y_i + \varepsilon - \sum_{j=1}^m (\alpha_j^* - \alpha_j)x_j^T x_i \quad (15)$$

If the feature mapping form is considered, Equation (9) will be shaped like the following:

$$w = \sum_{i=1}^m (\alpha_i^* - \alpha_i)\phi(x_i) \quad (16)$$

Then, the SVR can be expressed as $f(x) = \sum_{i=1}^m (\alpha_i^* - \alpha_i)K(X, X') + b$, where $K(X, X') = \phi(x_i)^T \phi(x_i)$ is the kernel function.

2.2.3. SVR Short-Term Traffic Flow Prediction Model

The SVR short-time traffic flow prediction model based on road correlation comprises a data processor, an input vector, a kernel function, and an output vector. The details are shown in Figure 4:

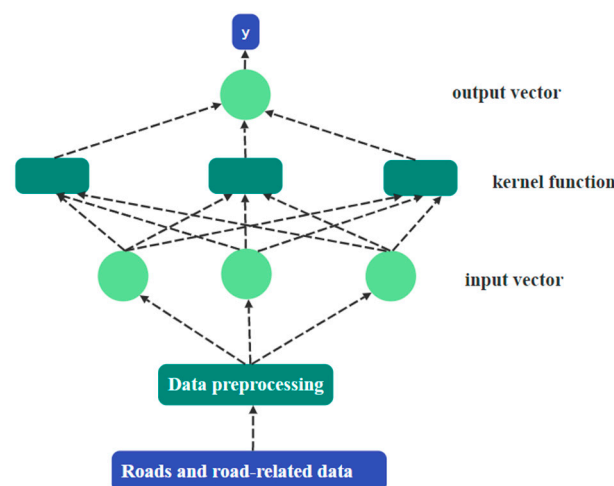


Figure 4. SVR short-term traffic flow prediction model based on road correlation.

This figure shows the workflow of the Support Vector Regression (SVR) model, which includes everything from the preprocessing of the road and related data, feature extraction, and mapping through the kernel function, to the model's processing of the support vectors through the hidden layer nodes and outputting the prediction results, and finally comparing the results with the actual target variables to evaluate the model's prediction performance.

The specific flow chart for SVR model prediction is shown in Figure 5.

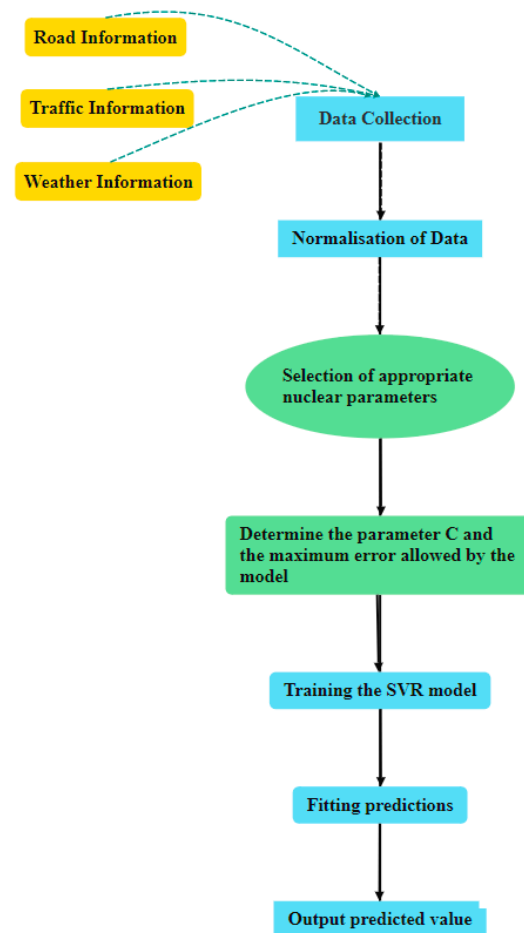


Figure 5. SVR model prediction flowchart.

There are several main steps in predicting traffic flow on post-correlation roads using the SVR model:

- (1) The dataset is prepared and normalized to set the input vector of the SVR;
- (2) Selection of a suitable kernel function;
- (3) Setting the parameters C and ε , the parameter C is the penalty parameter for the error term, which controls how much the model tolerates error, and ε is the maximum error allowed to define the regression model, which determines the shape of the regression curve;
- (4) Training the SVR model using optimal parameters;
- (5) Short-term traffic flow prediction using the trained SVR model;
- (6) By outputting the predicted values, i.e., based on the input feature vectors, the SVR model will output the prediction results corresponding to the target values.

2.2.4. Parametric Optimization

In this paper, the selection of the kernel parameter γ and the penalty parameter C is optimized by grid search combined with cross-validation. The specific steps are as follows:

- (1) Dataset preparation and division:

Data preprocessing: The traffic flow data collected by the Xi'an ITS is preprocessed, including filling missing values, removing outliers, and normalization. The specific methods are as follows:

Filling missing values: the interpolation method is used to fill the missing traffic flow data.

Remove outliers: the outliers are identified and removed by the Z-score method.

Normalization: all eigenvalues are normalized in the range of [0, 1] with the formula:

$$z = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (17)$$

Data division: The preprocessed dataset is divided into training set (80%) and test set (20%). From the training set, it is further divided into five mutually exclusive subsets for five-fold cross validation.

(2) Parameter candidate value setting:

Nuclear parameter γ : the candidate value of γ is set to [0.1, 0.2, ..., 10].

Penalty parameter C: the candidate value range of C is set to [0.1, 0.2, ..., 200].

(3) Grid search and cross-validation:

Parameter combinations: generate all possible (γ , C) parameter combinations, a total of $100 \times 2000 = 200,000$ parameter combinations need to be evaluated.

Performance metrics: root mean square error (RMSE), mean absolute error (MAE) and mean relative error (MRE) are selected as performance evaluation metrics.

Cross-validation cycle: for each pair of (γ , C) parameter combinations, five-fold cross-validation is performed. The specific steps are as follows:

Initialize the performance metrics: the variables should be set as follows: $total_rmse = 0$, $total_mae = 0$, and $total_mre = 0$.

Iterate through each subset:

For each subset, i ($i = 1, 2, \dots, 5$):

Training and validation set division: the i th subset is used as a validation set, and the remaining four subsets are merged to form a training set.

Model training: the training set data are used to train the SVR model and set the current γ and C parameters.

Model validation: the validation set data are used to validate the trained model, and the performance metrics (RMSE, MAE, MRE) of the model are calculated.

Record performance metrics: the performance metrics of the current validation set can result in the total performance metrics:

$$\begin{aligned} total_rmse+ &= rmse_i \\ total_mae+ &= mae_i \\ total_mre+ &= mre_i \end{aligned} \quad (18)$$

Calculate average performance indicator: the cumulative performance indicator is divided by 5 to obtain the average performance indicator for the current parameter combination:

$$\begin{aligned} avg_rmse &= \frac{total_rmse}{5} \\ avg_mae &= \frac{total_mae}{5} \\ avg_mre &= \frac{total_mre}{5} \end{aligned} \quad (19)$$

Selection of optimal parameter combinations: After iterating through all parameter combinations, the parameter combinations with the best average performance index (e.g., the smallest RMSE) are selected as the final kernel parameter γ and penalty parameter C. The optimal parameter combinations and their corresponding average performance indexes are recorded.

(4) Final model training and testing:

Final model training: The SVR model is retrained using the entire training set data and the selected optimal combination of parameters. This step is to ensure that the model achieves the best performance on all available data.

Test set evaluation: The final trained model is tested using the test set data to evaluate the performance of the model on unseen data. Performance metrics such as RMSE, MAE, and MRE are calculated for the test set.

Result analysis: The performance of the model on the test set is analyzed to verify the generalization ability and prediction accuracy of the model. If the performance metrics on the test set are close to the average performance metrics in cross-validation, the model has good generalization ability.

We tested various parameter combinations and recorded the performance metrics (e.g., RMSE, MAE, MRE) for each combination. This is shown in Table 4.

Table 4. Partially tested parameter combinations and their corresponding performance metrics.

γ	C	ε	RMSE	MAE	MRE
0.1	0.1	0.01	15.2	8.5	0.16
0.1	0.2	0.01	14.8	8.3	0.15
0.1	0.3	0.01	14.5	8.1	0.14
...	...	...	...	...	...
0.8	1.2	0.1	11.422	7.017	0.139
0.9	1.2	0.1	11.5	7.1	0.14
1.0	1.2	0.1	11.6	7.2	0.14

(1) Nuclear parameters

By setting $C = 10, \varepsilon = 0.01$, so that it varies gradually between (0, 10). Through parameter comparison experiments, with the setting of $C = 10$, the prediction error shows a gradual decrease as γ gradually increases from 0 to 10, while the training error gradually increases in that interval. However, as γ continues to increase to 10, the prediction error gradually increases while the training error gradually decreases. The change curves are shown in Figures 6 and 7.

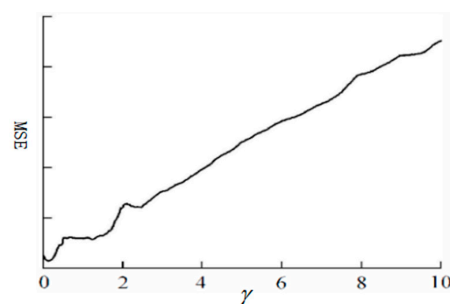


Figure 6. Variation curve of prediction error ($C = 10, \varepsilon = 0.01$).

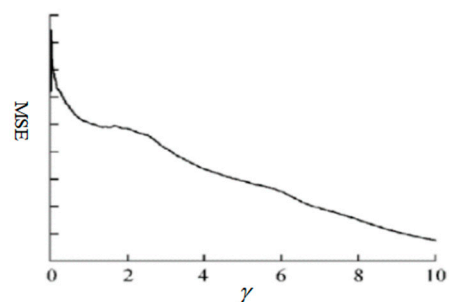


Figure 7. Variation curve of training error ($C = 10, \varepsilon = 0.01$).

(2) The penalty parameter C

By setting $\gamma = (1, 8)$, in the interval from 0 to 200, C constantly changes. At the beginning of the rise in the value of C in the interval, the change in the value of C is still within a small range, but then the training and prediction and, eventually as the value of C gradually increases, the prediction error and training error gradually stabilize. The variation curve is shown in Figures 8 and 9.

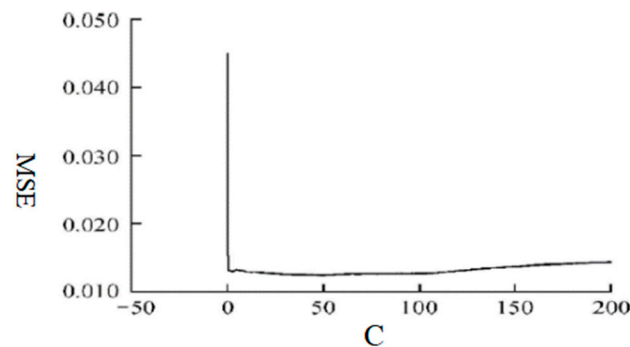


Figure 8. Variation curve of prediction error ($C = 0\sim 200$, $\varepsilon = 0.01$).

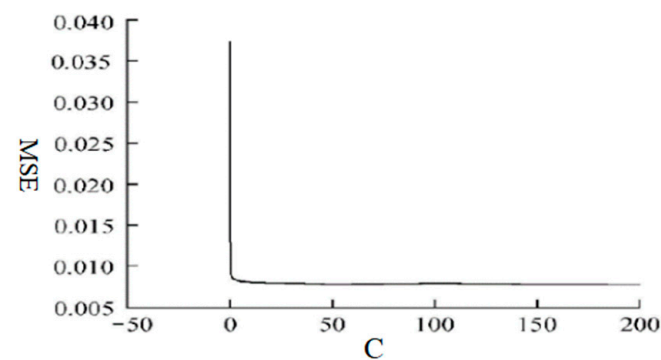


Figure 9. Variation curve of training error ($C = 0\sim 200$, $\varepsilon = 0.01$).

In summary, when the support vector machine is used for parameter selection, the variables are more of an influence on the measurement accuracy, and the values of the kernel parameter γ and the penalty parameter C cannot be too large or too small. The selection of appropriate SVR parameters is crucial for the prediction results of short-duration traffic flow prediction models. After several parameter training as well as corrections, the SVR model in this chapter was finalized with a penalty parameter C of 1.2466 and a kernel parameter γ of 0.8327.

To more fully assess the stability and reliability of model performance, 95% confidence intervals were added. These confidence intervals were computed over multiple (10) independent training and testing sessions to reflect the range of error variation under different runs or data configurations. For each parameter combination, we calculated the mean and standard error of the error metrics (e.g., RMSE, MAE) for each experiment.

Using the 95% confidence interval formula,

$$CI = \text{mean} \pm 1.96 \times SE \quad (20)$$

where $SE = \frac{s}{\sqrt{n}}$, s is the sample standard deviation, and n is the number of experiments, as shown in Figure 10.

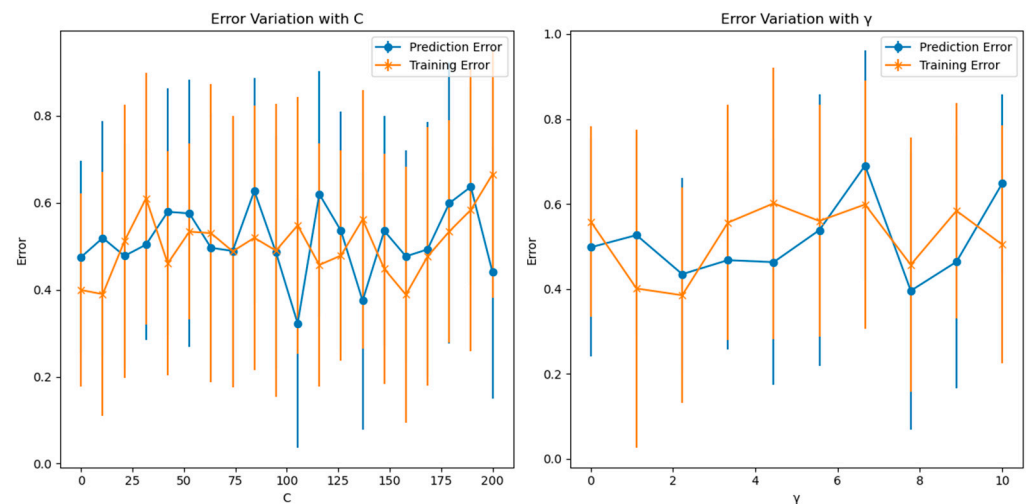


Figure 10. Error variation curves with 95% confidence intervals.

2.3. Association Rule–SVR Model

To enhance the precision of short-term traffic flow forecasting accuracy and to improve the prediction accuracy for branch roads with small traffic flow, we constructed a targeted association rule–SVR model. The model demonstrated high prediction accuracy in traffic flow prediction. The overall structural framework is shown in Figure 11. Utilizing the developed model, we are able to more effectively forecast the immediate traffic patterns on minor arteries with less traffic, thereby enhancing the comprehensive accuracy of predictions.

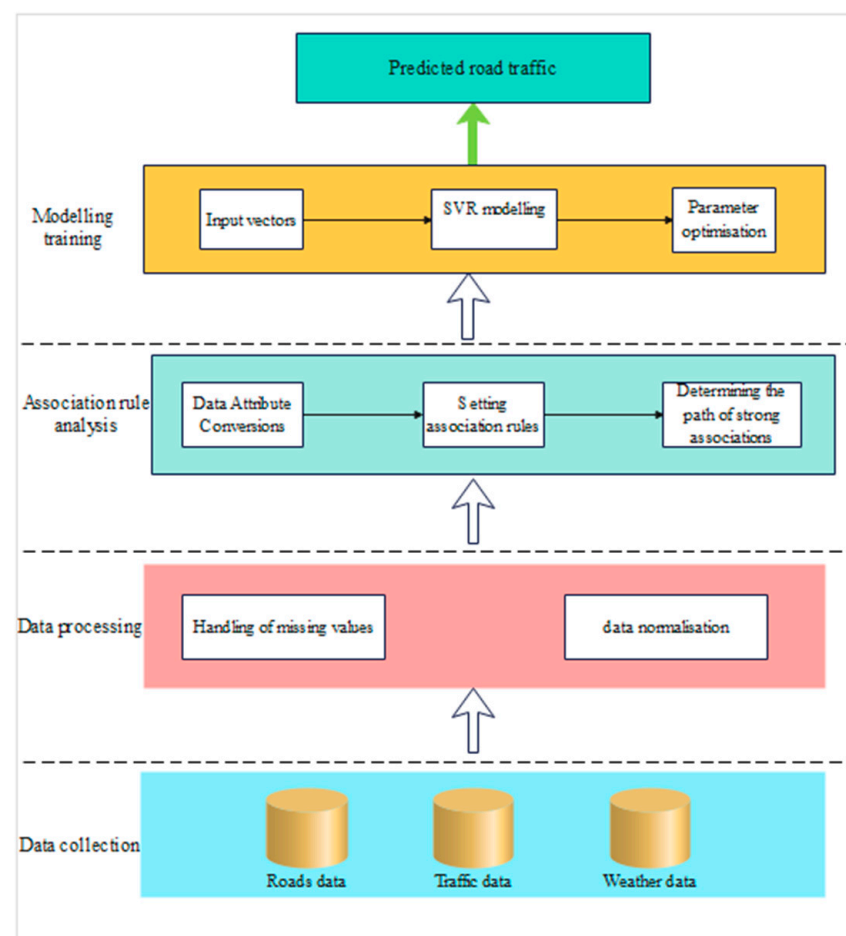


Figure 11. The structure of the association rule–SVR model.

The detailed procedure for the integrated association rule and SVR model in forecasting short-term traffic flow is outlined below:

- (1) Preprocessing of collected data such as road information, traffic information, and weather information;
- (2) Converting road data into attributes based on traffic flow information, congested, more congested, severely congested, smooth, and smoother, and perform road correlation analyses to identify strongly correlated roads;
- (3) The road traffic flow data associated with the target branch road and the road characteristics are used as input vectors of the SVR model, and then, the input parameters of the SVR model, such as the kernel function γ , the penalty factor C , etc., are set to establish the SVR model, and finally, the predicted value of the traffic flow is used as the output.

3. Simulation Experiments

3.1. Datasets

3.1.1. Data Collection

The data in this paper come from the data of Xi'an intelligent transportation system, which collects the daily data of the city roads in X city through the traffic control camera, and the data volume is large, and the data are real, which can be used as the data source for the research of short-time traffic flow prediction method in X city in this paper. Since the research object of this paper is short-time traffic flow prediction, the data collection interval should be as small as possible, so this paper selects the minimum period of data collection of Xi'an intelligent transportation system, i.e., every 10 min as the data collection interval to extract the data, and collects the bidirectional traffic flow of each road section within ten minutes as the database. This paper collects the city's traffic flow data from 1 January 2021 to 31 March 2022, to be used as the database for the establishment of the model in this paper.

3.1.2. Data Preprocessing

After certain preprocessing of the data in the early stage, including supplementing the missing parts of the traffic flow data of each road in X city collected in the early stage according to the data type, eliminating the deficiencies in the traffic flow information collected in the early stage, removing the redundant information, and making appropriate adjustments according to the actual situation, better results were achieved. Generally speaking, various technical means such as data cleaning, data integration, and data conversion can be used [34].

- (1) Missing value processing: Due to a variety of human and mechanical factors, the ordered raw data collected from traffic management information systems are often accompanied by serious deficiencies, a phenomenon that cannot be ignored and is often accompanied by serious consequences, for example, due to improper operation, damage to the collection equipment, and so on, which reduces the density of value of the raw data, thus bringing a negative impact on the forecast of traffic flow. The three most prevalent missing value filling techniques are deletion, patching, and neglect.
- (2) Data transformation: Through various data transformation methods, the data after initial processing are transformed into the data form needed by the model: firstly, through the smooth processing of the data, the noisy data in the initial data are eliminated, and they are excluded; after that, data clustering is carried out to summarize the various types of data, and the conceptual hierarchy is utilized to carry out a unified generalization of the various types of data, and then, the original data at the lower level are transformed into the higher level data. High-level data and, finally, through

attribute construction, new attribute types are constructed, and these new attribute categories are incorporated into the attribute set.

- (3) Normalization of raw data: By normalizing the data, different orders of magnitude are finally classified as the same magnitude for more efficient system analysis and processing. This method makes raw data more dimensionless by scaling it by a certain percentage and confining it to a predetermined range. Data can be effectively normalized through data normalization, which can be in any range $[0, 1]$. For the raw information $[0, 1]$, the normalization process needs to be applied, i.e., it is compressed at a predefined rate so that it can be mapped to a specific range, and thus, the information within that range can be effectively used for systematic analysis.

$$z = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (21)$$

In the above equation, z denotes the normalized data, x_i denotes the associated eigenvalue, $\min(x_i)$ is the lowest point of the eigencolumn, and $\max(x_i)$ is the highest point of the eigencolumn.

To verify the conclusions of the model, we randomly selected 10 main roads and 10 branch roads in Xi'an and processed the data with missing values. The specific selection of these roads is shown in Table 5:

Table 5. Table of randomly selected road sections.

Trunk Road	Spur Road
Jingjiu Road	Jindong Street
Taiyi Road	Dongyangshi
Cuihua Road	Juhuayuan
Dongda Street	Minxin Road
Fengqing Road	Yuchang Road
Dazhai Road	Wenti road
Wude Road	Xier West
Beichen Road	Zhenhua South Road
Hongqi road	Xiangrong Lane
Park North Road	Huaying Lane

As for the data, a total of 80,640 data from 1 April 2022 to 7 April 2022 in spring time, including the Qingming Festival, 22 July 2022 to 29 July 2022 in summer time, including weekends, 6 October 2022 to 13 October 2022 in autumn time, including National Day Holiday, and 1 December 2022 to 8 December 2022 in winter time are selected as the predicted data of road traffic flow in this simulation experiment.

According to the short-time traffic flow prediction index system established in this paper, the data preview of each index on 1 April 2022 is collected as shown in Table 6.

Table 6. Preview of selected road data for east new street.

Time	Location	Traffic Flow	Average Speed	Holidays or Not	Temperature	Horizontal Atmospheric Pressure	Ground Relative Humidity	Wind	Special Weather Phenomenon	Horizontal Visibility	Total Cloud Capacity
11:00	Dongxin Street	172	32KM/H	NO	16.7 °C	701.5	37	windless	rain	>10	sparse clouds
11:10	Dongxin Street	164	33KM/H	NO	16.9 °C	701.7	37	windless	rain	>10	sparse clouds
11:20	Dongxin Street	182	30KM/H	NO	17.9 °C	704.6	37	windless	rain	>10	sparse clouds
11:30	Dongxin Street	188	27KM/H	NO	17.9 °C	703.5	37	windless	rain	>10	sparse clouds
11:40	Dongxin Street	187	29KM/H	NO	18.2 °C	704.2	35	windless	rain	>10	sparse clouds
11:50	Dongxin Street	192	27KM/H	NO	18.5 °C	702.1	35	windless	rain	>10	sparse clouds

This table provides a preview of the selected road data for Dongxin Street on 1 April 2022. The data include various attributes such as time, location, traffic flow, average speed, holidays or not, temperature, horizontal atmospheric pressure, ground relative humidity, wind, special weather phenomenon, horizontal visibility, and total cloud capacity.

- (1) Weather conditions: The data include a variety of weather conditions beyond just rain. The “Special Weather Phenomenon” column indicates the presence of other weather conditions such as rain, which is shown in the example. Other conditions such as fog, snow, and sandstorms are also recorded in the dataset, although not shown in this excerpt.
- (2) Traffic conditions: The dataset includes traffic data for both peak and non-peak hours. The “Holidays or Not” column indicates whether the data were collected on a holiday. In this example, the data were collected on a non-holiday. The dataset also includes data collected during peak hours (e.g., morning rush hour from 7:00 to 9:00 and evening rush hour from 17:00 to 19:00).
- (3) Temporal variability: The dataset considers temporal variability by including data collected at different times of the day (morning, afternoon, and evening). The “Time” column shows the specific time of data collection, allowing for analysis of traffic flow patterns throughout the day. In this example, the data were collected between 11:00 and 11:50, which is during the midday period.

The above table uses Dongxin Street as an example. Between 11:00 a.m. and 11:50 a.m., the traffic flow on Dongxin Street showed an increasing trend from 172 to 192 vehicles, while the average speed decreased from 32 to 27 km/h, suggesting that traffic congestion may have been caused by rainfall. During the period, the temperature increased from 16.7 °C to 18.5 °C, the atmospheric pressure fluctuated between 702 and 704.6 mbar, and the relative humidity at the ground level stayed around 37% before decreasing to 35%. There was no wind and continuous rainfall throughout the observation period, visibility remained above 10 km, and the sky was sparsely cloudy. Table 7 shows the data distribution for different weather scenarios and time periods.

Table 7. Summary of data distribution across different weather scenarios and time periods.

Collection Period	Weather Condition	Time of Day	Number of Samples	Specific Observations
January 2021	Sunny	Morning (6 a.m.–12 p.m.)	2345	No holidays, typical traffic
January 2021	Sunny	Afternoon (12 p.m.–6 p.m.)	2123	No holidays, typical traffic
January 2021	Sunny	Evening (6 p.m.–12 a.m.)	1876	No holidays, typical traffic
January 2021	Snowy	Morning (6 a.m.–12 p.m.)	1234	Snowstorm, increased traffic accidents
January 2021	Snowy	Afternoon (12 p.m.–6 p.m.)	1456	Snowstorm, increased traffic accidents
January 2021	Snowy	Evening (6 p.m.–12 a.m.)	1098	Snowstorm, increased traffic accidents
April 2021	Rainy	Morning (6 a.m.–12 p.m.)	1567	No holidays, typical traffic
April 2021	Rainy	Afternoon (12 p.m.–6 p.m.)	1678	No holidays, typical traffic
April 2021	Rainy	Evening (6 p.m.–12 a.m.)	1456	No holidays, typical traffic
July 2021	Foggy	Morning (6 a.m.–12 p.m.)	1345	No holidays, typical traffic
July 2021	Foggy	Afternoon (12 p.m.–6 p.m.)	1234	No holidays, typical traffic
July 2021	Foggy	Evening (6 p.m.–12 a.m.)	1123	No holidays, typical traffic
October 2021	Sunny	Morning (6 a.m.–12 p.m.)	2456	No holidays, typical traffic
October 2021	Sunny	Afternoon (12 p.m.–6 p.m.)	2345	No holidays, typical traffic
October 2021	Sunny	Evening (6 p.m.–12 a.m.)	2098	No holidays, typical traffic

This table provides a summary of the data distribution across different weather scenarios and time periods. The collection period column indicates the specific month and year of data collection. The weather condition column classifies the weather conditions (e.g., sunny, rainy, snowy, foggy). The Time of Day column categorizes the time into morning, afternoon, evening, and night. The number of samples column shows the total observations collected under each weather and time combination. The specific observations column notes any extraordinary events, such as holidays or unusual congestion.

The dataset used in this study is designed to capture typical and atypical traffic patterns across different times of the year and weather conditions. The data collection periods span multiple months and seasons, ensuring a comprehensive representation of traffic flow under various conditions. For instance, the dataset includes data from both peak and off-peak hours, as well as data collected during holidays and non-holiday periods. This approach ensures that the dataset reflects a wide range of traffic conditions, making the results of our study more generalizable and applicable to real-world scenarios.

3.2. Evaluation Indicators

To more effectively assess the prediction's accuracy and the prediction performance of the model, this paper mainly introduces three evaluation indexes: the root mean square error (RMSE), the mean absolute error (MRE), and the mean relative error (MAE), whose specific formulas are expressed as follows. The smaller the values of RMSE, MRE, and MAE of the model, the better the prediction results.

$$RMSE = \sqrt{\frac{\sum_{i=1}^m (y_i - y_i')^2}{m}} \quad (22)$$

$$MRE = \frac{1}{m} \sum_{i=1}^m \frac{|y_i - y_i'|}{y_i} \quad (23)$$

$$MAE = \frac{1}{m} \sum_{i=1}^m |y_i - y_i'| \quad (24)$$

where y_i is the real traffic flow data collected, y_i' is the traffic flow data predicted by the prediction model, and m denotes the count of traffic flow data points.

3.3. Simulation of SVR Short-Time Traffic Flow Prediction Model Based on Associated Roads

3.3.1. Urban Road Linkage Analysis

First, an Apriori correlation analysis was performed on the twenty selected roads with 80% support and 90% confidence. Through this analysis, the set of frequent terms for each road, i.e., the associated roads for each road, is obtained. Taking Jiandong Street among the feeder roads as an example, there are six associated roads of Jiandong Street under the selected support and confidence levels, which are Taiyi Road, Youyi Road, Andong Street, Biaoxin Street, Yanta North Road, and Tai'an Street.

3.3.2. Analysis of SVR Short-Term Traffic Flow Prediction Model

After road correlation for each road segment, the SVR model was established with a penalty parameter C of 1.2466 and a kernel parameter gamma of 0.8327 based on the short-term traffic flow data of the target road as well as the correlated roads as the database. Taking the data on 1 April 2022 as an example, some of the model's prediction results for trunk road roads are shown in Figure 12, and some of the short-term traffic flow prediction results for feeder roads are shown in Figure 13.

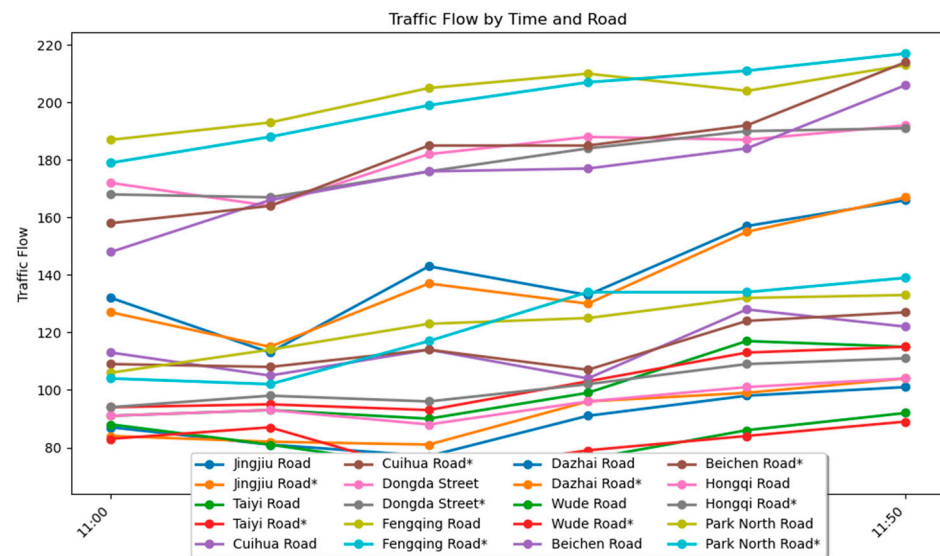


Figure 12. Prediction results of selected trunk roads based on SVR mode. Note: * are SVR predictions for associated roads.

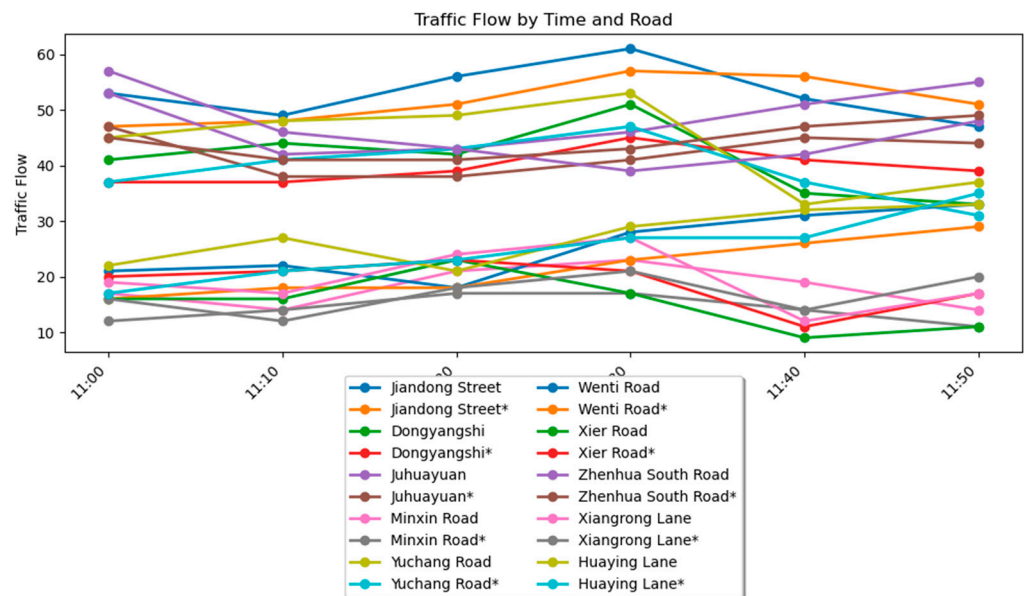


Figure 13. SVR model-based road prediction results for selected feeder roads. Note: * are SVR predictions for associated roads.

This is a bar chart of the change in the numerical value of traffic flow on different roadways between 11:00 and 11:50. The graph shows a gradual increase in values for all road sections, but the increase varies. The band * shows the prediction of SVR for the associated roads, and it can be seen that the model has high accuracy and stability in predicting traffic flow on different roads, can adapt to changes in traffic flow in real time, and demonstrates good applicability on different types of roads. Although there are slight differences in some specific time periods, overall, the SVR model provides an effective prediction tool for traffic management and planning with practical application value, while there is still room for further optimization.

The prediction results of twenty roads of the SVR short-time traffic flow prediction model for associated roads were analyzed, and the final result was that the R^2 of the overall model was 0.9261, the R^2 of the ten main roads was 0.9395, and the R^2 of the ten branch roads was 0.9127. These R^2 values indicate the proportion of the variance in traffic flow that is predictable from the model, with higher values suggesting a better fit of the model

to the data. The overall model's high R^2 value of 0.9261 suggests that it can explain 92.61% of the variability in traffic flow across all roads considered. The slightly higher R^2 value for main roads (0.9395) compared to branch roads (0.9127) indicates that the model performs slightly better on main roads, likely due to the more consistent traffic patterns and higher data availability on these roads.

The other results of the evaluation indexes are shown in Table 8:

Table 8. Comparison of road simulation results based on SVR model.

Model	R^2	D-W Tests	Error Variance	MAE	MRE
Overall model	0.9261	1.7764	35.142	7.426	0.132
Branch circuit model	0.9127	1.7461	37.621	7.511	0.141
Trunk road model	0.9395	1.7875	34.278	7.386	0.123

R^2 (coefficient of determination): R^2 is a statistical measure that represents the proportion of the variance for a dependent variable that is explained by an independent variable or variables in a regression model. In the context of traffic flow prediction, a higher R^2 value indicates that a larger proportion of the variability in traffic flow can be explained by the model. An R^2 value of 0.9261 for the overall model means that 92.61% of the variability in traffic flow across all roads is predictable by the model. The slightly higher R^2 value for main roads (0.9395) compared to branch roads (0.9127) suggests that the model fits the data of main roads slightly better, likely due to more consistent traffic patterns and higher data availability on main roads.

D-W tests (Durbin–Watson test): The Durbin–Watson test is a statistical test used to detect the presence of autocorrelation (a relationship between values separated from each other by a given time lag) in the residuals from a regression analysis. The test statistic ranges from 0 to 4, with values close to 2 indicating no significant autocorrelation. Values significantly less than 2 indicate positive autocorrelation, while values significantly greater than 2 indicate negative autocorrelation. In our results, the D-W test statistic values are close to 2 (1.7764 for the overall model, 1.7461 for the branch circuit model, and 1.7875 for the trunk road model), indicating that there is no significant autocorrelation in the residuals. This suggests that the model has effectively captured the underlying patterns in the data and that the residuals are randomly distributed.

Error variance: Error variance is a measure of the variability of the prediction errors. It provides an indication of how much the predicted values deviate from the actual values. A lower error variance indicates that the model's predictions are closer to the actual values, suggesting better prediction accuracy. In our results, the error variance for the overall model is 35.142, indicating a relatively low level of variability in the prediction errors. The slightly higher error variance for the branch circuit model (37.621) compared to the trunk road model (34.278) reflects the slightly more complex traffic patterns on branch roads, which may be more challenging for the model to predict accurately.

MAE (mean absolute error): MAE is a measure of the average magnitude of the errors in a set of predictions, without considering their direction. It is calculated as the average of the absolute differences between the predicted and actual values. A lower MAE indicates better prediction accuracy. In our results, the MAE for the overall model is 7.426, indicating that the average magnitude of the prediction errors is relatively small. The slightly higher MAE for the branch circuit model (7.511) compared to the trunk road model (7.386) suggests that the model's predictions for branch roads have slightly larger errors on average, which may be due to the more complex traffic patterns on branch roads.

MRE (mean relative error): MRE is a measure of the average relative magnitude of the errors in a set of predictions. It is calculated as the average of the absolute differences between the predicted and actual values, divided by the actual values. A lower MRE indicates better prediction accuracy relative to the actual values. In our results, the MRE for the overall model is 0.132, indicating that the average relative magnitude of the prediction errors is relatively small. The slightly higher MRE for the branch circuit model (0.141) compared to the trunk road model (0.123) suggests that the model's predictions for branch roads have slightly larger relative errors on average, which may be due to the more complex traffic patterns on branch roads.

In summary, compared with the prediction results of trunk roads, the SVR prediction model of associated roads established in this paper improves the road prediction accuracy of branch roads with less traffic flow, and by analyzing the overall model, it is observed that the model developed in this study is capable of fulfilling the requirements for short-term traffic flow forecasting.

3.4. Comparative Analysis of Models

When comparing models, we usually calculate the error to assess the predictive accuracy of the model [35]. Common error metrics include absolute and relative errors. Absolute error is the absolute value of the discrepancy between the forecasted and the actual measured value, which can measure the degree of discrepancy between the model's estimated output and the true observed data, and the smaller the value indicates that the model's prediction is more accurate. Relative error is the ratio between the absolute error and the actual observed value, relative error can reflect the relative accuracy of the model prediction, it will be compared with the actual observed value, and lower values imply a higher proximity of the model's predictions to the actual measured data. Both absolute and relative errors are commonly used metrics to assess the predictive accuracy of models, and by calculating these error metrics, we can compare the predictive performance of different models and select the best-performing model.

- (1) Linear regression: linear regression modeling is a simple but powerful statistical method whose basic goal is to find the optimal regression coefficients so that the difference between the predicted values of the model and the actual observations (i.e., residuals) is as small as possible.
- (2) Random Forest: a unified learning approach that enhances the precision and stability of forecasts through the creation of numerous decision trees.
- (3) RNN: its special feature is the connected structure of the network, which allows information to flow through time series data and can effectively encapsulate the temporal relationships within the sequential data.
- (4) GBDT: It minimizes the gradient of the loss function by iteratively constructing a decision tree to improve prediction accuracy.
- (5) LSTM [36]: It iteratively constructs a decision tree to minimize the gradient of the loss function to improve prediction accuracy.
- (6) STBiPGAT [37]: a spatiotemporal attention model that accurately captures the spatiotemporal dynamics of traffic flow.

Using the correlation data associated with each road segment as the basic dataset, a variety of prediction methods were used to compare with the SVR model established in this paper, and the outcomes are depicted in Figure 14.

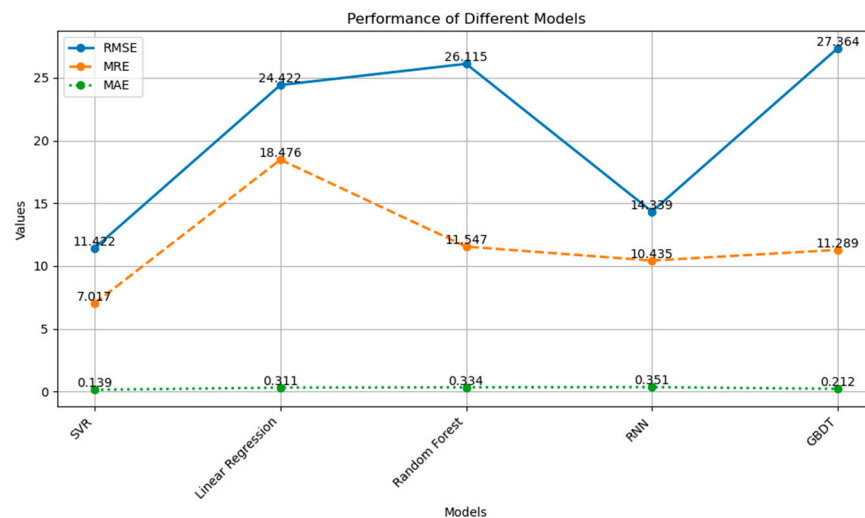


Figure 14. Comparison of model results.

As can be seen from Figure 14, by comparing the root mean square error, the mean absolute error, and the mean relative error of each model, it can be seen that the SVR model for the associated roads established in this paper performs better, and it is evident that the fitting effect of the SVR model is the best model among the compared models. Although the performance values of the STBiPGAT model are similar to those from the model introduced in this study, it fails to consider the influence of related road traffic.

Confidence intervals are indispensable for a more comprehensive assessment of model performance, especially in multiple experiments. Confidence intervals can provide a range that indicates the probability that a model performance metric may fall within that range over multiple repetitive experiments. The results of a single experiment may be affected by the randomness of the dataset, differences in model initialization, hyperparameter selection, and other factors. By calculating confidence intervals, the uncertainty in model performance can be assessed more accurately, thus providing a more reliable performance assessment. In Figure 13, the performance of the SVR model is compared with other models (e.g., LSTM, Random Forest, etc.). By adding confidence intervals, performance differences between models can be more accurately assessed. If the confidence intervals of two models do not overlap, this indicates that the difference in performance between them is statistically significant; if the confidence intervals overlap, further analysis may be required to determine whether the difference is significant. To calculate confidence intervals for RMSE, MAE, and MRE for each model, we performed multiple (10) independent training and testing sessions. For each assessment metric, we calculated its mean and standard error, and further calculated 95% confidence intervals. The specific formulas were calculated as follows:

$$\text{Confidence Interval} = \text{Mean} \pm 1.96 \times \frac{\text{Standard Error}}{\sqrt{n}} \quad (25)$$

where n is the number of repetitions of the experiment. The standard error is calculated as follows:

$$\text{Standard Error} = \frac{\text{Standard Deviation}}{\sqrt{n}} \quad (26)$$

In Figure 15, we will add confidence intervals for the RMSE, MAE, and MRE for each model. This can be accomplished by adding error bars to the bars, which will show the range of confidence intervals for each metric. The steps are as follows:

- (1) Data preparation: the results are collected from multiple experiments for each model.
- (2) Calculate means and confidence intervals: the means and 95% confidence intervals are calculated for each indicator using the above formulas.

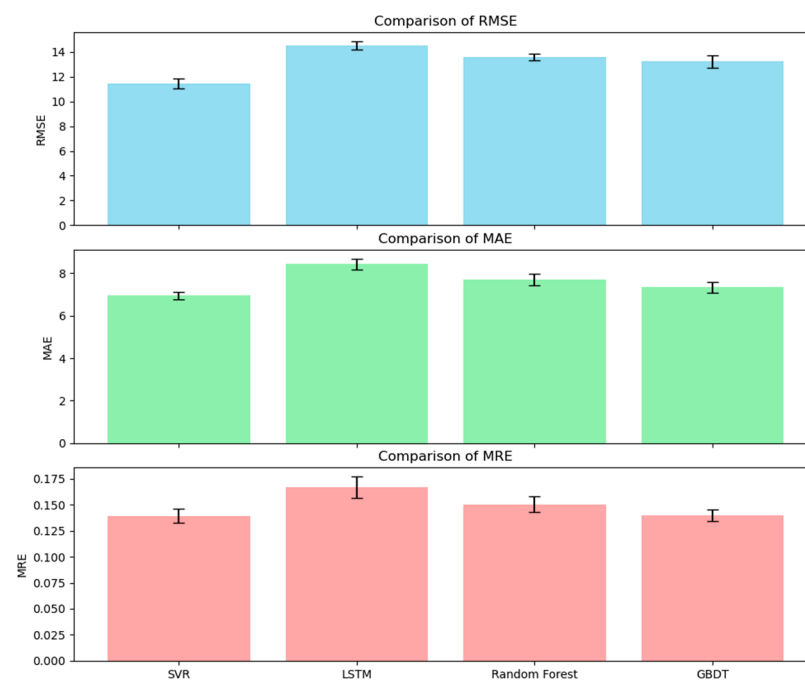


Figure 15. Comparison of different models at 95% confidence intervals.

As can be seen in Figure 15, the confidence intervals for the RMSE, MAE, and MRE of the SVR model are relatively narrow, which indicates that the model performs more consistently over multiple experiments. In contrast, the confidence intervals of other models, such as LSTM and Random Forest, are wider, indicating that there may be greater variability in the performance of these models. This result further validates the superiority and stability of the SVR model in short-term traffic flow prediction.

3.5. Model Evaluations

3.5.1. Accuracy Test

The information criterion and statistics of the SVR model for short-term traffic flow forecasting grounded in road association are shown in Tables 9 and 10:

Table 9. SVR model information criteria and statistics table.

Information Standard		Statistic	
AIC	6.0702	R^2	0.9167
BIC	7.7832	Adjusted R^2	0.9189
HQ	6.1134	D-W test	1.8144

Table 10. SVR model variance and error table.

Variance Analysis					
Source	Degrees of Freedom	Square Sum	Mean Square	F-Value	Pr > F
Model	15	136,171.667	67,417.894	90.8905	1
Inaccuracies	7	5208.3333	724.0476		
Corrected total	23	1,493,000			

Table 8 demonstrates the information criteria and statistics of the SVR short-term traffic flow prediction model. Specifically, it lists three different information criteria (AIC, BIC, and HQ) and their corresponding values, which are 6.0702, 7.7832, and 6.1134, respectively. The statistics of the model, including the results of the coefficient of determination (R^2), the adjusted coefficient of determination (Adjusted R^2), and the Durbin–Watson test (D-W test), are also given, which are 0.9167, 0.9189, and 1.8144, respectively. This indicates that the model has high goodness of fit and good autocorrelation.

Table 9 provides the ANOVA and error estimates for the SVR model. By comparing the mean square error (MSE) of the model with the inaccuracies of the mean square error, it can be found that the MSE of the model is much smaller than the MSE due to inaccuracies, which implies that the model itself introduces less error, and most of the error comes from the inaccuracy of the data. In addition, degrees of freedom, square sum, F-value, and $Pr > F$ -value are also listed in the table, which further support the stability and reliability of the model.

In summary, these two tables together demonstrate that the SVR short-time traffic flow prediction model established based on road association has a good fitting effect and high accuracy, and can meet the needs of short-time traffic flow prediction.

3.5.2. Road Tests

The comparison table of model evaluation indexes after testing using data from a total of 561 branch roads and 729 main roads in some areas of Xi'an is shown in Figure 16.

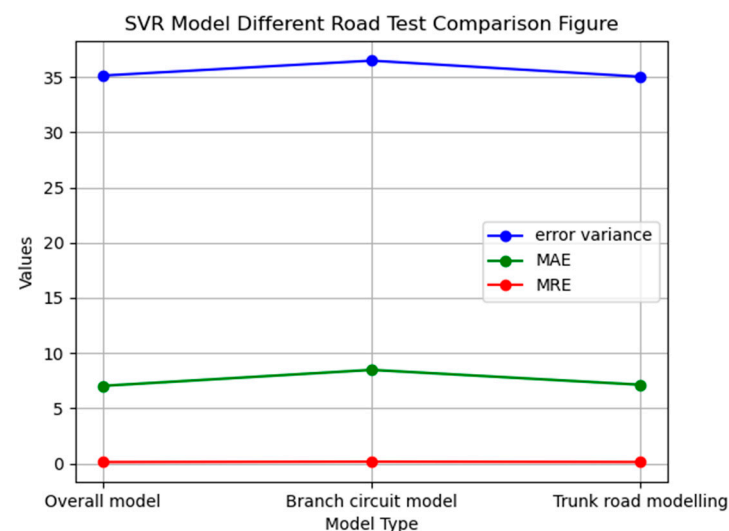


Figure 16. Comparison of SVR modeled feeder road tests.

As can be seen from Figure 16, after road correlation using the SVR model modeling, its overall accuracy has been close to the average accuracy of the overall model, and its accuracy has been able to meet the needs of the Xi'an city branch roads for short-term traffic flow prediction on the road.

4. Conclusions

Short-term traffic flow prediction is essential for modern traffic management and urban planning. It helps optimize traffic control, prevent accidents, support intelligent transportation systems, and enhance economic efficiency. Existing studies primarily focus on short-term traffic flow prediction for main roads. However, they overlook issues such as the lower traffic volume and prediction accuracy on side roads. To address these limitations, this paper proposes a prediction model that combines association rules with SVR. In

addition, this paper also expands the index system by reading a lot of literature, such as adding the weather and other indicators. In contrast to alternative forecasting models, the model developed herein is more effective, and the proposed model demonstrates improved performance, as evidenced by lower RMSE and MAE values, and meets the needs of short-term traffic flow prediction. The conclusions of this paper are as follows:

- (1) First, Apriori correlation analysis is carried out on 20 roads with 80% support and 90% confidence level. Through this analysis, the frequent term set of each road, i.e., the relevant road of each road, is obtained.
- (2) After road correlation for each road section, the SVR model with penalty parameter C of 1.2466 and kernel parameter γ of 0.8327 is established based on the short-term traffic flow data of the target road and the related roads as a database. The model predicts the related roads more accurately compared with the real ones.
- (3) Several prediction algorithms are used to compare the performance with this paper's algorithm, by comparing the root mean square error, the average absolute error, and the average relative error of each model, and the proposed SVR model achieved an RMSE of 11.422 and an MAE of 7.017, while the LSTM model had an RMSE of 14.5 and an MAE of 8.2, the Random Forest model had an RMSE of 13.8 and an MAE of 7.8, and the GBDT model had an RMSE of 13.2 and an MAE of 7.5. It can be seen that the proposed model outperforms other models in terms of RMSE, MAE, and MRE, demonstrating superior prediction accuracy and fitting effect.

However, it should be pointed out that there are also areas for improvement in this paper. In particular, in terms of constructing an indicator system, although this paper summarizes an indicator system based on a large amount of literature, there is still much room for improvement and enrichment. Considering their potential exacerbation of urban traffic congestion, this study incorporates horizontal visibility and total cloudiness into the short-term traffic volume forecasting index system of Xi'an to improve the accuracy and practicality of the prediction model. However, there are other factors that could further enrich the indicator system and enhance its practicality. For example, population density, local events, and traffic patterns in commercial areas are all factors that can significantly impact traffic flow. Future work could explore the inclusion of these factors in the indicator system to provide a more comprehensive and accurate prediction model. In order to solve this problem, the considered improvements are as follows:

- (1) Indicator expansion:
 - ① Population density: Incorporating population density data could help in understanding the impact of residential and commercial areas on traffic flow. Areas with higher population density are likely to experience higher traffic volumes, especially during peak hours.
 - ② Local events: Special events such as concerts, sports games, and festivals can cause significant changes in traffic patterns. Including data on local events could help in predicting traffic congestion more accurately.
 - ③ Traffic patterns in commercial areas: Commercial areas often have different traffic patterns compared to residential areas. Understanding these patterns and incorporating them into the model could improve the prediction accuracy in urban settings.
- (2) Data quality enhancement: The quality and quantity of traffic flow data are crucial for the performance of any predictive model. Future work could focus on increasing the data collection frequency and improving the accuracy of traffic monitoring devices. For example, deploying more advanced sensors and ensuring their proper maintenance can lead to higher data quality. Furthermore, integrating data from multiple sources, such as GPS data from vehicles and mobile applications, could provide a more comprehensive view of traffic conditions.

In summary, although this paper still needs to be improved in terms of the indicator system, its prediction effect can be enhanced through optimization and contributes to the study of intelligent transportation.

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Data Availability Statement: Data supporting the results of this study are available from the Traffic Police Detachment of the Xi’an Municipal Public Security Bureau, but the availability of these data is limited; these data were used under license for this study and are therefore not available to the public. However, with permission from the Traffic Police Detachment of the Xi’an Municipal Public Security Bureau, the authors can make these data available upon reasonable request. If you need these data, you can contact 2230520059@stu.xaut.edu.cn.

Conflicts of Interest: The authors declare no conflicts of interest.

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