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Original article | Transport and Transport-Technological Systems

RESEARCH ON THE EFFECTIVENESS OF DIFFERENT NEURAL NETWORK MODELS IN TRAFFIC FLOW PREDICTION

Jixiao Jiang

Abstract

This paper compares the effectiveness of support vector machine (SVM), convolutional neural network-long short-term memory (CNN-LSTM), and support vector machine-long short-term memory (SVM-LSTM) models for traffic flow prediction in intelligent transportation systems (ITS). This research aims to explore the application scenarios of different machine learning and neural network models in traffic flow forecasting, focusing on verifying the effectiveness of the CNN-LSTM and the SVM-LSTM models designed in this paper in integrating spatial feature extraction with time series modeling. Experimental validation is conducted on real-world long- and short-term traffic flow datasets, and the performance of each model is systematically evaluated in terms of the number of prediction errors, computational efficiency, and robustness. Through a comprehensive analysis of metrics such as the coefficient of determination (R^2) and root mean square error (RMSE), this research provides a basis for the appropriate selection of prediction models in ITS and offers theoretical support for future research in multimodal traffic data fusion modeling.

Purpose. Through systematic comparative studies, a more efficient and reliable model is screened out for the traffic flow prediction subsystem in ITS, and the effectiveness of the hybrid model in integrating multi-dimensional features is explored, thus providing an empirical basis for further optimization of model accuracy in the future.

Materials and methods. This research used a long-term traffic flow dataset from France and a short-term traffic flow dataset from Italy. Prediction experiments were conducted in the MATLAB environment using support vector machines (SVMs), CNN-LSTM models, and an SVM-LSTM model with a loss function. The method for determining model effectiveness is based on linear regression theory, focusing on calculating the number of error data and evaluating the data fit using metrics. The method for determining model effectiveness is based on linear regression theory, focusing on calculating the number of error data and evaluating the data fit using metrics.

Results. Experimental results based on real-world traffic flow datasets show that the SVM-LSTM model exhibits the best overall performance in long-term traffic flow prediction. The CNN-LSTM model demonstrates excellent time series modeling capabilities in short-term traffic flow prediction. In terms of computational efficiency, the SVM-LSTM model improves prediction accuracy by 10.2% compared to the CNN-LSTM model. Therefore, the fusion of SVM and LSTM combines the advantages of spatial feature extraction and time series modeling, and its deployment in ITS can improve traffic flow prediction efficiency.

Keywords*:* traffic flow prediction; machine learning; neural networks; modeling; intelligent transportation systems

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Научная статья | Транспортные и транспортно-технологические системы

ИССЛЕДОВАНИЕ ЭФФЕКТИВНОСТИ РАЗЛИЧНЫХ МОДЕЛЕЙ НЕЙРОННЫХ СЕТЕЙ ДЛЯ ПРОГНОЗИРОВАНИЯ ТРАНСПОРТНЫХ ПОТОКОВ

Цзисяо Цзян

Аннотация

Обоснование. Данная статья сравнивает эффективность моделей метода опорных векторов (SVM), сверточной нейронной сети с дол-

гой краткосрочной памятью (CNN-LSTM) и гибридной модели SVM-LSTM для прогнозирования транспортных потоков в интеллектуальных транспортных системах (ИТС). Целью данного исследования является изучение сценариев применения различных моделей машинного обучения и нейронных сетей в прогнозировании транспортных потоков с упором на проверку эффективности моделей CNN-LSTM и SVM-LSTM, разработанных в данной статье, при интеграции извлечения пространственных признаков с моделированием временных рядов. Экспериментальная проверка проводится на реальных наборах данных о долгосрочных и краткосрочных транспортных потоках, а производительность каждой модели систематически оценивается с точки зрения количества ошибок прогнозирования, вычислительной эффективности и надежности. Благодаря всестороннему анализу таких метрик, как коэффициент детерминации (R^2) и среднеквадратическая ошибка (RMSE), данное исследование обеспечивает основу для рационального выбора моделей прогнозирования в ИТС и предлагает теоретическую поддержку для будущих исследований в области моделирования слияния данных о многомодальных транспортных потоках.

Цель. В ходе систематических сравнительных исследований отбирается более эффективная и надежная модель для подсистемы прогнозирования транспортных потоков в ИТС, а также изучается эффективность гибридной модели при интеграции многомерных характеристик, что обеспечивает эмпирическую основу для дальнейшей оптимизации точности модели в будущем.

Материалы и методы. В этом исследовании использовались долгосрочные данные о транспортных потоках во Франции и краткосрочные данные о транспортных потоках в Италии. Эксперименты по прогнозированию проводились в среде MATLAB с использованием опорных векторных машин (SVM), моделей CNN-LSTM и модели SVM-LSTM с функцией потерь. Метод определения эффективности модели основан на теории линейной регрессии и фокусируется на подсчете количества ошибок в данных и оценке соответствия дан-

ных с помощью метрик. Метод определения эффективности модели основан на теории линейной регрессии и фокусируется на подсчете количества ошибок в данных и оценке соответствия данных с помощью метрик.

Результаты. Экспериментальные результаты, основанные на реальных наборах данных о транспортных потоках, показывают, что модель SVM-LSTM демонстрирует наилучшую общую производительность при долгосрочном прогнозировании транспортных потоков. Модель CNN-LSTM демонстрирует превосходные возможности моделирования временных рядов при краткосрочном прогнозировании транспортных потоков. С точки зрения вычислительной эффективности, модель SVM-LSTM сокращает время обучения на 10,2% по сравнению с моделью CNN-LSTM. Таким образом, сочетание SVM и LSTM сочетает преимущества извлечения пространственных признаков и моделирования временных рядов, а его применение в ИТС может повысить эффективность прогнозирования транспортных потоков.

Ключевые слова: прогнозирование транспортных потоков; машинное обучение; нейронные сети; моделирование; интеллектуальные транспортные системы

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Introduction

The accuracy of traffic flow prediction directly affects the implementation of ITS management [1]. Efficient traffic flow prediction can provide a scientific basis for early warning of traffic congestion and alleviate traffic pressure [2]. With the continuous development of ITS, methods based on machine learning and neural network models have shown significant advantages in accurately processing complex traffic data [3; 4]. These methods are not only capable of handling the irregular structure of traffic networks, but are also able to incorporate various traffic flow characteristics to achieve more accurate predictions [5; 6].

However, machine learning and single neural network models are sensitive to noise and missing values in traffic flow data, and their generalization ability is limited in large-scale datasets involving extreme events or unknown scenarios [7]. Furthermore, the effective integration of complex spatiotemporal dependencies and the accumulation of error data in long-term predictions also hinder practical applications. To address this issue, researchers integrated machine learning with neural network models for traffic flow prediction experiments, and the experimental results demonstrated prediction accuracy that is difficult to achieve with traditional methods [8; 9]. The core advantage of this model framework is that neural networks (particularly CNNs, LSTMs, and graph neural networks) can efficiently learn the dynamic evolution of traffic patterns from time series and identify the interactions between intersections within a road network [10; 11]. The introduction of a machine learning framework allows the neural network model to select key prediction indicators, further improving the robustness and accuracy of the predictions. Ali et al. combined the machine learning gated recurrent unit (GRU) and graph convolutional network (GCN) to identify spatial and temporal variations in road patterns, achieving highly accurate predictions [12]. Chauhan et al. used a bidirectional GRU to extract the spatiotemporal correlations of traffic flow on roads from sensor-generated data and significantly improved prediction efficiency by introducing attention [13]. This combination enables the model to not only accurately predict traffic flow and congestion levels, providing critical decision-making support for intelligent signal control, but also contributes to building more efficient modern transportation systems for cities.

However, these studies failed to explain the reasons for the efficiency improvement from the perspective of the internal mechanisms of the model architecture, and did not compare the extent to which the combination of machine learning and neural networks enhances prediction accuracy. To address this issue, this article systematically compares SVM, CNN-LSTM, and a novel SVM-LSTM model with a loss function. By analyzing the inherent mechanisms of different architectures in feature extraction and time series modeling, we uncover the root causes of efficiency differences. Furthermore, through controlled variable experiments, we quantitatively evaluate the actual improvement in prediction accuracy achieved by integrating machine learning and neural networks. These results not only provide a superior solution for traffic flow prediction but also provide empirical evidence for the value of model hybridization strategies, promoting their development in ITS.

Materials and methods

SVMs are primarily used for traffic flow classification and regression problems. Their core principle is to maximize the distance between two classes of samples and their corresponding hyperplane, separating them [14]. For linearly inseparable data, SVMs use a kernel function to map the data into a high-dimensional space, making it linearly separable. The SVM structure used in this paper is shown in Fig. 1.

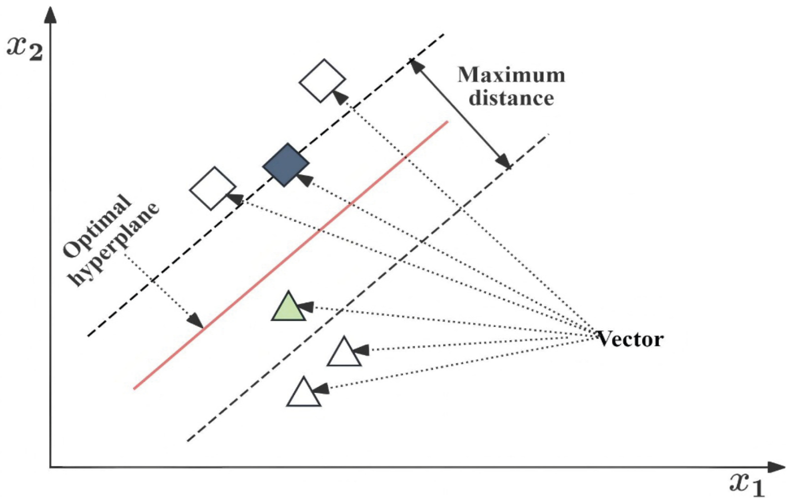


Fig. 1. SVM main structure

The linear kernel function in SVMs provides a concise and efficient solution to the linear separability problem. The linear kernel function used in this paper is expressed in Equation 1.

$$K(x_i, x) = x_i^T, x_j \tag{1}$$

where x_i and x_j denote the input vectors to the SVM; and T denotes the transposed matrix.

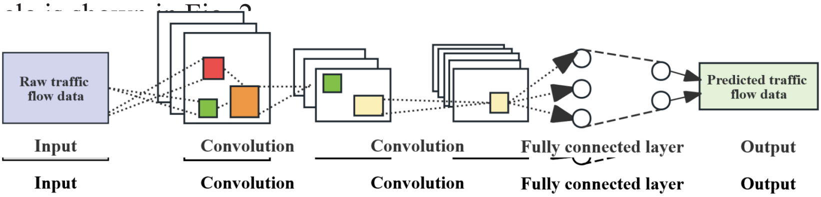
SVMs improve generalization by maximizing the number of samples closest to the decision boundary across all classification results. The core SVM model is shown in Equation 2.

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{n} y_i K(x_i, x_j) + b\right) \tag{2}$$

where y_i denotes the label of the training sample and b denotes the bias term.

By combining the linear kernel function with the sign function, SVM can directly learn the complex high-dimensional data in the input space and effectively solve the nonlinear traffic flow classification problem.

CNN is a deep learning model designed for processing grid-like sequence data. It extracts local features of traffic flow by sliding convolution kernels on input data, and stacks multiple layers to display more complex specific states. The CNN architecture used in this article is shown in Fig. 2.



Input
Convolution
Convolution
Fully connected layer
Output

Fig. 2. CNN architecture

The fully connected layer is a component of the CNN that integrates high-level information and outputs decisions. Its significance lies in nonlinearly mapping some of the features extracted by the convolutional layer. The fully connected layer can be expressed as Equation 3.

$$z = \sum_{i=1}^{n} w_i a_i + b_j \tag{3}$$

where w_i denotes the CNN model weights; a_i denotes the activation output of the i-th neuron; and b_j denotes the bias term.

The convolution operation is a mathematical operation that CNNs perform on the input traffic flow, performing a local weighted summation, expressed as Equation 4.

$$S(i,j) = \sum_{m=0}^{m-1} \sum_{n=0}^{n-1} I(i+m, j+m) \cdot F \tag{4}$$

where (i, j) denotes the spatial position coordinates in the output feature map; I denotes the input data; m and n denote the relative positions inside the convolution kernel; and F denotes the weight parameter of CNN.

The local weighting and information integration represented by Equations 3 and 4 can significantly reduce the number of model parameters, improving the computational efficiency and generalization ability of the CNN.

The gating mechanism and internal state of LSTM enable it to memorize the periodic patterns of traffic flow and flexibly analyze the characteristics contained in traffic flow [15]. The classic LSTM model structure and modeling equations are shown in Fig. 3.

In Fig. 3, X_t is the input traffic flow data (in vector form); H_t is the hidden state at the previous time step; C_t is the cell state at the previous time step; σ is the sigmoid activation function; *tanh* is the regulation function used to stabilize the model; W_f, W_i, W_C, and W_o are the weight matrices that the model needs to learn; b_f, b_i, b_C, and b_o are the bias terms that the model needs to learn.

For stable traffic flow prediction tasks, LSTM training requires optimization via an external loss function. The optimization objective of the entire model can be expressed as Equation 5.

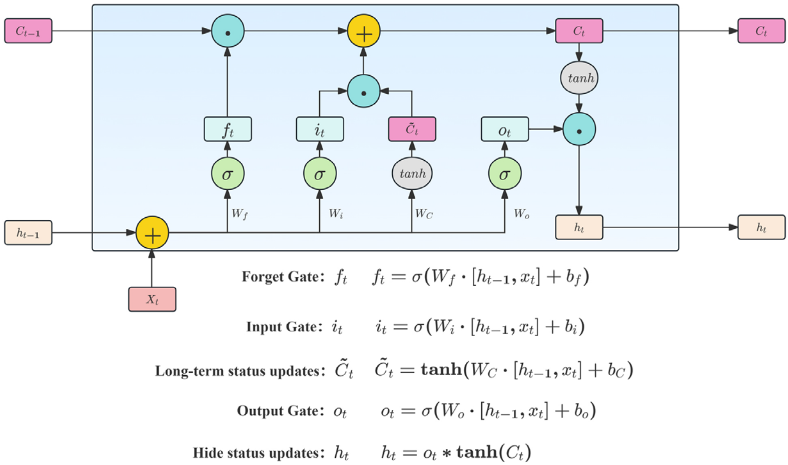


Fig. 3. LSTM model structure and modeling equations

$$\mathcal{L} = \sum_{i=0}^{N} \sum_{t=0}^{T} q(y_t, \hat{y}_t) \tag{5}$$

where N denotes the number of samples in deep training; T denotes the length of the input sequence; q denotes the point-by-point loss function, which measures the error between the predicted value and the true value; y_t denotes the original traffic flow of the i-th sample at time t; and $\hat{y}_t$ denotes the predicted traffic flow of the i-th sample at time t.

To ensure that the LSTM can effectively exploit the dynamic patterns of traffic flow data, a regularization term is added to the original loss function to prevent overfitting. This anti-overfitting process can be expressed as Equation 6.

$$\mathcal{L}_{regularized} = \mathcal{L} + \lambda \cdot \Omega(\theta) \tag{6}$$

where λ denotes the regularization strength hyperparameter; Ω denotes L2 regularization; and θ denotes all LSTM weight parameters.

To improve the generalization ability of the LSTM model, it is necessary to constrain the generation of model parameters so that the model can filter out noise and irrelevant details in the original data. This process can be expressed as Equation 7.

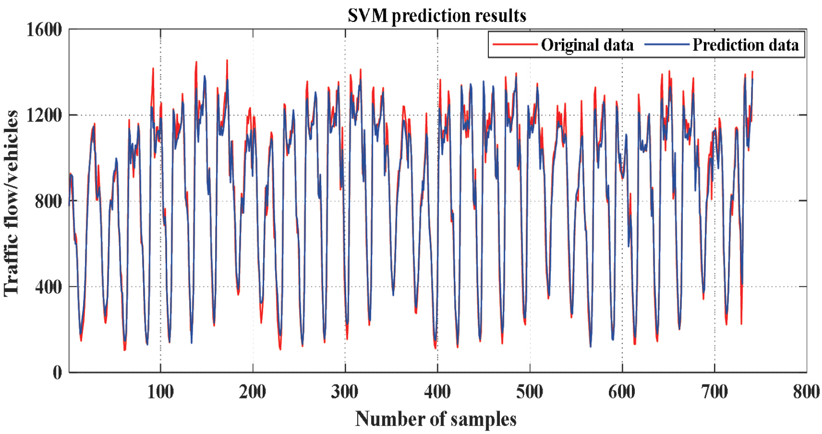
$$R_{\text{params}} = \rho \|W\|_F^2 \quad (7)$$

where ρ denotes the hybrid hyperparameter, which controls the ratio of the weight parameters to the weight matrix.

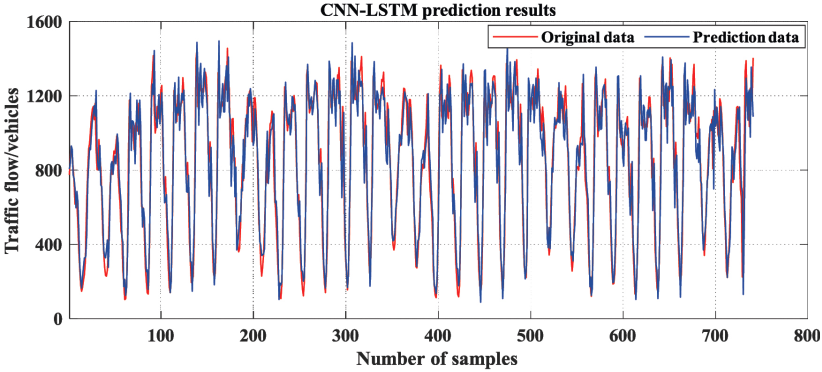
In the MATLAB environment, the SVM layer, CNN layer, and LSTM layer are stacked in series to build the model required for the experiment, and finally the prediction results are output through a unified fully connected layer.

Experiments and Discussion

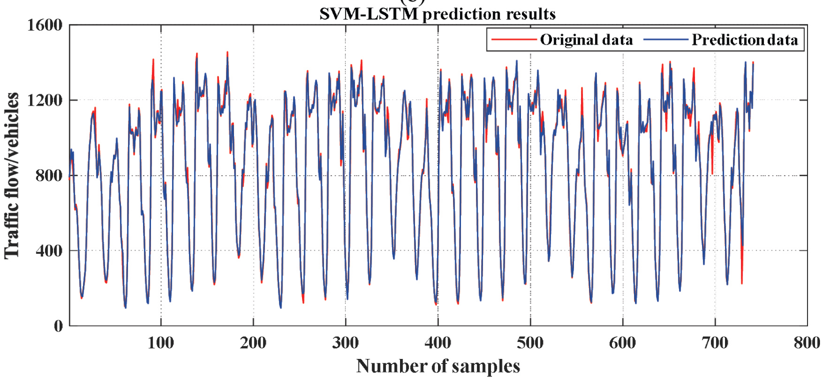
For traffic flow datasets from France and Italy (UTD19), abnormal sensor readings are first identified and corrected through threshold filtering, followed by time series interpolation to fill missing values. Finally, multi-source data undergo normalization to eliminate dimensional effects, thereby providing high-quality data for prediction experiments. For the French road dataset, we selected traffic flow data from detector No. 52 in January 2016, sampled every hour for a total of 744 data points. For the Italian road dataset, we selected traffic flow data from detector No. 2082 on September 26-27, 2016, sampled every five minutes for a total of 576 data points. The prediction results of different models are shown in Fig. 4.



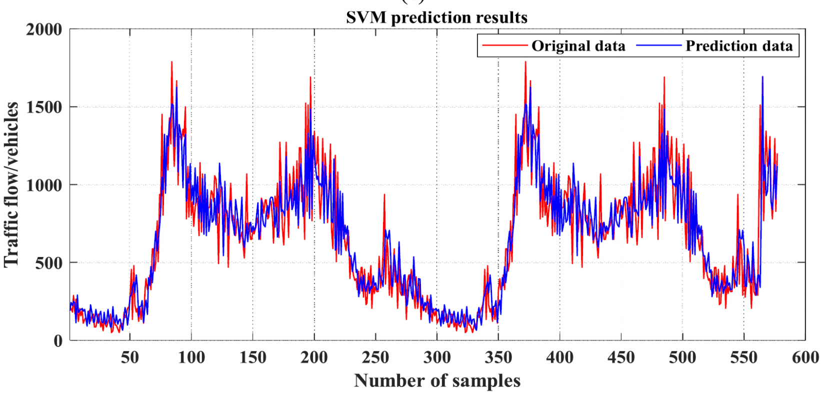
(a)


CNN-LSTM prediction results
Original data
Prediction data
Traffic flow/vehicles
0
400
800
1200
1600
100
200
300
400
500
600
700
800
Number of samples

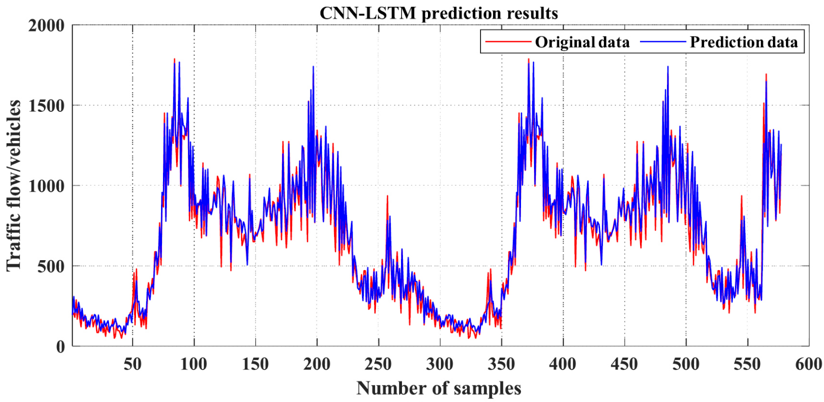
(b)


SVM-LSTM prediction results
Original data
Prediction data
Traffic flow/vehicles
0
400
800
1200
1600
100
200
300
400
500
600
700
800
Number of samples

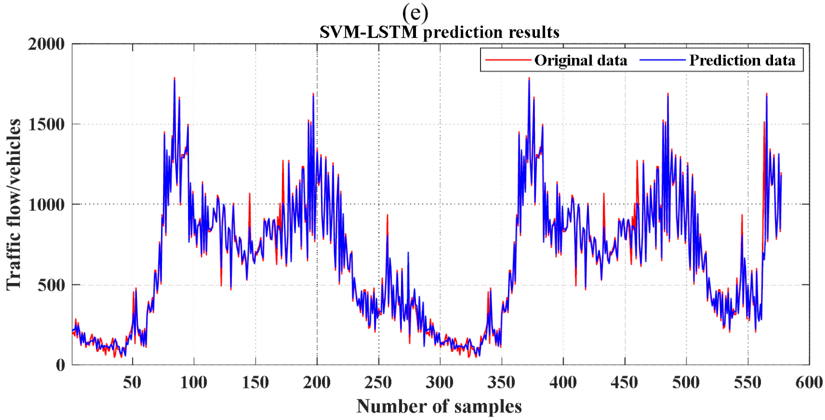
(c)


SVM prediction results
Original data
Prediction data
Traffic flow/vehicles
0
500
1000
1500
2000
50
100
150
200
250
300
350
400
450
500
550
600
Number of samples

(d)



(e)



(f)

Fig. 4. Comparison of traffic flow predictions by different models: (a) Prediction results of the SVM model on the French road dataset, (b) Prediction results of the CNN-LSTM model on the French road dataset, (c) Prediction results of the SVM-LSTM model on the French road dataset, (d) Prediction results of the SVM model on the Italian road dataset, (e) Prediction results of the CNN-LSTM model on the Italian road dataset, (f) Prediction results of the SVM-LSTM model on the Italian road dataset

Fig. 4 shows that in both long-term and short-term traffic flow prediction, the SVM has the worst prediction accuracy, while the CNN-LSTM and SVM-LSTM models perform well in data fit. Detailed evaluation metrics for the three models are shown in Table 1.

Table 1.

Results of evaluation metrics of different models

Detector number	Model	Number of error data	R^2	RMSE
No. 52	SVM	174	0.715	65.409
	CNN-LSTM	128	0.824	57.083
	SVM-LSTM	81	0.907	29.154
No. 2082	SVM	115	0.655	83.927
	CNN-LSTM	69	0.791	60.624
	SVM-LSTM	43	0.884	35.012

According to Table 1, in both long-term and short-term traffic flow prediction, the SVM model exhibits the highest error due to the limited capability of its kernel function in handling nonlinear data, preventing it from effectively capturing temporal dynamics like LSTM. The SVM-LSTM model achieves the best results due to the complementary advantages of its structure and loss function. In contrast, the CNN in the CNN-LSTM model focuses more on extracting feature relationships between adjacent detectors. Furthermore, the spatial dependence of the experimental data is weak, resulting in inferior performance compared to the SVM-LSTM combination, which is specialized for time series modeling.

To test the effectiveness of the synergistic mechanism between time series modeling and the loss function in the SVM-LSTM model, reveal the model's generalization ability on other datasets and its shortcomings such as noise sensitivity, and provide clear guidance for its application in ITS, this paper conducted verification experiments using data from detectors 156-158 in France's road dataset from May and detectors 2254-2256 in Italy from September 28-30.

The May data from detectors 156-158 was used because it offers stable meteorological conditions during this season, avoiding the impact of extreme weather and making it a suitable benchmark scenario. Consecutively numbered detectors are located on consecutive sections of the main road, allowing various models to effectively capture the spatiotemporal correlation characteristics of traffic flow. A comparison of various evaluation metrics for detectors 156-158 is shown in Fig. 5.

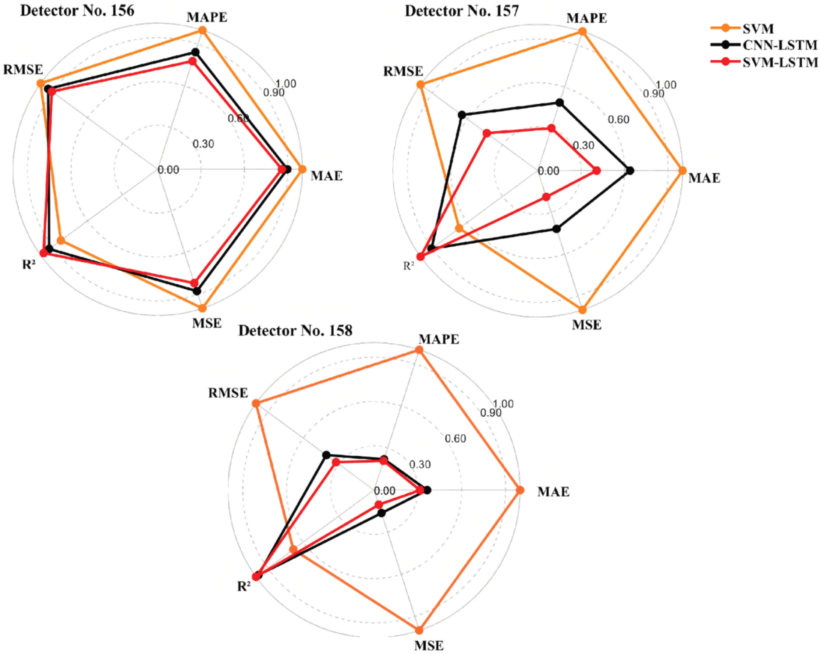


Fig. 5. Comparison of prediction evaluation metrics of different detectors

Fig. 5 shows that the performance of the three models on detector 156 is similar, but the SVM-LSTM model still demonstrates the best performance. For detectors 157 and 158, the prediction ability of SVM-LSTM is significantly better than that of SVM and CNN-LSTM models, which proves that it can maintain good generalization in high-noise scenarios.

The data from detectors 2254 to 2256 covers the weekend holiday period from September 28 to 30. The abnormal congestion patterns caused by peak weekend travel and the asymmetric traffic waveforms generated by return trips can effectively test the ability of various models to handle sudden changes in traffic conditions. Moreover, these detectors are located at critical nodes of the urban expressway, making them highly sensitive to traffic fluctuations. This makes them particularly suitable for validating the generalization capability of models in complex road networks. The evaluation metrics obtained from detectors 2254-2256 are shown in Table 2.

Table 2.

Evaluation metrics results of detectors No. 2254-2256

Detector number	Model	Number of error data	R^2	RMSE
No. 2254	SVM	168	0.741	87.249
	CNN-LSTM	115	0.820	64.857
	SVM-LSTM	72	0.901	37.740
No. 2255	SVM	154	0.767	78.355
	CNN-LSTM	104	0.853	57.325
	SVM-LSTM	63	0.919	34.791
No. 2256	SVM	137	0.784	76.585
	CNN-LSTM	92	0.861	56.847
	SVM-LSTM	57	0.924	30.172

Table 2 shows that compared with the SVM model, the SVM-LSTM model's R^2 value increases by 21.6% and its RMSE decreases by 55.8%. Compared with the CNN-LSTM model, the SVM-LSTM model's R^2 value increases by 10.2% and its RMSE decreases by 40.8%. This demonstrates that the SVM-LSTM model can more effectively handle the nonlinear characteristics and temporal dependencies in traffic flow data, thereby achieving more efficient prediction.

Conclusions

This paper systematically compares the performance of three models, SVM, CNN-LSTM, and SVM-LSTM, in traffic flow prediction and draws a clear conclusion: the SVM-LSTM hybrid model shows significant advantages in both prediction accuracy and stability. Experimental results on traffic flow datasets in France and Italy show that the model achieves a maximum R^2 of 0.907 and a minimum RMSE of 29.154 in long-term predictions. It also performs well in short-term predictions, with R^2 further improved to 0.924 and RMSE reduced to 30.172. These evaluation metrics fully demonstrate the SVM-LSTM model's effectiveness in handling the nonlinear characteristics and temporal dependencies of traffic flow data.

The SVM-LSTM model's outstanding performance stems primarily from its inclusion of a loss function. This model effectively captures the complex nonlinear patterns in traffic flow data through its SVM component, while simultaneously utilizing an LSTM network to process time series, enabling it to maintain optimal forecasting performance despite sudden traffic changes, peak congestion, and complex road network fluctuations. Therefore, this model is a preferred choice for deployment in ITS systems, enabling accurate predictions of traffic flow changes at key nodes over the next 5-30 minutes, providing data support for adaptive signal control systems. Furthermore, traffic management departments can leverage the model's predictive capabilities to establish early warning mechanisms and proactively deploy emergency management measures based on the forecast results, thereby enhancing the overall ITS response capabilities.

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DATA ABOUT THE AUTHOR

Jixiao Jiang, Postgraduate Student, Department of Transportation and Organization
Don State Technical University
1, Gagarin Sq., Rostov-on-Don, 344000, Russian Federation
jiangjixiao@outlook.com
ORCID: https://orcid.org/0009-0009-4376-790X

ДАННЫЕ ОБ АВТОРАХ

Цзисяо Цзян, аспирант, кафедра Организация перевозок и дорожного движения
Донской государственный технический университет
площадь Гагарина, 1, г. Ростов-на-Дону, 344000, Российская Федерация
jiangjixiao@outlook.com
ORCID: https://orcid.org/0009-0009-4376-790X

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