Construction and Empirical Study of Short-term Prediction Model for Urban Road Speed

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Abstract. This study addresses short-term traffic speed prediction for urban road networks, a critical component of intelligent transportation systems for easing congestion, optimizing traffic signal control, and improving travel efficiency. Using real-world traffic speed data, the performance of a Long Short-Term Memory deep learning model is compared with three traditional approaches: Naive Moving Average, Linear Regression, and Random Forest. All models are evaluated on the same test set using Mean Absolute Error, Root Mean Squared Error, and coefficient of determination. Experimental results show that the LSTM model achieves the highest accuracy, with MAE = 0.49 km/h, RMSE = 0.61 km/h, and R^2 = 0.9321, significantly outperforming Naive Moving Average (MAE = 1.95, RMSE = 2.466, R^2 = 0.1109), Linear Regression (MAE = 0.96, RMSE = 1.169, R^2 = 0.8004), and Random Forest (MAE = 1.10, RMSE = 1.29, R^2 = 0.7554). These findings demonstrate that LSTM not only accurately captures overall speed trends but also adapts well to short-term fluctuations, highlighting its potential for real-time traffic forecasting and congestion mitigation in urban environments.

Keywords: Intelligent transportation, Deep learning, Random Forest.

1 Introduction

With the continuous growth of urban population and car ownership, traffic congestion has become a major challenge facing urban transportation systems. Real-time monitoring and accurate short-term prediction of road traffic speed are crucial to alleviate traffic congestion, optimize traffic signal control, and improve the overall efficiency of traffic flow [1]. Traffic speed is the most basic reflection of the traffic status of the city. short-term speed prediction is also one of the key parts of intelligent transportation systems（ITS）. Traditional method ARIMA and Kalman filtering are widely used in our daily life, but they cannot learn the nonlinear and dynamic features of traffic data well. While deep learning method can learn the sequential feature very well, and the model like long short term memory（LSTM） is very suitable to learn the complex fluctuations of traffic data [1,2]. Recently, researchers introduced attention mechanism to LSTM networks. This allows those models to focus more on important features and critical time steps [3]. Researchers also tried to design hybrid

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models e.g. use CNN in combination with LSTM and obtain more accurate predictions [4]. In addition, with the emergence of high-resolution traffic data from various sources such as AMap or urban sensors, high-resolution traffic data is also widely available nowadays [5]. Such data provides a good starting point to train and validate those models in real time and apply them to real life. In this talk, I will present new opportunities for intelligent traffic forecasting, control and urban mobility management.

2 Methodology

2.1 Data Source and Description

This study uses a real-world traffic speed dataset provided by the Kaggle platform [6]. This dataset contains multiple road segments in a city, and the observation data is collected at three key time periods on weekdays and weekends: 8:00 AM, 2:00 PM, and 8:00 PM. Each record contains the segment number, timestamp, average speed, and an indicator of whether it corresponds to a weekday or weekend day.

To help readers understand the patterns in the data, the research plotted a boxplot showing how speed varies across different times of day and between weekdays and weekends (see Figure 1). Figure 1 makes it clear that traffic speeds tend to be lower during weekday rush hours and generally higher on weekends, which fits common expectations for urban road networks [6].

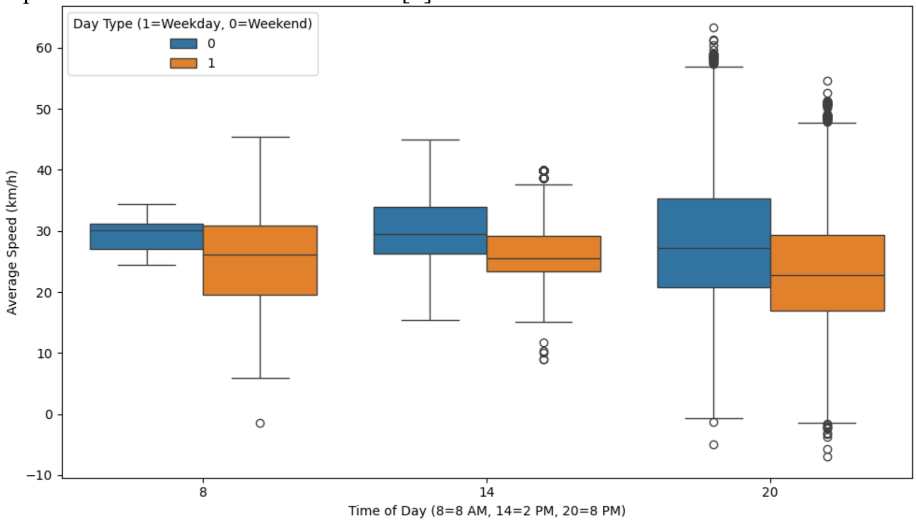

Fig. 1. Boxplot of speed distribution at different times and day types.

2.2 Data Preprocessing and Sample Construction

Before building our prediction model, this research cleaned the dataset by removing any missing or clearly abnormal values, and sorted the records to preserve their time sequence. To focus on periods when traffic is busiest and most relevant for city management, the research only kept data between 8 AM and 6 PM.

Because traffic data can be noisy—with sudden spikes or dips—the paper applied a moving average smoothing with a window size of 7, which helps to emphasize the main speed trends while reducing the impact of outliers [7]. Figure 2 compares the original speed series to the smoothed version, showing how this step makes patterns in the data easier to see.

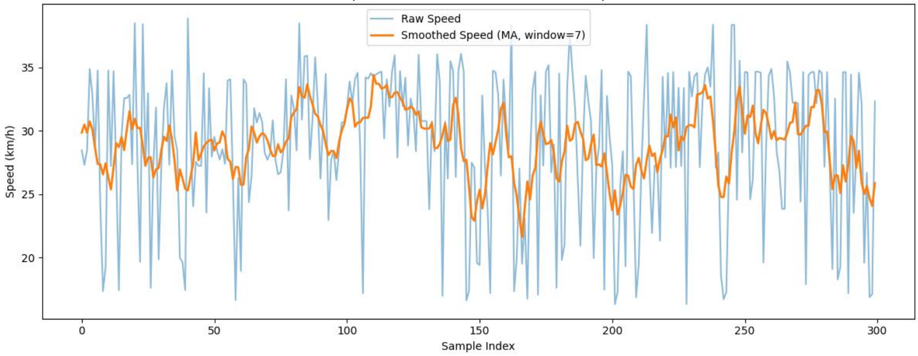

Fig. 2. Comparison of raw and smoothed traffic speed series.

The research also created new features to help the model make better predictions. For example, the research used sine and cosine transformations of the hour of day to encode daily cycles, and included the weekday/weekend flag as another input. All features were normalized to a [0,1] range so that the neural network could learn efficiently.

To turn our time series data into a format suitable for deep learning, the paper used a sliding window approach. In each sample, the previous 12 time steps—containing the smoothed speed and all auxiliary features—were used as inputs, while the next time step's speed was used as the prediction target. The samples were split into training and testing sets at a ratio of 80:20, making sure the time order was preserved throughout [7].

2.3 LSTM Model Design and Model Evaluation

For prediction, we used a single-layer LSTM neural network with 32 hidden units and a dense (fully connected) output layer. The mean squared error (MSE) loss function and the Adam optimizer was used for training. The batch size was 16, and the model was trained for 20 epochs. To avoid overfitting the training data, we monitored the validation set loss and used early stopping if the validation set loss did not increase.

The predictive performance of each model was evaluated using three standard metrics: mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2). These metrics are defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (3)$$

Where y_i denotes the true value， $\hat{y}_1$ denotes the predicted value,$\bar{y}_1$ is the mean of all true values, and n is the number of samples in the test set.

To better visualize how well the model could follow real trends, the research smoothed both the predicted and true speed series using a moving average (window size 5) and plotted the first 200 points. This approach makes it easy to compare the model's predictions to the actual speed patterns, and helps to show whether it really captures the dynamics of city traffic.

3 Results

3.1 Model Performance on the Test Set

In order to intuitively demonstrate the fitting ability of the deep learning model, this paper first compares the predicted value of the LSTM model with the actual speed (after smoothing) in the first 200 samples of the test set. The results are shown in Figure 3. The LSTM prediction curve is highly consistent with the actual value, and the main trend, local fluctuations, and high and low peak areas can be well captured. There are only slight deviations in very few sections with drastic changes. In terms of quantitative indicators, the MAE of LSTM on the test set is 0.49 km/h, the RMSE is 0.61 km/h, and the determination coefficient R^2 is as high as 0.9321, which further verifies its high applicability and strong generalization ability for short-term vehicle speed prediction on urban roads.

In order to comprehensively evaluate the prediction performance of different methods, this paper selected three traditional methods, Naive Moving Average, Linear Regression, and Random Forest, for comparative analysis with LSTM. Table 1 shows the error and goodness of fit of each model on the test set. It can be seen that the LSTM model is superior to other methods in all evaluation indicators. Although such traditional machine learning methods like linear regression and random forest can capture some main trends, the error increases significantly in high volatility or drastic change intervals. The Naive Moving Average baseline model has the largest overall error, and R^2 is far below 0.5, indicating that it is difficult to cope with complex actual traffic flow scenarios.

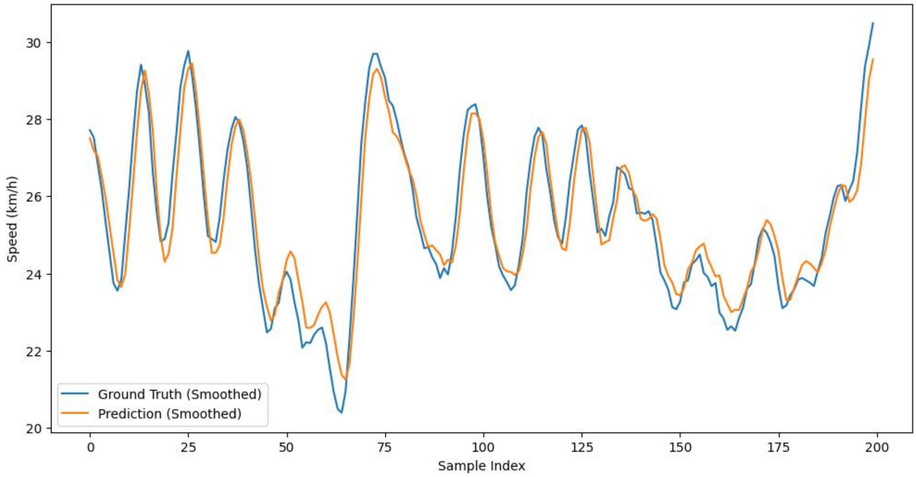

Fig. 3. LSTM prediction versus ground truth (smoothed, first 200 samples).

Table 1. Performance comparison of different models on the test set.

Model	**MAE (km/h)**	**RMSE (km/h)**	**R^2**
Naive Moving Avg	1.95	2.466	0.1109
Linear Regression	0.96	1.169	0.8004
Random Forest	1.1	1.29	0.7554
LSTM	0.49	0.61	0.9321

3.2 Visualization of Prediction Trends

To further compare the performance of different methods, this paper selected three traditional models: Naive Moving Average, Linear Regression, and Random Forest, and plotted their prediction curves and true values on the same data segment (the first 200 samples of the test set), as shown in Figures 4–6.

Figure 4 shows that the moving average model responds slowly to the drastic changes in traffic speed, and its main trend fitting ability is weak, resulting in large prediction errors.

The linear regression model in Figure 5 fits the main trend well, but there are still obvious prediction errors and certain lags at speed peaks and mutations.

Figure 6 shows the performance of the random forest model. Compared with linear regression, its description of local fluctuations has been improved, but it's fitting accuracy in the area of drastic fluctuations is still lower than that of LSTM.

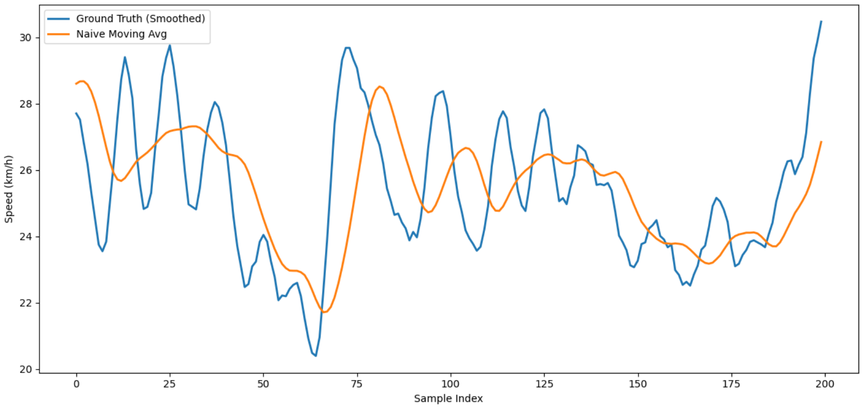

Fig. 4. Naive Moving Average prediction vs. ground truth (smoothed, first 200 samples).

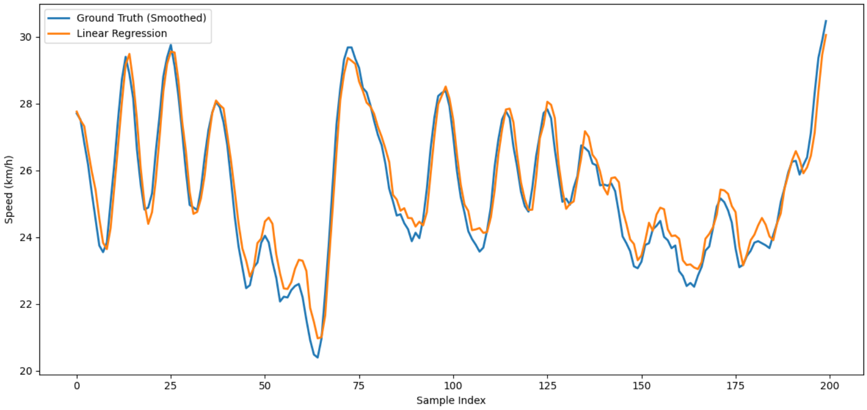

Fig. 5. Linear Regression prediction vs. ground truth (smoothed, first 200 samples).

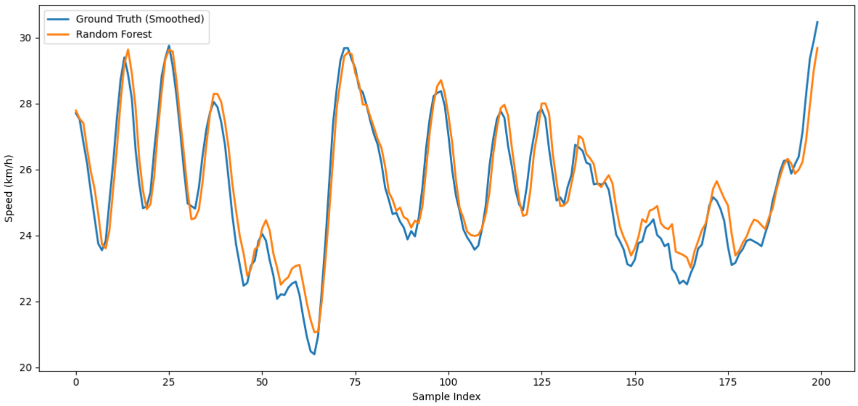

Fig. 6. Random Forest prediction vs. ground truth (smoothed, first 200 samples).

3.3 Extended Evaluation: Full Test Set and Error Analysis

To further assess model robustness, predictions were also compared over the entire test set. Similar patterns were observed: the LSTM consistently maintained the closest fit to the ground truth across varying traffic conditions and time intervals, while the other models displayed more pronounced errors and loss of detail in capturing local fluctuations.

In addition, Figure 7 presents the residual errors of all models over the full test set. The LSTM model exhibits the smallest and most stable errors, whereas the Naive baseline shows large and frequent deviations. These findings reinforce the quantitative results in Table 1, highlighting the advantages of deep learning for capturing the complex, nonlinear, and dynamic characteristics of urban road traffic.

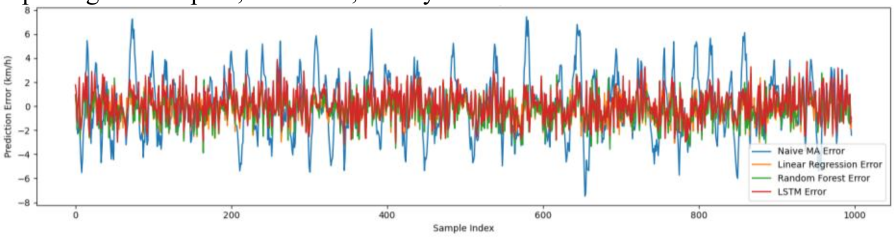

Fig. 7. Prediction error comparison among all models (full test set).

3.4 Summary

In summary, both the quantitative metrics and visual comparisons demonstrate that the LSTM model provides superior short-term speed prediction in urban road networks. It outperforms both traditional statistical methods and classic machine learning baselines, particularly in periods of rapid traffic change or high volatility. These results provide strong evidence for the adoption of deep learning approaches in real-world intelligent transportation systems.

4 Discussion

First, the data used in this study is from a single source and covers a limited number of road sections. Although this facilitates the initial verification of the model, it limits its generalization ability in more complex urban environments. In reality, traffic speed can be affected by many factors such as weather conditions, traffic accidents, holidays, and large-scale events [2]. Previous studies have shown that incorporating heterogeneous data sources can significantly enhance model robustness [8]. Future research should try to introduce multi-source heterogeneous data to improve the robustness and adaptability of the model in complex traffic scenarios [5]. In addition, the ability of the model to be applied across regions can also be improved through methods such as transfer learning [9].

Second, although the LSTM model achieves high accuracy, it functions as a “black box” model, which limits interpretability for transportation planners and decisionmakers. As highlighted by recent research, model interpretability is critical for gaining trust and facilitating real-world deployment [10]. In recent years, some studies have begun to explore combining attention mechanisms or developing interpretable deep learning frameworks to highlight key variables or time windows [3]. Future work could explore interpretable deep learning frameworks or attention mechanisms that highlight influential features and time steps.

Third, the training and inference of the LSTM model require high computing resources. In scenarios that require large-scale deployment or real-time prediction, delays or resource bottlenecks may occur [6]. In the future, we can consider adopting lightweight technologies such as model compression, parameter pruning, and knowledge distillation to improve operational efficiency while maintaining model performance [4]. In addition, we can also combine cloud and edge computing architectures to optimize model deployment methods and improve the feasibility of practical applications.

Fourth, this study mainly models a single road segment and does not explicitly consider the spatial dependencies between road segments in the road network. In real urban traffic, congestion on one road segment often spreads quickly to surrounding roads [7]. In the future, we can consider combining spatial modeling methods such as graph neural networks (GNNs) with LSTMs to achieve spatiotemporal joint modeling, thereby improving traffic prediction capabilities at the network level [11].

In conclusion, while the LSTM model shows significant advantages in short-term traffic forecasting, wider application still requires improvements in some areas such as data diversity, model interpretability, computational efficiency, and spatial dependency modeling. Continued exploration in these areas is expected to propel deep learning models from research into practical application, enabling them to better serve urban traffic management and smart mobility initiatives.

5 Conclusion

Based on actual traffic data, this study systematically compares the performance of LSTM and various traditional methods in short-term speed prediction of urban roads. The results show that the LSTM model is superior to methods such as sliding average, linear regression and random forest in terms of fitting accuracy and trend capture ability, and can more accurately reflect the dynamic changes of urban traffic flow. Combined with the model experimental results, this paper recommends that deep learning prediction methods be applied to practical scenarios such as intelligent signal control, traffic congestion warning and travel service optimization. Future research can further expand the scope of application of the model and introduce more multi-source data to continuously improve the level of intelligent urban traffic management.

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