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Logistics Demand Forecasting for a Logistics Company Based on a CNN-LSTM Hybrid Model

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ABSTRACT

As technological advancements in AI unfold, advanced machine learning techniques are increasingly utilized within logistics operations. logistics demand forecasting, as a core task in logistics management is shaped by multiple influencing factors, including weather as well as economic conditions, showing intricate spatiotemporal patterns. To address this, a fusion model integrating CNNs and LSTMs is proposed for enhanced performance in this study to improve the precision of logistics demand prediction. During this model, input data is processed by CNN to obtain relevant features, while LSTM is employed to learn and predict the extracted feature data, ultimately yielding the final prediction results. Public freight volume data from Beijing is selected as experimental data, and the forecasting model is implemented using Python. Comparative experiments with standalone CNN and LSTM models show that, compared to single deep learning architectures, the CNN-LSTM hybrid model demonstrates more stable and reliable performance in multi-dimensional and dynamic logistics demand forecasting. The study indicates that logistics demand forecasting based on this model can provide more accurate demand predictions for logistics companies, thereby optimizing resource allocation, reducing operational costs, and offering broad application prospects.

KEYWORDS

prediction of logistics requirements; convolution-based neural networks; memory-based recurrent networks; CNN-LSTM

1 Introduction

prediction of logistics requirements involves predicting changes and trends in market demand indicators using scientific methods, derived from both previous and current logistics demand patterns and their associated influencing factors. It is a critical component in addressing challenges in the logistics industry. As artificial intelligence algorithms continues to advance, an escalating number of neural network models have been applied to this field. Over the past decade, research methods can be segmented into two key classifications: traditional machine learning models, such as regression analysis models, ARIMA models, and grey models (GM), and neural network models, such as clustering algorithms, BP neural networks, CNNs, LSTMs, and attention mechanisms. For example, Li Hao[1] et al. used ARIMA models to establish a linear time series prediction model based on production and consumption data from Luzhou from 2010 to 2021. Zhang Le[2] et al. proposed a GM(1,1)-MLP neural network hybrid model, demonstrating through experiments that combining GM(1, 1) for trend prediction with MLP neural networks for nonlinear mapping significantly improves prediction precision. Neural network models possess strong fitting capabilities. RAN Mao-liang[3] et al. proposed an EEMD-LMD-LSTM-LEC hybrid model, using logistics order data from July to December 2019 for experimentation. Results showed that the model had the lowest prediction error, significantly outperforming 11 comparative models, including ARIMA, BP neural networks, and LSTM. Wang[4] et al. introduced a grey neural network hybrid forecasting model based on research on logistics demand in the Yangtze River Delta, demonstrating that BP neural networks have strong nonlinear learning capabilities. The grey neural network hybrid model, using GM(1,1) forecast values as BP neural network inputs, improves prediction precision, making it suitable for complex logistics demand prediction. DUAN Zong-tao[5] et al. Developed a hybrid model integrating CNN, LSTM, and ResNet to enhance the prediction of urban taxi demand, based on taxi GPS trajectory data from Xi'an. By incorporating external factors such as weather and holidays, their deep neural network model effectively captured spatial, temporal, and long-term trend characteristics of urban taxi demand, significantly outperforming traditional quantitative approaches (ARIMA) and single neural network models (CNN, LSTM, ConvLSTM, ST-ResNet). This model is also applicable to prediction of logistics requirements.

2 Problem Description

As a core component of logistics management, prediction of logistics requirements plays a vital role in optimizing resource management, streamlining operations, and lowering expenditures. However, in practical applications, logistics demand is governed by several key elements, including weather, economic conditions, seasonal fluctuations, holidays, and special events. The diversity and complexity of these factors lead to multi-dimensional, space-time challenges in prediction of logistics requirements.

Traditional forecasting methods often struggle with these complexities, especially when dealing with long-sequence and multi-dimensional feature data, leading to underfitting and reduced prediction accuracy. Capturing and predicting the dynamic changes in logistics demand remains a crucial challenge in both academia and industry. With the ongoing breakthroughs in deep learning and neural networks, researchers have attempted to apply these methods to prediction of logistics requirements. CNNs and LSTMs are two important advanced machine learning techniques that excel in feature extraction and sequence modeling, respectively. CNNs are adept at capturing local features from input data, effectively extracting key information affecting logistics demand. LSTMs, on the other hand, are well-suited for modeling complex temporal changes by retaining long-term dependencies in sequential data. However, using CNN or LSTM alone often results in poor generalization and underfitting when handling multi-dimensional and long-sequence logistics demand data. To resolve this issue, a CNN-LSTM hybrid model is proposed in this paper, utilizing the advantages of both frameworks. The CNN module focuses on spatial pattern extraction, whereas the LSTM component captures sequential dependencies within the extracted features. This hybrid approach enhances both accuracy and stability in prediction of logistics requirements.

3 Logistics Demand Forecasting Model Based on Neural Networks

3.1 Convolutional Neural Network (CNN) Model

CNNs are a class of advanced machine learning techniques designed to automatically extract features from data. Unlike traditional fully connected neural networks, CNNs introduce key structures such as convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply sliding filters to input data, extracting local features effectively. Pooling layers reduce feature map dimensions, lowering computational complexity and preventing overfitting. Fully connected layers output final predictions. The schematic diagram of the convolutional neural network structure is shown in Figure 1.

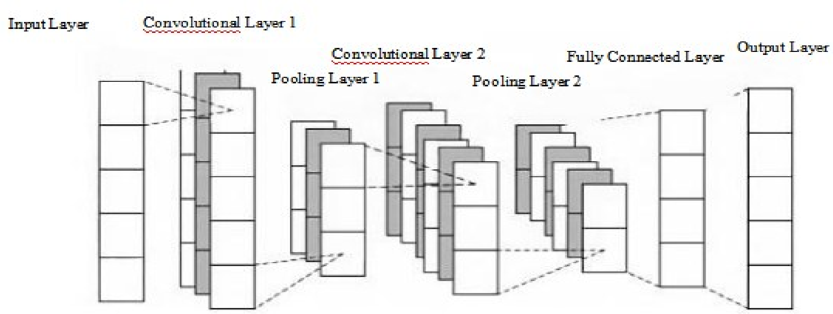

Figure 1 The structural schematic of the convolutional neural network

3.2 Long Short-Term Memory (LSTM) Model

As an enhanced version of a recurrent neural network (RNN), LSTM excels at capturing and maintaining long-range dependencies in sequential inputs.It introduces three gate mechanisms: input gate, forget gate, and output gate.

Input gate: Regulates the writing of new input into the memory unit.

Forget gate: Determines how much previous information should be eliminated.

Output gate: Regulates the extent to the information which from memory cells affect the output.

This structure allows LSTM to maintain important information over long time periods, mitigating gradient vanishing issues and ensuring its suitability for predicting time-dependent patterns. The schematic diagram of the LSTM structure is shown in Figure 2.

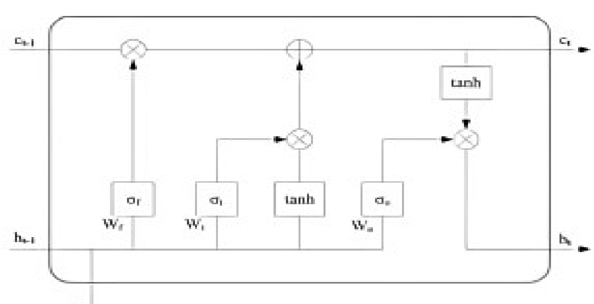

Figure 2 The schematic diagram of the LSTM structure

3.3 CNN-LSTM Hybrid Model

To better predict changes in logistics demand, this paper constructs a CNN-LSTM hybrid model, which consists of an input layer, CNN layer, LSTM layer, fully connected layer, and output layer, as shown in the structure diagram.

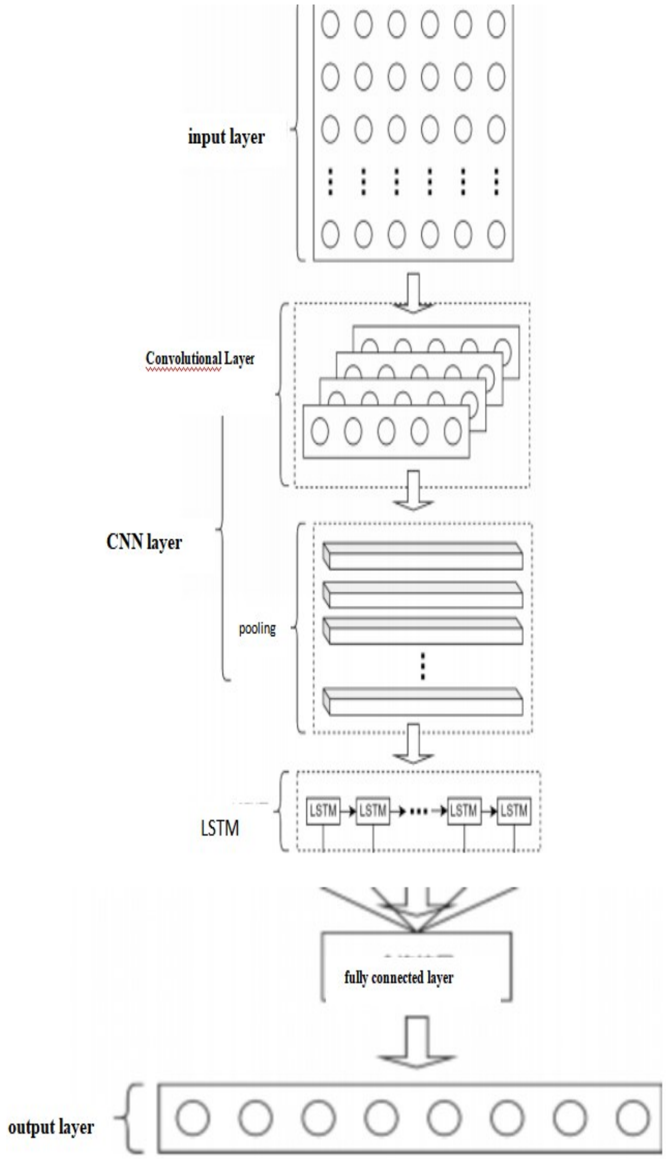

Figure 3 The schematic diagram of the CNN-LSTM hybrid structure

During the experiment, the preprocessed data is first fed into the model through the input layer. Next, the convolutional layer is used to extract spatial features from the input data. Although CNNs are typically applied to image data, in the case of time series data, the use of one-dimensional convolutional kernels can effectively capture local temporal features from the input sequence.

The convolution process applies a kernel (also referred to as a filter) to the input data, allowing the model to extract local patterns from the dataset. This process helps in identifying crucial features that contribute to the prediction task. The mathematical formulation of the convolution operation is as follows:

$$y_t = \sum_{i=1}^{k} x_{t+i-1} \cdot w_i + b$$

Where: y_t represents the output of the convolutional layer, x_t denotes the features of the input data, w_i represents the weights of the convolutional kernel, b is the bias term, k denotes the size of the convolutional kernel

Subsequently, dimensionality reduction is performed through the pooling layer to obtain the output data. The pooling operation is commonly implemented using Max Pooling, By capturing the most prominent value in a designated window, it compresses feature maps while safeguarding essential information.The mathematical expression for max pooling is as follows:

$$y_{i,j} = \max_{p,q} \left(x_{i+p,j+q} \right)$$

Where:

$y_{i,j}$ represents the **output after pooling**

$x_{i+p,j+q}$ denotes the **input within the pooling window**

Subsequently, the output data is passed to the LSTM layer for processing. The LSTM layer incorporates multiple gating mechanisms, including the Forget Gate, Input Gate, Cell State, and Output Gate. These mechanisms coordinate the flow of data within the LSTM network, ensuring the preservation of long-term relationships in sequential datasets.Where:

Forget Gate: Controls how much past information should be discarded.

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right)$$

Input Gate: Determines the amount of new information to be retained in the memory unit.

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right)$$

Cell State: Stores the long-term memory of the network, updated at each time step.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Output Gate: Controls the portion of stored information that is forwarded to the next layer as output.

$$h_t = o_t \cdot \tanh\left(C_t\right)$$

Subsequently, the fully connected layer maps the output of the LSTM layer to the final predicted value, Which is subsequently processed by the output layer to produce the final prediction outcome.

4 Experiment Section

The data used in this experiment comes from publicly available datasets provided by the National Bureau of Statistics of China. The dataset consists of freight volume data in Beijing, with the period from 1993 to 2012 used as the training set, and the period from 2013 to 2023 used as the forecasting dataset.

4.1 Experimental Data Preprocessing

Due to substantial variations in the magnitude of the input data, Min-Max Normalization is used for standardization, ensuring better model training. The normalization process follows Equation, where the normalized value is computed using the following formula:

$$\boldsymbol{x'} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Where: $\boldsymbol{x'}$ indicates the normalized value, x represents the initial input data, $\min(x)$ refers to the dataset's minimum value, $\max(x)$ corresponds to its maximum value.

4.2 Analysis of Results

The comparison of the predicted results from the three models with the actual values is illustrated in Figures 4 and 5. It can be observed that the predictions generated by the CNN-LSTM hybrid model are significantly closer to the actual values compared to those of the standalone CNN and LSTM models. Furthermore, the error percentage is reduced by approximately 2% to 5%, demonstrating the superior predictive performance of the hybrid model.

Table 1 Observed value, Predicted value and Prediction Errors for Different Models

Year	Observed Value	CNN		LSTM		CNN-LSTM	
		Predicted Value	Percentage Error	Predicted Value	Percentage Error	Predicted Value	Percentage Error
2013	25748	24524.97	-4.75%	23268.4676	-9.63%	25055.3788	-2.69%
2014	26551	28080.3376	5.76%	28210.4375	6.25%	26880.2324	1.24%
2015	20078	18220.785	-9.25%	18608.2904	-7.32%	19184.529	-4.45%
2016	20734	22116.9578	6.67%	22869.602	10.30%	21434.8092	3.38%
2017	20110	17602.283	-12.47%	17379.062	-13.58%	19269.402	-4.18%
2018	20873	22820.4509	9.33%	22100.3324	5.88%	21467.8805	2.85%
2019	22808	23932.4344	4.93%	24746.68	8.50%	23225.3864	1.83%
2020	22203	20686.5351	-6.83%	20657.6712	-6.96%	21594.6378	-2.74%
2021	23425	21679.8375	-7.45%	22340.4225	-4.63%	23183.7225	-1.03%
2022	18918	19977.408	5.60%	20728.4526	9.57%	18473.427	-2.35%
2023	19707	21332.8275	8.25%	18154.0884	-7.88%	20302.1514	3.02%

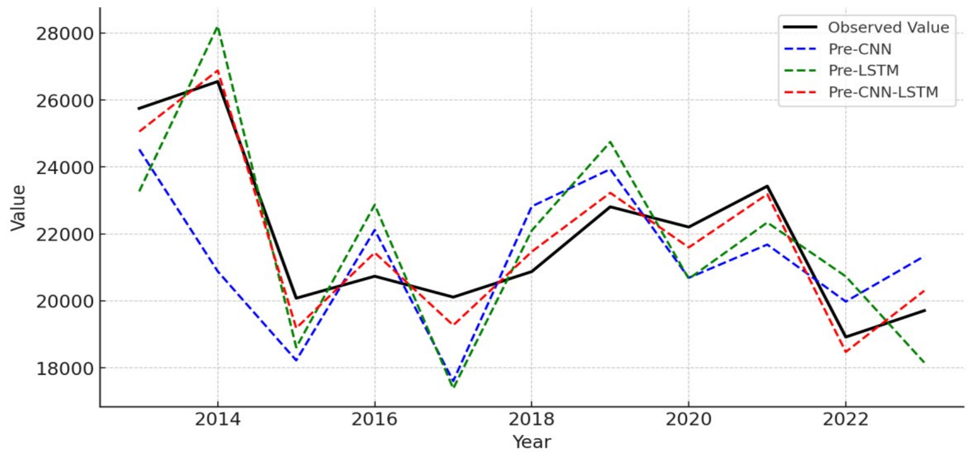

Figure 4 Comparison Between Actual and Predicted Values

4.3 Model Performance Comparison

To ensure an unbiased and comprehensive evaluation of the CNN-LSTM model's performance, this research undertakes a comparative analysis under identical experimental conditions, using the same training and testing datasets. The CNN-LSTM model is compared with CNN, LSTM, and CNN-LSTM neural network models.

For performance evaluation, The assessment is conducted using the following four evaluation metrics.

Mean Absolute Error (MAE)

Root Mean Square Error (RMSE)

Mean Absolute Percentage Error (MAPE)

Coefficient of Determination (R^2)

Where: y_i represents the actual value in the test dataset. $\hat{y}_i$ represents the predicted value output by the model. n is the number of samples. The formula for MAE is given as follows:

$$\mathrm{MAE} = \frac{1}{n}\left| y_i - \hat{y}_i \right|$$

A smaller MAE value signifies that the model has greater predictive precision.

The formula for RMSEis given as follows, where y_i represents the actual value in the test dataset. $\hat{y}_i$ represents the predicted value output by the model. A smaller RMSE value signifies improved predictive performance of the model:

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

The formula for MAPE is given as follows, where y_i represents the actual value in the test dataset. $\hat{y}_i$ represents the predicted value output by the model. A lower RMSE value indicates higher prediction accuracy of the model:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100$$

The formula for Coefficient of Determination (R^2) has a value range of 0 to 1 which is given as follows, The closer R^2 is to 1, the better the model's performance, indicating a stronger ability to explain the variance in the actual data. where y_i represents the actual value in the test dataset. $\hat{y}_i$ represents the predicted value output by the model. $\bar{y}$ represents the **Average** value:

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

To conduct a thorough evaluation of various models' effectiveness, we compare the prediction errors of CNN, LSTM, and CNN-LSTM using key evaluation metrics, including RMSE, MAE, MAPE and R^2.

Table 2 Comparison Table of Prediction Errors for Different Models

Error	RMSE/MW	MAE/MW	MAPE/%	R^2
CNN	5.85	5.45	5.23	0.45
LSTM	6.75	4.12	5.86	0.64
CNN-LSTM	3.22	2.73	2.88	0.82

From the table, we observe the following trends:

The CNN-LSTM hybrid model achieves the lowest RMSE, MAE, and MAPE, indicating superior prediction accuracy.

Compared to the LSTM model, the CNN model demonstrates superior performance in terms of error metrics, suggesting that convolutional feature extraction contributes positively to the forecasting process.

The LSTM model has the highest RMSE and MAPE, suggesting that while LSTM can capture temporal dependencies, it may struggle with complex spatial feature extraction compared to CNN.

The CNN-LSTM model efficiently integrates the strengths of both CNN and LSTM, leading to higher accuracy and more stable performance in logistics demand forecasting.

Thus, among all models tested, the CNN-LSTM model demonstrates the most superior performance, making it a promising approach for logistics demand forecasting.

5 Conclusion

Based on the characteristics of multi-dimensional logistics demand data, this paper proposes a CNN-LSTM hybrid model to forecast the upcoming freight capacity in Beijing. In this model, CNN specializes in detecting and extracting meaningful features from input data, While LSTM refines the extracted features through sequential learning to generate predictions. The CNN-LSTM architecture effectively leverages the temporal characteristics of logistics demand data, thereby improving both prediction precision and model performance.

Experimental results demonstrate that, in contrast to traditional neural network models, the CNN-LSTM model exhibits strong predictive capabilities for complex nonlinear problems. Across all models examined, the CNN-LSTM model achieves the smallest MAE and RMSE, while its coefficient of determination (R^2) is the closest to 1, indicating that this model provides highly accurate predictions.

These findings suggest that the CNN-LSTM model is well-suited for prediction of logistics requirements, offering valuable decision-making support for logistics and freight-related enterprises. By providing more accurate demand predictions, By utilizing this model, businesses can streamline resource distribution, cut costs, and enhance operational performance. Moreover, the introduction of the CNN-LSTM model serves as a reference for scholars conducting in-depth research in the field of prediction of logistics requirements. Future exploration will center on refining model parameters to advance forecasting effectiveness. Additionally, We will assess how this model can be adapted for various practical applications.in a broader range of temporal data prediction domains, such as:

Gold price prediction

Stock price forecasting

Petroleum price analysis and forecasting

Seismic activity prediction

Weather condition modeling and prediction

By extending the applicability of the CNN-LSTM model to these fields, we aim to further validate its robustness and effectiveness in handling diverse and complex temporal data prediction tasks.

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