Predicting future sales of vegetable category based on grid search optimized long and short term neural networks

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Abstract. In this study, a method of automatic prediction of vegetable sales volume was proposed by using long and short term neural network (LSTM) to solve the problem of quantity judgment in vegetable supply chain management. This text constructed a trained and optimized LSTM forecasting model by collecting historical sales data and selling and wholesale prices of vegetable markets. After the optimal parameters were determined by grid search, the model underwent 10 training cycles. The model evaluation for each vegetable category led to the following conclusion: the model performed well in predicting sales. By using the evaluation metrics of Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), it was found that the model predictions were close to the true values. In addition, the prediction results are summarized, showing the model's accurate prediction of vegetable sales volume. The results of the comparison chart between the real and predicted sales volume of each category of vegetables show that the model has good performance and accuracy in predicting the sales volume of vegetables, and the accurate forecast quantity can provide supply chain managers with more accurate inventory replenishment and pricing strategies.

Keywords: Prediction Model,Long And Short Term Neural Network, Vegetable Supply Chain, Grid Search.

1. Introduction

Accurate forecasting of sales is essential for accurate replenishment, pricing decisions, inventory adjustments and establishing a robust supply chain [1]. A well-functioning supply chain ensures competitiveness in the vegetable market by ensuring timely replenishment of all types of vegetables, maintaining their freshness, minimizing inventory losses, and understanding customer demand for different vegetable products at different times [2].LSTM can provide accurate sales volume forecasts for vegetables with seasonal and continuous long-term patterns [1]. Traditional neural network prediction algorithms, such as RNN and seasonal prediction algorithms, have limitations in predicting long time series [3].

However, the complex structure of the LSTM model leads to complex parameters, and finding the optimal model can be time-consuming. To improve the prediction accuracy, a Grid Search method was incorporated into the LSTM model. The evaluation criteria selected were Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE). MAPE calculates the percentage error between the actual and predicted values, and MAPE and MSE were used as criteria to assess the model fit in the training and test sets, aiming to find the best prediction model [4].Additionally, the choice of data indicators also affects the model fit. Before performing model prediction, the data sources were refined to establish relevant indicators. The construction of indicators related to market sales prediction referred to articles such as "Four steps to forecast total market demand" [5] and "Farmer harvest decisions and vegetable loss in primary production" [6]. These indicators included daily total vegetable market sales, market shares of each vegetable type, daily sales volume for each type, and average selling prices. Random forest and correlation analysis were used to determine the correlation between the indicators and the target variables, and the indicators were selected after screening. Moreover, considering the impact of seasonal or cyclical factors on vegetable sales, a time window was applied to the data samples for the final model training [7].

2. Fundamentals of LSTM Neural Networks and Web Searching

2.1. Structure of LSTM neural network

LSTM neural network is a recurrent neural network unlike traditional neural networks it is able to store previous historical data and perform operations and predictions based on that data, it is a model that allows data to exist [8]. At time t h data in A training model will be trained over time along with the trained model of the previous time. the LSTM model is capable of learning long term dependencies for dealing with 'long term dependencies' problem type.

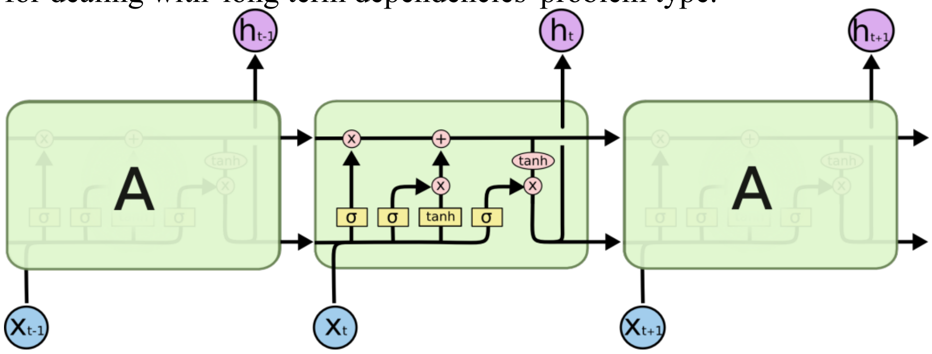

Fig. 1. Structure of LSTM network

LSTM consists of input layer, forgetting layer, output layer, memory cell

After the information is imported the information will go through the sigmoid layer to decide whether the information goes or stays, and the information is passed to the input layer with 1, 0 digital control switches.

Construct new candidate vectors for state more finally can be that time trained information.

passed in by the output layer to the next time node.

$$f_t=\delta(W_f*[h_{t-1},x_t]+b_f) \tag{1}$$

$$i_t = \delta(W_i*[h_{t-1},x_t]+b_i)\ ,\quad C_t = f_t*C_{t-1}+i_t*\tilde{C}_t \tag{2}$$

$$\tilde{C}_t = \tanh(W_C*[h_{t-1},x_t]+b_C) \tag{3}$$

The number of LSTM layers can be nested multilayer LSTM model each layer consists of an input layer, a forgetting layer, and an output layer there are memory cells to pass the update information on the time axis. The choice of hyperparameters has an important impact on the performance of the model and convergence speed. In order to achieve the optimal model is required to undergo further optimization, this paper uses network search to optimize the hyperparameter configuration of the LSTM model.

2.2. Determination of hyperparameters of the LSTM model

Grid search is a complete search on a subset of the given hyperparameters while training the algorithm, in the parameter space of the algorithms of machine learning certain parameters are infinite so the grid search is performed by iteratively traversing the values of each hyperparameter by means of nested loops given the boundaries are parallelized [9].

For the hyperparameters in this paper, the study predicts the sales of each category of vegetables for the next 10 days. At the same time this paper based on grid search optimization LSTM model hyperparameters should be set range, this paper belongs to the prediction of continuous values so the final output layer Dense should be 1 for nested LSTM model for LSTM, neuron, the number of layers of the Dense were given a range of the grid search to find out the optimal number of weights of the model within the given number of ranges and saved in the specified folder.

3. Results

3.1. Modeling

Predicting Vegetable Sales Grid-based Search Optimization LSTM model has a Jupyter Notebook compiler implementation with Python as the main compilation language.

The data sources of vegetables for the last 3 years were collected on the Internet, the data were processed, and after dealing with missing values, the data were sorted by date. Calculate the daily sales volume, sales volume and wholesale price of each category of vegetables and the total daily sales volume, so as to calculate the average selling price and market share of each category, and then do the correlation between the characteristics and the target value through the random forest and the correlation function, and do the correlation between the indicators to screen the indicators. Finally, the sales chart of each category in the past three years. Create a function for generating training data sets and target values and return the results, import the MinMaxScaler class for the normalization of features, after normalization, import the deque class.

The data is time windowed and determined by the number of days in memory, and finally the time feature window feature data, the target variable data, and the time window feature data for the number of days required for prediction are converted into NumPy arrays to return the results.

Create the parameter list by traversing the parameter list through multiple loops, and create a ModelCheckpoint callback object to save the parameters of the most recent model in the validation set. Call the created data processing function to form the training dataset and target values based on the historical days and predicted days, and divide the training and testing sets. Create Sequential model object, create LSTM layer to set the input shape and activation function, add LSTM layer through multiple loops to increase the complexity of the model to deal with the data, add Dropout layer to reduce the complexity of the model and improve the generalization ability, and create a sense layer for the output layer. The model is coded, the loss function is MSE and the evaluation metric is MAPE, and the optimizer is specified as Adam.Finally, the model is trained again and the ModelCheckpoint callback is used to save the weights of the model with the best performance in the validation set.

3.2. Analysis of experimental results

The true values of the aquatic root and stem category of vegetables in recent years, taken as an example, are generally in good agreement with the predicted values after model training, although there are some errors. The model performance is evaluated using mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE) [10]. As shown in Table 1, the LSTM model based on grid search optimization performs well in predicting sales. The values of MSE and RMSE indicate that the model's predictions are close to the true values, and the MAPE suggests a relatively low average prediction error. Therefore, the grid-based search optimization LSTM model has practical value in predicting vegetable sales.

Figure 1 clearly illustrates the comparison between the actual sales and forecasted sales of different vegetable categories. By visually examining the trends of actual and forecasted sales, we can further validate the accuracy and reliability of the model.

Table 1. Evaluation of vegetable models by category

vegetable category	MSE	RMSE	MAPE
Foliage	2149.04	46.36	0.22
cauliflower (Brassica oleracea var. botrytis)	124.17	11.14	0.33
Aquatic rhizomes	51.73	7.20	0.32
eggplant	76.77	8.76	0.29
capsicum	1073.54	32.76	0.23
edible fungi	536.24	23.16	0.27

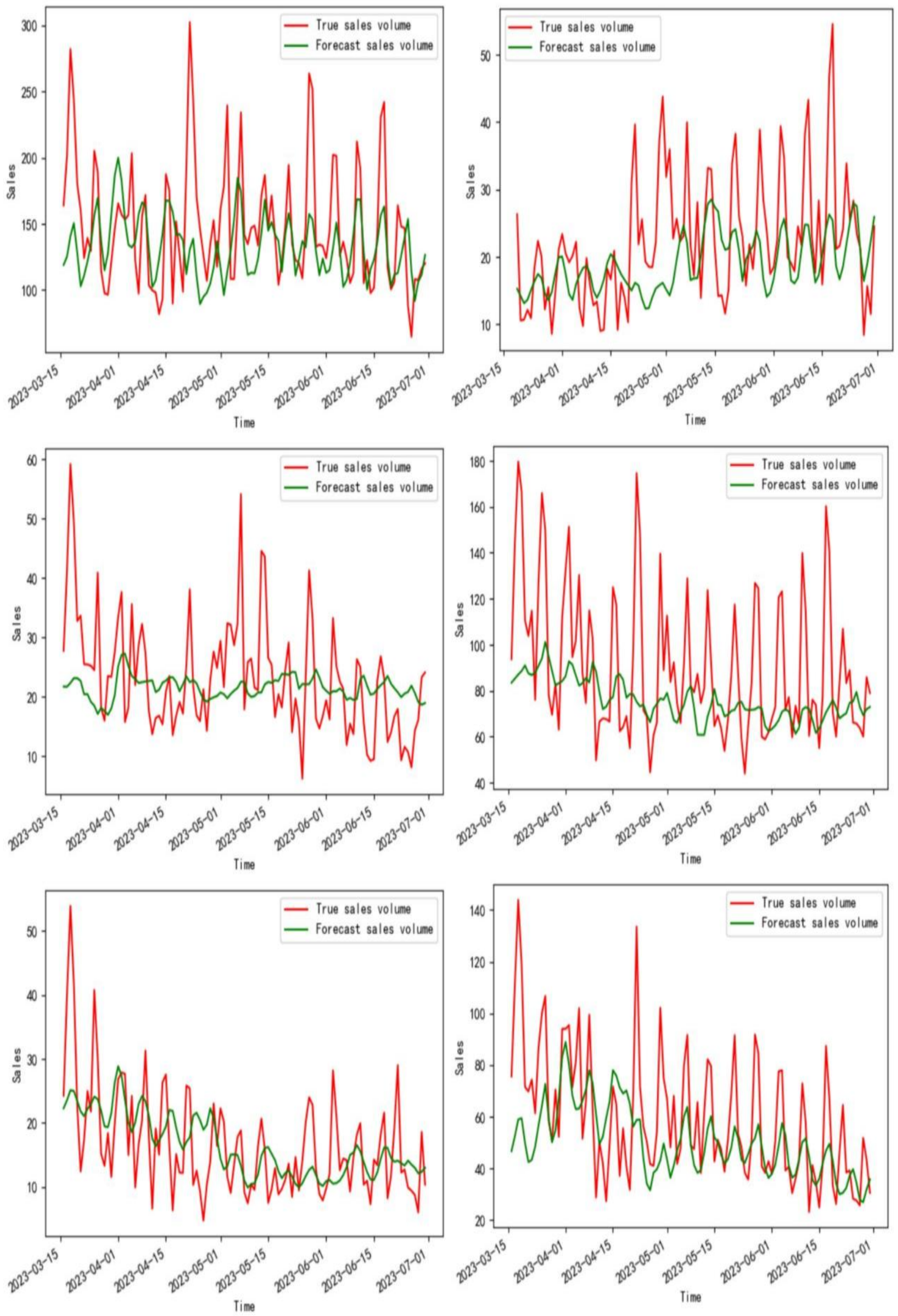

Figure 1 Comparison of real and forecasted sales of vegetables by category in recent years (sorted from top to bottom)

Table 2. Projected Sales Volume of Vegetables by Category for the Next 10 Days

number of days	Foliage forecasts sales volume	Cauliflower forecast sales volume	Aquatic rhizomes Forecasted sales volume	Forecasted sales of eggplant	Pepper forecast sales volume	Forecasted sales of edible mushrooms
2023-07-01	155.83	16.36	12.58	28.54	73.17	40.42
2023-07-02	170.43	17.44	13.02	30.46	79.25	44.38
2023-07-03	122.99	16.99	13.14	22.88	83.60	39.84
2023-07-04	94.98	16.13	12.56	17.64	75.83	32.54
2023-07-05	112.90	15.45	12.50	23.33	70.79	31.46
2023-07-06	121.74	15.58	13.74	24.60	71.89	34.76
2023-07-07	130.52	15.35	13.72	24.27	75.59	38.44
2023-07-08	107.71	14.79	11.73	19.67	75.83	33.60
2023-07-09	107.60	14.23	10.25	19.77	74.04	27.70
2023-07-10	89.90	14.59	9.98	17.11	73.96	25.22

According to the model's predictions, vegetable sales volume was forecasted. The predicted sales volume for each vegetable category is analyzed and presented in a trend chart for the next 10 days, as shown in Table 2:Foliage:The sales volume of foliage shows significant fluctuations between different days in the next 10 days. For example, on 2023-07-02, the sales volume peaks at 170.43, while on 2023-07-10, it reaches the lowest point at 89.90.Cauliflower:The sales volume of cauliflower vegetables is relatively stable, with a small range of fluctuations. It varies within roughly the same range, with the highest sales volume of 17.44 and the lowest of 14.23.AquaticRoots:The sales volume of aquatic root vegetables shows a decreasing trend in the next 10 days. The predicted sales volume gradually decreases from 12.58 to a minimum of 9.98.Eggplant:The sales volume of eggplant fluctuates between days with an overall decreasing trend.Pepper:Pepper vegetables show some fluctuation in sales volume over the next 10 days. Predicted sales volume varies somewhat between days. The highest sales volume is 83.60, and the lowest sales volume is 70.79.Edible Mushrooms:The forecasted sales volume for edible mushroom vegetables for the next 10 days shows some fluctuation. The predicted sales volume has a downward trend change between different dates. The highest sales volume is 44.38, and the lowest sales volume is 25.22.

Comprehensive analysis, the forecast sales of different categories of vegetables to a certain degree of volatility, cauliflower and pepper class overall trend is relatively stable, flowers and leaves, aquatic roots and mushrooms as a whole trend down. Eggplant sales fluctuations are more variable. The results of these analyses can help decision makers understand the trends and changes in product sales, so as to develop reasonable sales strategies and plans.

4. Conclusions

The sales volume of different categories of vegetables has the characteristics of changing trends over time and the market law provides the basis for the establishment of prediction models, but the classical recurrent neural network method cannot memorize the data of long time series, which leads to the inaccuracy of long time prediction accuracy. In this paper, the LSTM model can be applied to long and short-term memory characteristics to establish a vegetable sales volume prediction model, which can effectively capture the long-term dependence of sales volume in the time series, and optimize the model performance by traversing the given parameter combinations to find the best model parameters through the grid search. The experimental results show that the LSTM recurrent neural network model has good predictive properties and has certain practical application value.In the future, the results of this study are expected to be further extended and applied. The LSTM-based vegetable sales volume prediction model can be enhanced in terms of accuracy and robustness by incorporating additional factors such as weather conditions, consumer preferences, and marketing activities. In addition, the model can be extended to other agricultural sectors beyond vegetables, such as fruits or grains, to provide valuable insights for supply chain management in various agricultural industries. In addition, combining real-time data with advanced forecasting techniques, such as hybrid models that incorporate machine learning and statistical methods, can further improve forecasting accuracy and enable more proactive supply chain decision-making. In conclusion, this research has great potential for future development and application to help optimize agricultural supply chain management.

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