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Forecasting Corn Futures Prices Using the LSTM Model

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Abstract

The central government's No. 1 document introduced new requirements for “maintaining the stability of agricultural product prices.” However, recent years have seen significant fluctuations in corn prices in China, highlighting the importance of exploring the trends of corn futures prices for stabilizing spot corn prices. Given the increasingly complex financial market environment, traditional linear econometric methods and machine learning approaches face inherent limitations in price forecasting. This study utilizes extensive data and applies the Long-Short Term Memory (LSTM) deep learning model to forecast corn futures prices. During the model training process, historical corn futures data were used as hidden input feature variables, along with additional indicators such as spot corn prices, real-time quotes from corn deep processing enterprises, downstream product prices in the corn industry chain, prices of similar substitutes, and the Baidu Search Index for “corn prices.” The model was trained and fine-tuned with hyperparameters to assess its predictive accuracy under different time windows, learning rates, and iteration counts. Experimental results indicate that incorporating external influencing factors significantly enhances the model's predictive accuracy compared to using only historical price data. The model with a learning rate of 0.01, 50 iterations, a time window of 5, and 4 hidden layers achieved the highest accuracy. The findings demonstrate that integrating external factors and optimizing hyperparameters substantially improve the LSTM model's predictive precision, outperforming models that rely solely on historical data. The study provides policy recommendations on promoting advanced technology, enhancing data collection and information sharing, and improving market transparency and fairness. Additionally, the conclusion discusses the extensive application potential and promising development prospects of the LSTM model in corn futures price forecasting. This model enables market participants to obtain more accurate market trend forecasts, facilitating more informed investment decisions. The research also offers new insights and methodological references for scholars in financial forecasting, contributing to the further advancement of this field.

Keywords

LSTM model, price prediction, corn futures

1. Introduction

1.1 Research Background and Significance

The 2024 Central No. 1 Document further emphasizes comprehensive rural revitalization, including the continuation of the producer subsidy policy for corn to stabilize agricultural production and market prices. Statistics indicate that China's corn planting area reached 66.33 million mu in 2023, with production maintaining a growth trend above 270 million tons for three consecutive years. In 2023, domestic corn output reached 288.84 million tons (approximately 2.89 billion tons). Given the numerous factors influencing corn prices, China has actively developed the corn futures market since 2004 to stabilize market prices. The corn futures market is crucial to China's agricultural economy, offering a transparent trading platform for farmers, traders, and processors. It reflects market expectations of future supply and demand through price discovery, providing a valuable decision-making basis for participants. The futures market serves as an effective risk management tool, helping participants lock in future prices, reducing losses from market volatility, and enhancing liquidity and efficiency through active trading. Additionally, it informs government macroeconomic policies, promotes synergy along the industry chain, and encourages financial innovation, making it essential for price formation, risk management, market efficiency, and economic development.

Research on corn futures price forecasting is highly valuable for market participants. Accurate price forecasts can guide investors in market trend analysis, optimize investment strategies, and enhance returns. Traders can leverage predictions to refine their trading strategies, maximizing profits while minimizing risks. For farmers, futures price forecasting aids in planning planting schedules and sales strategies, supporting better decision-making. However, traditional forecasting methods—such as fundamental analysis, technical analysis, and econometric models—have inherent limitations. Fundamental analysis relies on data that may be challenging to obtain or prone to inaccuracies; technical analysis assumes historical patterns repeat, disregarding potential shocks; and econometric models often struggle with capturing the nonlinear dynamics of financial markets, making them less effective in volatile conditions.

The LSTM (Long-Short Term Memory) deep learning model addresses these challenges by capturing long-term dependencies, managing nonlinear relationships, and adapting to large-scale data. Its unique memory cell structure effectively handles sequential data, retaining and utilizing historical information during prediction. The model's strong nonlinear capabilities enable it to learn and simulate complex market behaviors, outperforming traditional linear models in accuracy. Additionally, LSTM's adaptability allows it to learn from extensive data without manual parameter adjustments, maintaining robust performance across varying market conditions. The model's ability to process large datasets further enhances predictive accuracy, extracting valuable insights for market forecasts. This study, therefore, explores corn futures price forecasting using the LSTM model, highlighting its potential to provide more accurate market insights for market participants, aiding informed decision-making in a complex trading environment.

1.2 Literature Review on Domestic and International Research

A review of domestic and international literature indicates that price forecasting methods can be mainly divided into two categories: linear models from econometrics and nonlinear models, focusing primarily on machine learning and deep learning approaches.

1.2.1 Price Forecasting Based on Linear Models

In the realm of traditional linear forecasting models for corn futures, Ding Lijun (2007) employed the Johansen cointegration test and VECM modeling, discovering that the U.S. corn futures market has a strong guiding influence on China's corn futures prices, and highlighted the importance of intelligent price forecasting for corn futures. Yang and Liu (2009) established return and volatility sequences for corn and soybean futures, demonstrating empirically that agricultural futures prices possess strong structural memory during cyclical changes. Han and Long (2012) utilized a VECM-GA-BP hybrid model to successfully predict corn futures prices on the Dalian Commodity Exchange, confirming the predictability of China's corn futures prices with notable forecasting accuracy. Ren et al. (2012) employed chaotic time series methods to forecast corn futures opening prices, finding that a prediction approach combining chaos theory and least squares support vector machines outperformed others, indicating the short-term predictability of China's corn futures prices. Hu (2016) used a state space model to forecast corn futures prices and compared it with a differenced ARMA model, finding the state space model's results to be more precise, though with a relative error around 2%. Fernandez and Morley (2019) investigated the interdependence among agricultural prices, crude oil prices, macroeconomic variables, and the S&P index, highlighting that biofuel policies—where corn is a key raw material for clean energy production—have led to a strong interdependence between crude oil and corn prices. Hu (2019) developed a forecasting model for corn futures prices based on Vector Autoregression (VAR), achieving over 85% accuracy. Liu (2020) designed a new VAR-GARCH model, identifying a significant correlation between the price volatility sequences of corn spot and futures markets in both China and the U.S.

1.2.2 Price Forecasting Based on Machine Learning

Machine learning methods widely used in price forecasting include decision trees, support vector regression models, artificial neural networks, and random forest models. Fu and Zhang (2017) combined time series, K-nearest neighbor, and support vector machine algorithms to predict CSI 300 index trends, finding that integrated models outperform single forecasting methods in stock trend prediction accuracy. Kang et al. (2011) proposed an improved BP algorithm that significantly expands the scope of corn futures price forecasting. Li and Zhou (2014) utilized wavelet denoising to analyze corn futures price trends, confirming that wavelet neural networks can accurately predict future price directions. Wang et al. (2020) employed a complex system management approach, integrating regression models, RPROP neural networks, and VAR models, showing that ensemble models, particularly those utilizing Bootstrap methods, outperform single models with a MAPE of 5.064%. Zeng et al. (2023) developed the DE-TFT forecasting model using multi-source heterogeneous data, including policy and pandemic-related texts, demonstrating that incorporating Baidu indices and news texts enhances corn futures price prediction accuracy.

1.2.3 Price Forecasting Based on Deep Learning

Deep learning-based forecasting models, including CNN, RNN, LSTM, and FNN, have become increasingly prevalent. Chen (2020) designed an LSTM-based model incorporating wavelet denoising, stacked autoencoder, and LSTM modules for financial time series predictions. Liang (2021) applied dynamic regression and LSTM neural networks to forecast corn futures, using 16 exogenous variables influencing prices. Liu and Shan (2021) combined EMD with LSTM for stock index predictions, finding that model suitability varies with different indices due to data fluctuations. Fan et al. (2021) developed a multi-layer LSTM model for soybean futures, showing superior performance over traditional regression models. Wang and Zhang (2022) constructed a CNN-LSTM model for iron ore futures, identifying a four-day window as optimal. Deng et al. (2023) introduced the EDM-VMD-LSTM hybrid model for stock price prediction, achieving higher accuracy than other methods. Wu et al. (2024) applied a CNN-BiLSTM-Attention model to carbon emission price forecasts, showing strong performance after noise reduction. LSTM, introduced by Hochreiter and Schmidhuber (1997) and later enhanced by Graves (2012), has proven effective in financial forecasting. Dhar et al. (2010) used decision trees and random forests to predict stock returns, highlighting their effectiveness in risk reduction. Lecun et al. (2015) articulated deep learning’s breakthrough in overcoming local minima.

1.2.4 Research Review

Futures and other financial time series are influenced by factors such as the spot prices of underlying assets, market supply and demand dynamics, information asymmetry, government policies, and external shocks. Agricultural commodities like corn also exhibit cyclical characteristics, which complicate the use of traditional linear models for price forecasting. Traditional machine learning methods often encounter issues like local optimization, extensive parameter training requirements, and overfitting.As artificial intelligence technologies have advanced, research on corn futures price forecasting has become increasingly prominent in finance and agricultural economics. Accurate price forecasts not only provide crucial guidance for market participants but also contribute to market stability and risk mitigation. Studies consistently highlight that effective forecasting models must account for a variety of variables, including historical price data, supply and demand fundamentals, macroeconomic indicators, and market sentiment. The application of advanced methods, such as machine learning and big data analytics, has significantly enhanced the precision of price forecasts.

1.3 Research Object, Method, and Technical Roadmap

1.3.1 Research Object

This study targets the closing prices of corn futures on the Dalian Commodity Exchange, employing an LSTM deep learning model for prediction. The model is trained using historical price data to capture patterns and trends. Additional influential factors, such as spot corn prices, quotations from corn deep processing enterprises, ethanol prices, soybean meal futures prices, and internet sentiment captured via the Baidu search index for “corn price,” are incorporated as auxiliary inputs to improve prediction accuracy.

1.3.2 Research Method

(1) Literature Research Method

This study systematically reviews domestic and international literature on China's corn futures market using CNKI, online resources, and relevant texts. By understanding existing research, it identifies key factors affecting the market and attempts to forecast futures closing prices, providing valuable insights for the market's development.

(2) Theoretical Analysis Method

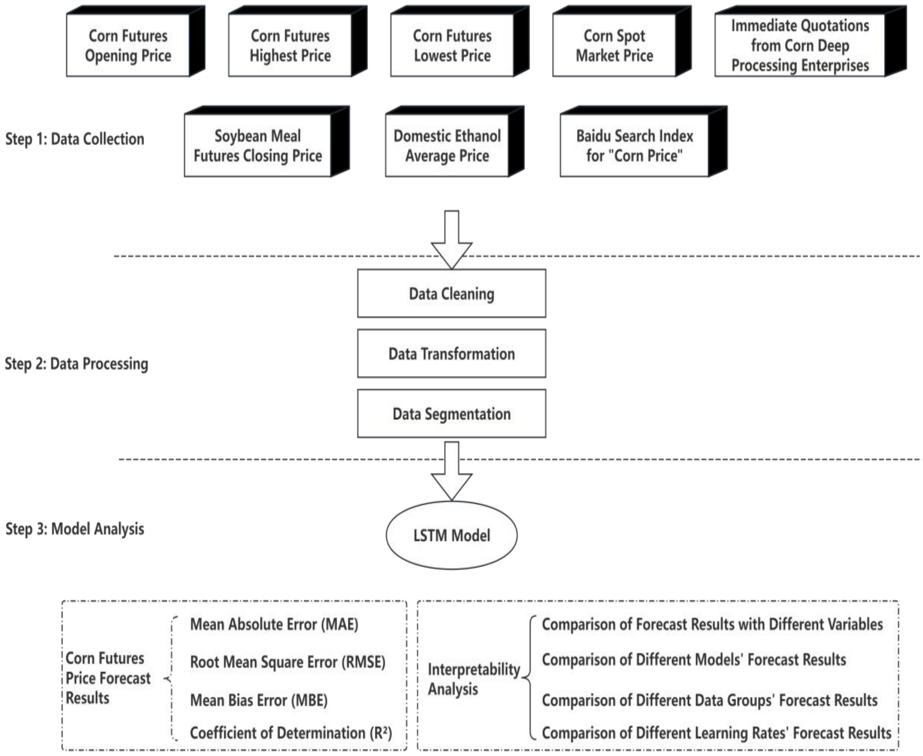
Leveraging economic theories, this study examines factors influencing corn futures prices, including fundamentals and supply chain aspects. This approach provides a strong theoretical foundation for price forecasting and a comprehensive view of market dynamics and price formation.

(3) Empirical Analysis Method

The main contracts of corn futures on the Dalian Commodity Exchange serve as the primary focus. By integrating trading data, supply-demand factors, internet sentiment indices, and downstream product prices, key input features are identified for the forecasting model. The LSTM neural network-based model predicts corn futures closing prices, with continuous simulations and optimizations enhancing accuracy. A thorough evaluation and analysis of the forecast results are conducted to validate the model's performance.

1.3.3 Research Technical Roadmap

Figure 1: Technical Road map



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2. Definition of Relevant Concepts and Theoretical Foundation

2.1 Definition of Relevant Concepts

2.1.1 LSTM Model

The Long-Short Term Memory (LSTM) model is an advanced type of Recurrent Neural Network (RNN) specifically designed to manage long-term dependencies in time series data. Its unique architecture, featuring memory cells and gating mechanisms, allows it to retain and utilize information from long ago without the gradient issues typical of standard RNNs. This advantage makes LSTM highly effective in sequential data contexts, such as corn futures price forecasting, where it learns and retains complex historical price trends, enabling more accurate future predictions.

2.1.2 Corn Futures Price

Corn futures price refers to the agreed-upon price of a futures contract between buyers and sellers for corn at a certain time and place. This price is affected by numerous factors, including corn supply and demand, seasonal changes, domestic and international policy shifts, global market dynamics, and speculative actions.

2.1.3 Price Forecasting

Price forecasting is a fundamental task in financial analysis and market research, aiming to estimate future price movements using historical data, market insights, and predictive models. In the corn futures market, precise price forecasting is crucial for helping market participants make better trading decisions. The LSTM model excels in this role by capturing nonlinear and long-term dependencies in the data, significantly improving prediction accuracy. This approach plays a vital role in guiding trading strategies, risk management, and market analysis.

2.1.4 Model Optimization

Optimizing the LSTM model is an ongoing effort in forecasting corn futures prices. Optimization strategies include adjusting hyperparameters (e.g., learning rate, batch size, iterations) and modifying network architecture (e.g., altering the number of LSTM layers and hidden units) to achieve the best fit for the data. Such optimizations enhance the accuracy and stability of the LSTM model, making it more effective in forecasting corn futures prices.

2.2 Theoretical Foundations

2.2.1 Deep Learning Theory

The LSTM model is an essential model in deep learning, rooted in neural network and deep learning advancements. Deep learning emphasizes automatic feature learning through deep network structures. As a variant of RNN, LSTM uses gating mechanisms and memory cells to effectively address the vanishing and exploding gradient problems often encountered by traditional RNNs when processing long-term sequences.

2.2.2 Time Series Analysis

Time series analysis is a critical branch of statistics that studies the characteristics and trends of time-dependent data. For dynamic data like corn futures prices, time series analysis provides a robust theoretical and methodological framework, including stationarity testing, model order determination, parameter estimation, and forecasting. LSTM's application in time series forecasting relies heavily on this theoretical foundation.

2.2.3 Nonlinear Dynamic Systems

Corn futures pricing is a typical example of a nonlinear dynamic system, influenced by various interconnected and nonlinear factors. LSTM models have a strong theoretical advantage in handling such complexities. This theoretical support is drawn from nonlinear dynamic systems research, including chaos theory and fractal theory, which help explain the intricate, unpredictable interactions within the system.

2.2.4 Information Fusion Theory

In price forecasting, integrating additional relevant information, such as technical indicators and fundamental data, alongside basic price data, enhances prediction accuracy. Information fusion theory provides the framework for effectively merging these diverse inputs. LSTM models can automatically discern and learn the relationships among multi-dimensional data inputs, improving overall forecasting performance.

3. Research Design

3.1 Indicator Selection and Data Sources

(1) This study selects the daily closing price of corn futures as the primary output variable and utilizes deep learning models to predict these prices.

(2) Data on daily trading of corn futures—including opening price, highest price, lowest price, and trading volume—are used as latent features, ensuring that the intrinsic trends of corn futures prices are captured.

(3) The study incorporates spot trading prices of corn and immediate quotations from corn deep processing enterprises. Recognizing that the financial futures market relies on the real economy, these spot prices are included to improve model precision.

(4) Prices of soybean meal futures and domestic ethanol are also included. Given that spot market supply and demand affect corn futures, changes in substitute and downstream product prices are factored into the forecasting model.

(5) Baidu Index search volumes for “corn price” are used as a proxy for online sentiment. Besides hedgers, the corn futures market involves numerous speculators whose decisions are influenced by internet sentiment, impacting futures prices. Hence, the model integrates big data search metrics to reflect how internet sentiment affects corn futures prices in China.

Data for corn futures and soybean meal futures are sourced from the Dalian Commodity Exchange. Spot purchase prices of corn, quotations from deep processing enterprises, and average domestic ethanol prices are sourced from the Eastmoney Choice database. Baidu Index provides the search volume data for “corn price.”

3.2 Data Description and Processing

3.2.1 Data Cleaning

The study gathered 4,762 sets of daily corn futures trading data from May 7, 2004, to May 7, 2024. It also included 3,242 records of daily spot purchase prices from eight regions (Harbin, Changchun, Shenyang, Tongliao, Jining, Shijiazhuang, Anyang, and Bengbu) from April 5, 2012, to May 7, 2024, averaged to reflect regional pricing. Additionally, 2,702 records from 13 corn deep-processing enterprises were collected from December 10, 2012, to May 7, 2024, and averaged daily. Soybean meal futures data comprising 5,777 sets from July 17, 2000, to May 7, 2024, were also included. From January 1, 2008, to May 7, 2024, the study compiled 5,276 daily alcohol price records from Hebei, Jilin, and Heilongjiang, averaged for analysis. Lastly, 4,875 sets of daily Baidu search volumes for “corn price” from January 1, 2011, to May 7, 2024, were collected.

After aligning the data based on the corn futures closing price variable and removing missing values, the final dataset comprised 2,449 records from April 4, 2014, to May 7, 2024.

3.2.2 Data Splitting

The dataset was divided, with 80% (1,960 records) allocated to training and 20% (489 records) used for testing to assess model performance.

3.2.3 Data Normalization

To ensure optimal convergence of the LSTM model, normalization was performed on the training and test sets, with calculations as outlined in Formula (1):

$$\mathrm{x} = \frac{x' - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Here, x' is the raw data,xmin and xmax are the minimum and maximum values within the dataset, standardizing x to a 0-1 range.

3.3 Model Construction

3.3.1 Gate Controllers in the LSTM Model

The LSTM model incorporates three key gate controllers—input, forget, and output gates—that regulate the flow of information at each time step. The following equations describe the specific computations of these gates:

$$h^{(t)} = o\tanh(c^{(t)}) \tag{2}$$

$$c^{(t)} = fc^{(t-1)} + i\tanh([x^{(t)}, h^{(t-1)}] + b_c) \tag{3}$$

$$o = sigmoid(w[x^{(t)}, h^{(t-1)}] + b_o) \tag{4}$$

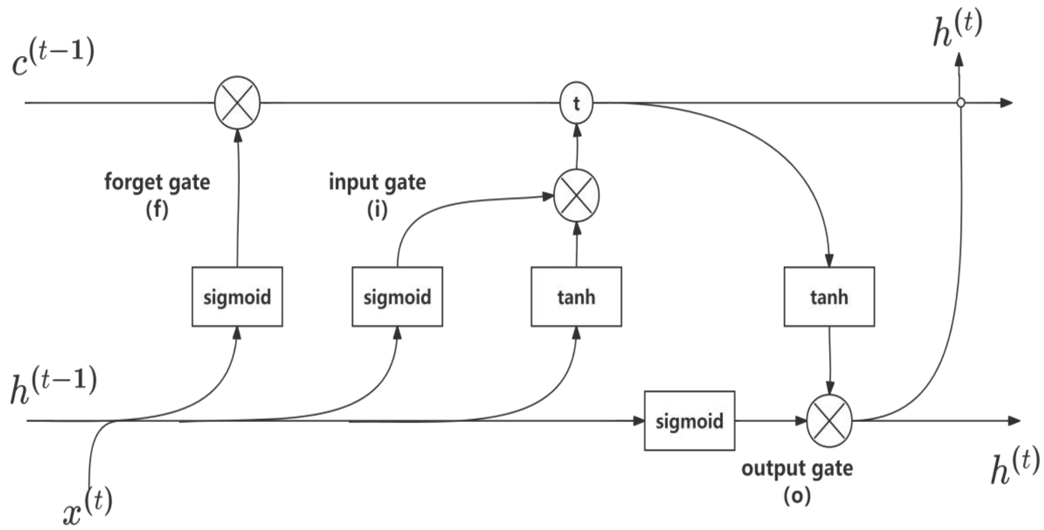
$$f = sigmoid(w[x^{(t)}, h^{(t-1)}] + b_f) \tag{5}$$

$$i = sigmoid(w[x^{(t)}, h^{(t-1)}] + b_i) \tag{6}$$

In the formulas, $x^{(t)}$ denotes the input array used for predicting corn futures prices at time ttt, and $h^{(t)}$ is the predicted corn futures price output by the model at this time. The variable $c^{(t)}$ captures the memory state of the LSTM model concerning corn futures prices. Within the equations, "o" represents the output gate, "f" the forget gate, and "i" the input gate of the LSTM model. The terms bc, bo, bf, b_c, b_o, b_f, b_i and b_c are the respective biases, with "w" representing the weights. The activation functions used are sigmoid()and tanh(), where tanh() refers to the hyperbolic tangent function.

3.3.2 Structure of the LSTM Memory Cell

Figure 2: Diagram of the LSTM Model Memory Cell Structure



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Hochreiter and Schmidhuber (1997) developed the Long-Short Term Memory (LSTM) network model, which gained traction after Graves (2012) expanded upon it. LSTM's unique controllable self-loops create pathways that maintain gradient flow, addressing the vanishing gradient problem common in RNNs. The structure of the LSTM memory cell is shown in (Figure 2). The operational steps of the model are as follows:

(1) Forget Gate Activation: The previous time step's output and the current input are processed through a sigmoid function to create the forget gate fff. This forget gate "f" then modulates the memory state from the prior time step, selectively retaining relevant information.

(2) Input Gate Activation: The previous output and the current input are processed through a sigmoid function to derive the input gate "i". This input gate "i" is then applied to the input data, which has been processed through the hyperbolic tangent function to refine the incoming information.

(3) Memory Update: The memory state processed by the forget gate in the first step is combined with the input data adjusted by the input gate in the second step, producing the updated memory state for the current moment.

(4) Memory Transformation: The current memory state is refined by processing it through the hyperbolic tangent function.

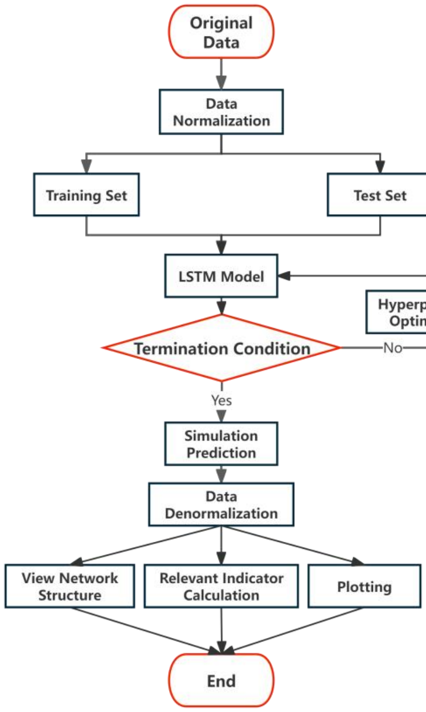
(5) Output Gate Activation: The previous output and the current input are processed through the sigmoid function to generate the output gate. This output gate is applied to the refined memory state obtained in the fourth step, producing the output information for the current time step.

(6) Sequential Flow: The output of the current time step, together with the input information for the next time step, is passed forward as the input for the subsequent step.

3.3.3 Experimental Process

The workflow of the LSTM deep learning model is outlined in (Figure 3) and includes several key stages: data normalization, splitting the dataset into training and test sets, LSTM model creation, hyperparameter tuning, prediction of simulation results, visualization through plotting, and the computation of relevant performance indicators.

Figure 3: Overall Process Flow of LSTM Model



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3.3.4 Evaluation Metrics

Based on a review of the literature and reference to existing scholarly research, this study selects four metrics—Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Bias Error (MBE), and Coefficient of Determination (R^2)—as evaluation metrics to compare the stability of the model. The detailed calculation formulas are as follows

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - y'_i| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2} \tag{8}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i) \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y'_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{10}$$

Where y_i is the original value, y'_i is the predicted value, and $\bar{y}_i$ is the mean of the original data. The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values range from [0, +∞), while the Mean Bias Error (MBE) ranges from (-∞, +∞). The Coefficient of Determination (R^2) ranges from [0, 1]. In the experimental results, the closer the values of MAE, RMSE, and MBE are to 0, and the closer the R^2 value is to 1, the better the model's predictive performance.

4. Empirical Research

4.1 Model Hyperparameter Adjustment

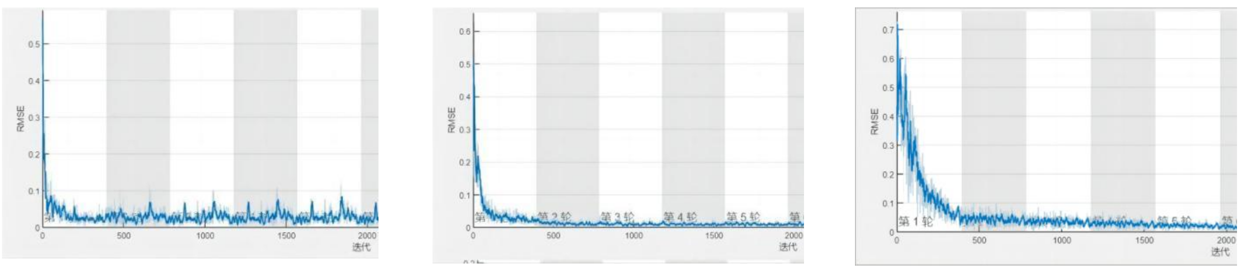
During the use of the LSTM model for price prediction, the setting of model hyperparameters greatly impacts the prediction accuracy. This study conducts comparative experiments focusing on four parameters that affect the model's prediction accuracy: different learning rates, different iteration numbers, different window periods, and different hidden network layers. The experimental results are described as follows.

4.1.1 Comparison of LSTM Model Prediction Effects with Different Learning Rates

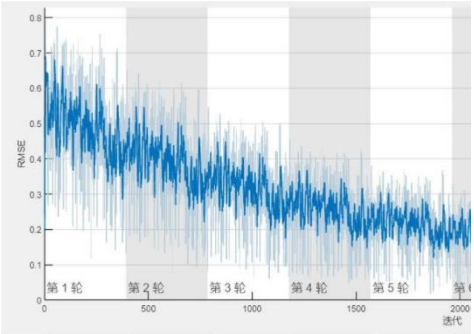
The learning rate mainly reflects the magnitude of gradient updates in the model's network. If the learning rate is set too high, the model may oscillate around the optimal value without converging. Conversely, if the learning rate is set too low, the model training speed will be excessively slow. Given the large volume of data used for training, and referencing other scholarly research, this study keeps the following parameters constant: 50 iterations, a window period of 5 trading days, 4 hidden layers, and 9 input hidden feature variables. Five models with different learning rates were tested, set at 0.1, 0.01, 0.001, 0.0001, and 0.00001.

Figure 4 shows the learning progress of models with different iteration counts. In Figure 4(a), the learning rate is 0.1, which is the largest among the models. However, it can be observed that as the number of iterations increases, the model continuously oscillates around a value without converging. When the learning rate is set to 0.01, the model gradually converges to a certain value as the iterations increase. As the learning rate decreases, the model's convergence speed slows down; in the smallest group with a learning rate of 0.00001, as shown in Figure 4(e), the model exhibits horizontal oscillation within the same iteration period and does not show downward convergence, indicating that a very large number of iterations would be required to meet the model's learning requirements. The comparative study found that the optimal learning rate setting is 0.01.

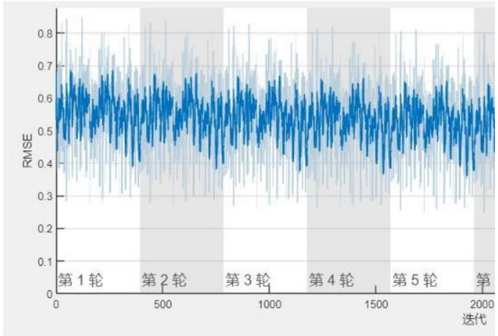
Figure 4: Loss Function Curves under Different Learning Rates



(a) Learning Rate 0.1 (b) Learning Rate 0.01 (c) Learning Rate0.001



(d) Learning Rate 0.0001



(e) Learning Rate0.00001

Source: Compiled and Drawn by the Author

4.1.2 Comparison of LSTM Model Prediction Effects with Different Iteration Counts

Table 1: Table of Relevant Metrics Corresponding to Different Iteration Training Counts

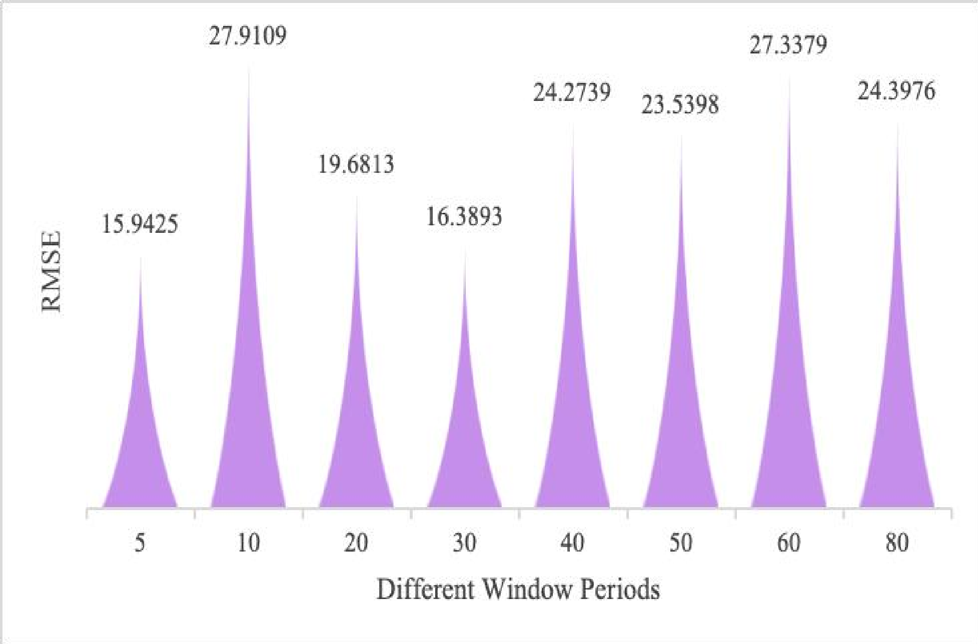
Iteration Count	R^2		MAE		MBE		RMSE	
	training set	test set	training set	test set	training set	test set	training set	test set
10	0.9988	0.9870	10.0474	21.3076	-0.3076	-0.7420	14.2159	26.0759
50	0.9990	0.9918	9.9168	12.2901	4.5845	-5.9452	12.9594	15.9425
100	0.9982	0.9724	13.1846	22.6730	-10.3498	-13.5264	17.2167	29.1871
200	0.9941	0.9225	26.8471	40.8036	-25.7927	-40.4000	31.3087	48.9417
300	0.9986	0.9793	11.2614	15.8991	-1.6996	-11.9120	15.4498	25.2912
400	0.9975	0.9590	17.2301	30.3913	15.1392	24.9802	20.4180	35.6058

The model completes one iteration by fully training all data samples in the training set once. This study also designed a comparative experiment, setting the learning rate to the optimal value of 0.01, while keeping other parameters constant across all model groups: a window period of 5 trading days, 4 hidden layers, and 9 input hidden feature variables. Six models with different iteration counts were tested, with iteration numbers set to 10, 50, 100, 200, 300, and 400, respectively.

Training and prediction were conducted for the six groups of models, and relevant metrics were calculated for both the training and prediction sets (see Table 1), including Coefficient of Determination (R^2), Mean Absolute Error (MAE), Mean Bias Error (MBE), and Root Mean Square Error (RMSE). Referring to the metric formulas and evaluation methods outlined in Section 3, the study found that when the iteration count is set to 50 (see the highlighted part in Table 1), the LSTM model achieves the best metric values. This indicates that when predicting corn futures prices using the selected variables, the optimal iteration count for the LSTM model should be set to 50.

4.1.3 Comparison of LSTM Model Prediction Effects with Different Window Periods

Figure 5: Comparison of RMSE Metrics for Model Predictions Across Different Time Windows



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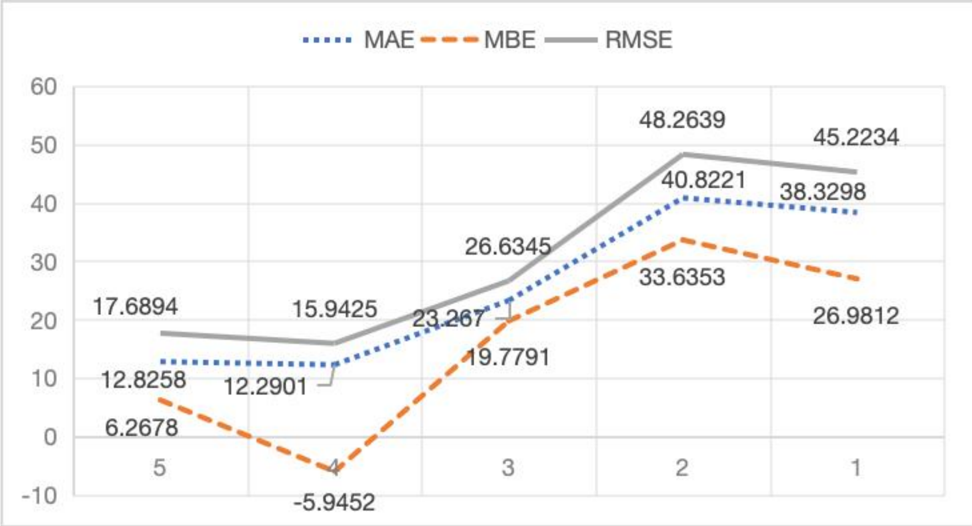
Futures prices are influenced by various factors, including market supply and demand fluctuations, policy changes, and the cyclical nature of agricultural products. Investors in the corn futures market often use candlestick charts with different time intervals to guide their investment decisions. Similarly, determining the optimal time window for the LSTM model is essential during training. This section of the article explores the optimal time window through comparative experiments. The model's learning rate was set at 0.01, the number of iterations at 50, with the hidden layer parameter fixed at 5, and the number of input feature variables set at 9. Eight models were trained with time windows of 5, 10, 20, 30, 40, 50, 60, and 80 trading days, respectively. Each model was trained and predicted using identical input variables. The root mean square error (RMSE) of the predicted prices for these models is presented in (Figure 5).

The findings indicate that the model achieved the lowest RMSE when the learning time window was set to 5 trading days, establishing the 5-day window as the optimal parameter for corn futures price predictions.

4.1.4 Comparison of Prediction Performance of LSTM Models with Different Hidden Layers

Hidden layers in LSTM models are designed to capture the underlying feature relationships within data. If set too low, the model may not fully identify hidden patterns; if set too high, it increases training time, hardware demands, and the risk of overfitting. To determine the optimal hidden layer configuration, a comparative experiment was conducted using the best parameter values identified earlier as the baseline settings, with the only variation being the number of hidden layers set at 1, 2, 3, 4, and 5. Each model was trained using the same input data.(Figure 6) displays the evaluation metrics for the predicted prices of each group. According to the evaluation standards outlined in (Formulas 2-5), the results indicate that the model with 4 hidden layers achieved the best prediction accuracy. Therefore, for forecasting corn futures prices in this study, the optimal hidden layer setting for the LSTM model should be 4.

Figure 6: Comparison of Relevant Metrics for Model Predictions Across Different Hidden Layers



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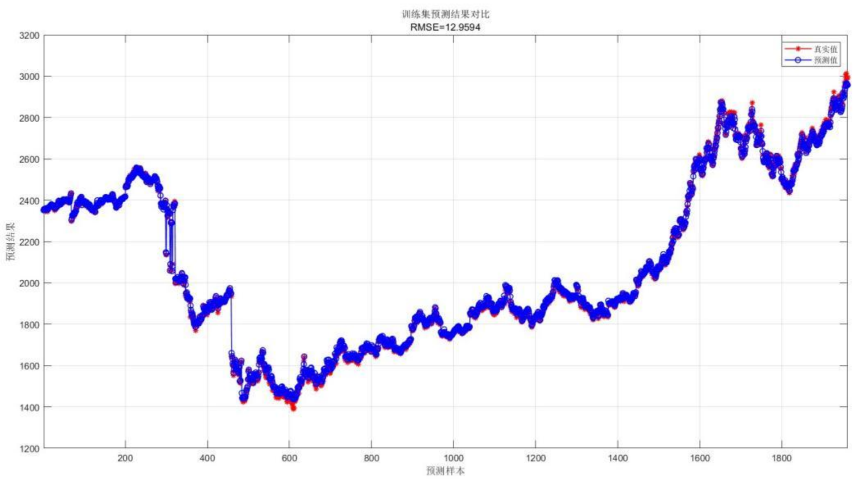
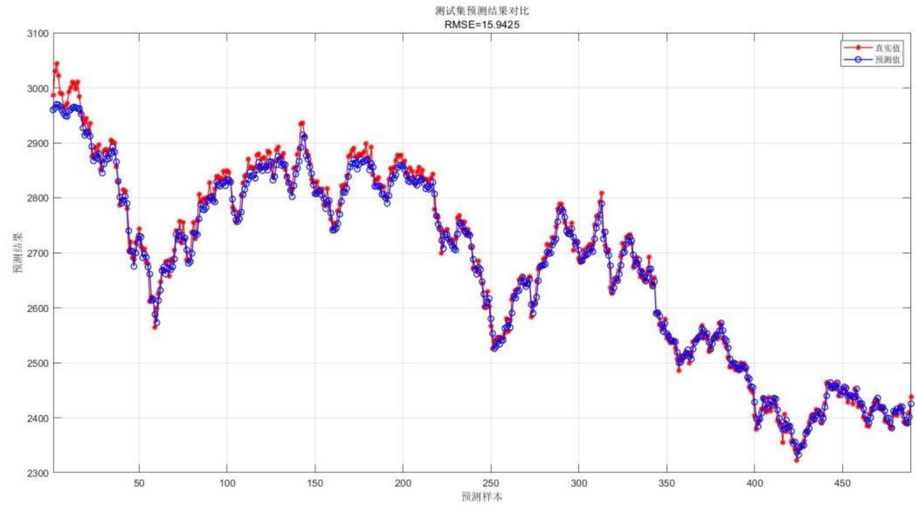
4.2 Visualization Analysis of Prediction Results Using Optimal Parameters

Figure 7: Comparison of Predicted vs. Actual Prices in the Training Set Under Optimal Hyperparameters



Source: Compiled and Drawn by the Author

Figure 8: Comparison of Model Prediction Results and Test Data Under Optimal Hyperparameters



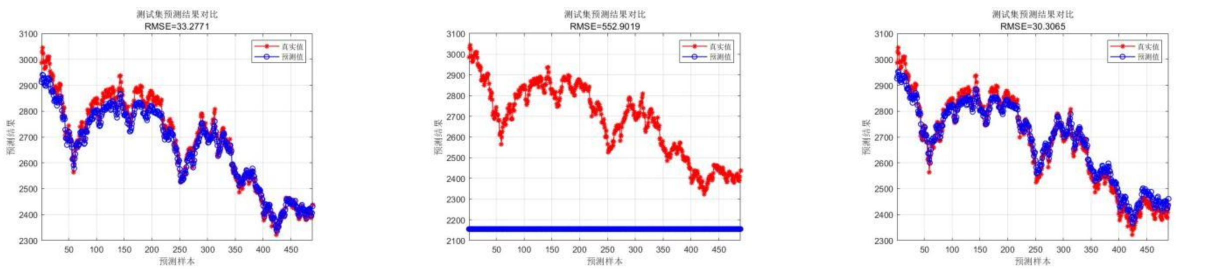
Source: Compiled and Drawn by the Author

Based on the results of the comparative experiments, the LSTM model's hyperparameters were set optimally: a learning rate of 0.01, 50 iterations, a 5-day learning window, and 4 hidden layers. A total of 1,960 arrays were used as the training set, while the remaining 489 arrays served as the test set to compare predicted prices with actual data. The model was trained over 50 rounds, with each round consisting of a full iteration of 392 transformed arrays, totaling 19,600 iterations.

As shown in (Figure 7), the comparison between the predicted and actual corn futures prices in the training set yields a root mean square error (RMSE) of 12.9594, demonstrating a strong fit between the predicted and actual values. (Figure 8) illustrates the comparison between the predicted and actual prices in the prediction set, with an RMSE of 15.9425. Overall, the predicted prices closely align with the actual values, meeting expectations and accurately capturing the trend of corn futures prices.

4.3 Comparative Experiment

Figure 9: Comparison of Predicted vs. Actual Prices in the Prediction Set After Excluding Different Variables



(1) Exclusion of the Search Index | Exclusion of Soybean Meal and Alcohol Prices | Exclusion of Corn Spot Prices and Corporate Quotes

Source: Compiled and Drawn by the Author

As shown in Figure 9-(1), initially excluding the Baidu search index for the "corn price" keyword from the 9 variables resulted in significantly poorer predictive performance compared to when all variables were used. Next, as depicted in Figure 9-(2), further exclusion of soybean meal futures prices and alcohol prices in the corn product supply chain caused the predicted results to deviate entirely from actual prices, highlighting the critical influence of supply chain and similar product prices on corn futures pricing. Finally, when domestic spot prices and immediate quotes from corn processing companies were excluded, as shown in Figure 9-(3), the model's prediction accuracy fell below that of the model incorporating all 9 implicit variables. This confirms the rationality and reliability of the selected variables.

5. Conclusion

5.1 Research Conclusions

This study employs the LSTM deep learning model to conduct comprehensive predictive research on corn futures prices. By integrating multiple factors, including historical futures data, spot prices, corporate quotes, downstream product prices, substitute prices, and online sentiment indices, a precise and holistic predictive model was constructed. Key findings are as follows:

5.1.1 Effectiveness of the LSTM Model

The LSTM model significantly outperforms traditional linear models and other machine learning methods in capturing long-term dependencies and managing the nonlinear characteristics of financial markets. It offers enhanced accuracy and stability in price forecasting, demonstrating adaptability and robustness in complex financial environments.

5.1.2 Importance of Parameter Optimization

Comparative experiments highlighted the substantial impact of parameters such as learning rate, iteration count, window period, and hidden layer number on model accuracy. Optimizing these parameters, specifically setting the learning rate to 0.01, iterations to 50, window period to 5, and hidden layers to 4, achieved the highest prediction accuracy, providing crucial insights for future applications of LSTM models in price forecasting.

5.1.3 Value of Multi-Source Information Integration

Incorporating additional external factors, including spot prices, processing quotes, substitute prices, and sentiment indices, significantly enhanced the model's predictive accuracy, underscoring the importance of a multi-faceted approach in price prediction.

5.1.4 Broader Application Potential

The LSTM model demonstrated excellent performance in experimental phases, with substantial potential for practical use in the corn futures market. When combined with existing prediction tools, it promises more precise and timely decision support, helping market participants better navigate trends and seize opportunities.

5.2 Policy Recommendations

The study on predicting corn futures prices using the LSTM model highlights the significant advantages of deep learning technologies in financial market forecasting. To fully leverage this potential and support the healthy growth of the agricultural futures market, the following policy recommendations are proposed:

5.2.1 Promote the Use of Advanced Predictive Models

The government should encourage the adoption of deep learning models like LSTM across agricultural futures markets. Financial institutions, agricultural businesses, and research organizations should integrate these advanced predictive tools to enhance decision-making efficiency and risk management. Establishing specialized funds or reward systems can further incentivize technological advancements and model optimization.

5.2.2 Strengthen Data Collection and Information-Sharing Mechanisms

Improving the agricultural futures market's data collection framework is essential for ensuring that data is comprehensive, accurate, and timely. Developing cross-sectoral and cross-industry information-sharing platforms can integrate diverse market data, providing valuable insights for market participants.

5.2.3 Enhance Market Transparency and Fairness

Strengthening regulatory oversight to prevent market manipulation and fraud is crucial for maintaining market fairness and stability. Regularly publishing market reports and predictive analyses can boost market transparency, reduce information asymmetry, and enhance market predictability.

Implementing these policy measures—promoting advanced technologies, enhancing data collection and information sharing, and improving market transparency and fairness—will drive the agricultural futures market toward greater efficiency, transparency, and standardization.

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Conflicts of Interest

The authors declare no conflict of interest.

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