Deep Learning-Based Intelligent Prediction of Corn and Soybean Futures Prices (Postprint)

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Abstract

Corn and soybeans are both dryland crops of the same season, and the "land competition" contradiction is particularly prominent; simultaneously understanding the prices of both crops is essential. Compared with spot prices, agricultural futures prices possess price discovery functions. Therefore, the analysis and prediction of corn and soybean futures prices are of significant importance for planting structure adjustment and farmers' crop variety selection. This study first analyzed the correlation between corn and soybean futures prices; through correlation calculations and Granger causality tests, it was found that corn and soybean futures exhibit strong positive correlation, and soybean futures prices are the Granger cause of corn futures prices. Secondly, based on the Long Short-Term Memory (LSTM) model, corn and soybean futures prices were predicted, and the attention mechanism was introduced to optimize the futures price prediction model. Comparison results show that compared with the Autoregressive Integrated Moving Average (ARIMA) model and the Support Vector Regression (SVR) model, the LSTM model is superior across all metrics, and compared with the single LSTM model, the Attention-LSTM model with the added attention mechanism is superior across all metrics. Specifically, the Mean Absolute Error (MAE) of corn and soybean futures prediction results improved by 3.8% and 3.3%, respectively, Root Mean Square Error (RMSE) improved by 0.6% and 1.8%, respectively, and Mean Absolute Percentage Error (MAPE) improved by 4.8% and 2.9%, respectively, proving that the addition of the attention mechanism can help the model extract effective information and enhance performance. Finally, using the LSTM model combined with historical soybean futures prices to jointly predict corn futures prices, MAE improved by 6.9%, RMSE improved by 1.1%, and MAPE improved by 5.3%. Experimental results demonstrate that this study' s use of the Attention-LSTM model to predict corn and soybean futures prices, compared with general prediction models, the Attention-LSTM model can improve the prediction accuracy of soybean and corn futures prices, and combining relevant agricultural futures price data can enhance the prediction performance of single agricultural futures models.

Full Text

Intelligent Forecasting of Corn and Soybean Futures Prices Based on Deep Learning

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Abstract: Corn and soybean are upland grain crops grown in the same season, and the competition for land between them is particularly prominent in China. Simultaneously understanding the prices of both crops is therefore essential. Compared with spot prices, agricultural futures prices possess a price discovery function. Consequently, the analysis and prediction of corn and soybean futures prices hold significant importance for adjusting planting structures and assisting farmers in crop variety selection. This study first analyzed the correlation between corn and soybean futures prices. Through correlation calculations and Granger causality tests, we found that corn and soybean futures exhibit a strong positive correlation, and that soybean futures prices are a Granger cause of corn futures prices. Second, we employed a Long Short-Term Memory (LSTM) model to predict corn and soybean futures prices and introduced an Attention mechanism to optimize the futures price prediction model. Comparative results demonstrate that the Attention-LSTM model outperforms the Autoregressive Integrated Moving Average (ARIMA) model, Support Vector Regression (SVR) model, and the standalone LSTM model across all evaluation metrics. Specifically, the Mean Absolute Error (MAE) for corn and soybean futures predictions improved by 3.8% and 3.3%, respectively; Root Mean Square Error (RMSE) improved by 0.6% and 1.8%; and Mean Absolute Percentage Error (MAPE) improved by 4.8% and 2.9%. This confirms that Attention mechanisms help models extract effective information and enhance performance. Finally, we used the Attention-LSTM model combined with historical soybean futures prices to jointly predict corn futures prices. Experimental results show that the proposed Attention-LSTM model improves prediction accuracy for both soybean and corn futures prices compared with general prediction models, and that incorporating correlated agricultural futures price data can enhance the predictive performance of individual agricultural product futures models.

Keywords: corn and soybean futures; futures price forecasting; LSTM model; Attention mechanism; deep learning; support vector regression

1 Introduction

Against the backdrop of recurring COVID-19 outbreaks and a complex and volatile international environment, strengthening China' s soybean self-sufficiency capability is crucial for ensuring food security [1]. The "Opinions of the Central Committee of the Communist Party of China and the State Council on Comprehensively Promoting Key Tasks for Rural Revitalization in 2022" explicitly states that "great efforts should be made to implement soybean and oilseed production capacity enhancement projects." Corn and soybean are both upland crops grown in the same season, creating a prominent "land competition" conflict. In recent years, due to the higher comparative benefits of corn, most farmers have switched from soybean to corn cultivation, further reducing domestic soybean planting area [2]. Agricultural futures markets were originally established to resolve grain supply-demand contradictions and stabilize production-marketing relationships [3]. Futures markets possess a price discovery function that can more accurately reveal future price trends, thereby serving agricultural production and management [4]. Therefore, corn and soybean futures price forecasting is of significant importance for management departments to formulate subsidy policies and for farmers to select crop varieties.

Futures price forecasting methods can be categorized into traditional statistical approaches and artificial intelligence methods. Common statistical models include the Autoregressive Integrated Moving Average (ARIMA) model [5], Engle' s [6] Autoregressive Conditional Heteroskedasticity (ARCH) model, and Bollerslev' s [7] Generalized ARCH (GARCH) model. However, statistical models have limitations because they cannot capture nonlinear characteristics in futures price series. With the advent of the big data era and rapid development of neural networks, researchers have applied neural networks to agricultural futures price forecasting. Liu [8] combined Ensemble Empirical Mode Decomposition (EEMD) with LSTM to improve agricultural futures price model performance. Luo [9] proposed a decomposition-based LSTM model that demonstrated excellent performance in agricultural futures price forecasting. Jarrah and Salina [10] applied Recurrent Neural Networks (RNN) to predict Saudi futures market prices, achieving more accurate results than ARIMA models.

RNN and LSTM models have shown good performance in futures price forecasting [11-14]. However, these models convert input sequences into a fixed-length vector to preserve all information, which can lead to limited memory and information loss. The introduction of Attention mechanisms [15] can mitigate this information loss to some extent. Attention assigns different weights to input sequences through training, thereby increasing the weight of important information and reducing the weight of irrelevant information. In recent years, research and applications of Attention mechanisms have become a hot topic, with numerous studies in machine translation, image classification [16,17], and many works in transportation and financial risk prediction combining Attention with LSTM models, all achieving favorable results [18,19]. However, the application of Attention mechanisms in agricultural futures price forecasting remains limited. Therefore, this study employs an Attention-enhanced LSTM model to predict agricultural futures prices, assigning different weights to each step of LSTM output to improve model performance. Through comparative experiments, we verify the effectiveness of Attention mechanisms in agricultural futures forecasting.

Furthermore, existing agricultural futures price forecasting primarily uses historical prices of single futures contracts while neglecting the role of related agricultural futures prices. This study analyzes the correlation between corn and soybean futures prices and conducts experiments combining historical soybean futures prices with corn futures prices to predict corn futures prices, thereby exploring the value of related agricultural futures historical price data for improving prediction accuracy.

2 Materials and Methods

2.1 Data Sources

We selected corn and soybean (No. 1 soybean) continuous prices from the Dalian Commodity Exchange via Sina Finance - Futures (https://finance.sina.com.cn/futuremarket/) as our data source. We collected all daily trading data for corn and soybean futures from January 4, 2005, to March 9, 2022, comprising 4,159 corn futures data points and 4,182 soybean futures data points.

2.2 Data Preprocessing and Model Development

2.2.1 Data Preprocessing Quantitative analysis methods for price forecasting fall into two categories. The first is causal regression analysis, which assumes a causal relationship between prices and their influencing factors, using regression analysis to identify these relationships for modeling and prediction. The second is time series analysis, which assumes that all factor influences are reflected in prices and that past patterns will continue into the future, thus using only historical prices for prediction. This study adopts the time series analysis approach, using historical prices under the assumption that past patterns will persist.

Following the approach of Fan et al. [20], we used 10 days of historical closing prices to predict the next day’ s closing price. To facilitate model convergence, we applied MinMaxScaler() to normalize closing prices to the 0-1 range. Labels were processed using formula (1), representing the change in current closing price relative to the previous day’ s closing price:

$$\text{label}[i] = \frac{\text{close}[i] - \text{close}[i-1]}{\text{close}[i-1]}$$

The dataset was divided into training and testing sets, with the first 80% of data used for training and the remaining 20% for testing model performance.

2.2.2 Corn and Soybean Futures Price Prediction Model Futures historical prices represent typical time series data. The LSTM model [21] can automatically convert historical information into fixed-length vectors. However, standalone LSTM models do not completely solve the gradient vanishing problem and cannot effectively determine which historical data are important for current price prediction, reducing information utilization efficiency. Attention mechanisms can assign different weights to information at different times, compensating for this LSTM limitation.

The Attention-LSTM model architecture has achieved good results in transportation, quantitative investment, and other applications [19]. Drawing on relevant practices from other fields, this study proposes an agricultural futures price prediction model based on Attention-LSTM. The overall model structure is shown in [Figure 1: see original paper] and comprises three layers: an LSTM layer, an Attention layer, and a linear layer.

(1) **LSTM Layer**: The LSTM model serves as the first layer of the prediction model. The hidden state h_t at the current time step is determined by the current input x_t and the previous time step' s hidden state h_{t-1}, as calculated by formula (2):

$$h_t = \text{LSTM}(x_t, h_{t-1})$$

(2) **Attention Layer**: The second layer is the Attention layer, which learns weight values $[w_1, w_2, ..., w_{10}]$ corresponding to outputs at different time steps from the LSTM model. These weights can be understood as representing "the importance of features extracted at different time steps." Through weighted summation, the final output vector H is obtained, as calculated by formula (3):

$$H = \sum_{i=1}^{10} w_i h_i$$

(3) **Linear Layer**: This layer takes the Attention layer' s output H as input and produces the final prediction result after computation. The loss function is calculated by combining this with the actual futures price x_{11} on day 11 to enable network updating.

2.2.3 Corn Futures Price Prediction Combined with Soybean Futures Prices Existing agricultural futures price forecasting uses only single agricultural product futures prices as training data without 挖掘挖掘 the value of related agricultural futures price data. Through analysis, we found that corn and soybean futures prices have a strong positive correlation, and soybean futures prices are a Granger cause of corn futures prices (see Section 3 for details). Therefore, this study conducted experiments using soybean futures data to jointly predict corn futures prices and observed whether model performance improved.

The model structure for predicting corn futures prices combined with soybean futures prices is shown in [Figure 2: see original paper] and comprises three components: LSTM models, weighted summation, and a linear layer.

(1) **LSTM Models**: This study uses two separate LSTM models (LSTM1 and LSTM2) to process the input sequences of corn futures prices $[x_1, x_2, ..., x_{10}]$ and soybean futures prices $[x'_1, x'_2, ..., x'_{10}]$, respectively. The outputs of the two models are h_{10} and h'_{10}. For simplicity, this experiment does not use Attention mechanisms to weight all time step outputs but directly assumes that all information from the input sequences is extracted into the final time step outputs h_{10} and h'_{10}.

(2) **Weighted Summation**: Two parameters w_1 and w_2 are learned to assign different weights to h_{10} and h'_{10}, which can be understood as "the degree of attention the entire model pays to corn futures prices and soybean futures prices," achieving the integration of historical price data from both futures. The final output vector H is obtained through weighted summation, as calculated by formula (4):

$$H = h_{10}w_1 + h'_{10}w_2$$

(3) **Linear Layer**: The Attention layer' s output H is fed into the linear layer, which computes and outputs the final prediction result. The loss is calculated using the actual corn futures price x_{11} on day 11 to enable network updating.

2.2.4 Experimental Design This study conducted two experiments: (1) Attention-LSTM-based corn and soybean futures price prediction, and (2) corn futures price prediction combined with historical soybean prices.

(1) **Attention-LSTM for Corn and Soybean Futures Price Prediction**: Model parameters were set as follows: LSTM hidden layers = 2, hidden layer nodes = 128, dropout = 0.2, training epochs = 400.

(2) **Corn Futures Price Prediction Combined with Historical Soybean Prices**: Model parameters were set as follows: LSTM hidden layers = 2, hidden layer nodes = 64, dropout = 0.2, training epochs = 400.

ARIMA, Support Vector Regression (SVR), and LSTM models are commonly used for agricultural futures price prediction. This study selected ARIMA, SVR, and LSTM as baseline models for comparison with our proposed models.

2.2.5 Evaluation Metrics We selected three commonly used regression prediction evaluation metrics to measure model performance: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), calculated using formulas (5)-(7):

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

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

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

where y_i represents actual data and $\hat{y}_i$ represents predicted data.

3 Results and Analysis

3.1 Correlation Analysis of Corn and Soybean Futures Prices

[Figure 3: see original paper] shows the changes in corn and soybean futures prices from January 4, 2005, to March 9, 2022. The figure reveals certain synchronous trends in corn and soybean futures prices, as the two crops are substitutes for each other and are both primarily grown in Northeast China during the same season.

To further investigate whether corn and soybean futures prices are correlated and whether one futures price has predictive value for the other, we calculated the correlation coefficient between them and conducted a Granger causality test.

(1) **Correlation Test**: By calculating the correlation between corn and soybean futures prices, we found a strong positive correlation, with a correlation coefficient of 0.841042. The correlation coefficient matrix for the two futures prices is shown in .

(2) **Granger Causality Test**: To further explore the causal relationship between corn and soybean futures prices, we conducted a Granger causality test, with results shown in . The table indicates that soybean futures prices are a Granger cause of corn futures prices, while corn futures prices are not a Granger cause of soybean futures prices. This result suggests that changes in soybean futures prices influence corn futures price changes to some extent, but not vice versa. In reality, corn futures prices may not

necessarily affect soybean futures prices, and such influence is not significant in this experiment.

In summary, corn and soybean futures prices exhibit a strong positive correlation, and soybean futures prices are a Granger cause of corn futures prices. Therefore, soybean futures prices have predictive value for corn futures prices. Consequently, this study combines historical soybean futures prices with corn futures prices to predict corn futures prices.

3.2 Prediction Performance for Corn and Soybean Futures

Using MAE, RMSE, and MAPE as evaluation criteria, we compared the performance of our Attention-LSTM model with commonly used ARIMA, SVR, and LSTM models. The prediction results for corn and soybean futures prices are shown in and , respectively.

Analysis of the data in and yields the following conclusions. Compared with ARIMA and SVR models, the LSTM model performs better across all metrics, validating the advantages of LSTM for agricultural futures price forecasting. Compared with the standalone LSTM model, the Attention-LSTM model with added Attention mechanism performs better across all metrics. Specifically, MAE improved by 3.8% and 3.3%, RMSE improved by 0.6% and 1.8%, and MAPE improved by 4.8% and 2.9% for corn and soybean futures predictions, respectively. This demonstrates that the Attention mechanism helps the model extract effective information and improve performance.

To more intuitively display model prediction effects, we used the last 20% of corn futures data for price prediction. The Attention-LSTM model' s prediction results are shown in [Figure 4: see original paper]. The figure demonstrates that the Attention-LSTM model can effectively fit corn futures prices, including at time points with large price fluctuations.

To better illustrate the performance difference between the Attention-LSTM model and the standalone LSTM model, we selected the first 100 days of the corn futures prediction interval and compared the prediction results of both models, as shown in [Figure 5: see original paper]. The results indicate that after adding Attention, the predictions are closer to actual values, further confirming that Attention mechanisms can effectively assess the importance of output information at different time steps and improve model prediction performance.

3.3 Corn Futures Price Prediction Combined with Soybean Futures Prices

Since corn and soybean futures prices exhibit strong positive correlation and soybean futures prices are a Granger cause of corn futures prices, this section incorporates historical soybean futures prices together with corn futures historical prices to predict corn futures prices. In the data processing stage, we first aligned the historical closing prices of corn and soybean futures, then filled missing data using arithmetic sequences.

The training data construction follows the same approach as in Section 2.2.1, using the previous 10 days of historical closing prices for both corn and soybean to jointly predict the 11th day' s corn futures price. This experiment uses two independent LSTM models to process the historical prices of corn and soybean futures separately, followed by weighted summation for joint prediction. The model structure is shown in [Figure 2: see original paper].

Model performance was compared with that of models trained using only corn futures historical data, with results shown in . The table reveals that compared with using only corn futures prices, adding soybean futures historical prices improves all model metrics, with MAE improving by 6.9%, RMSE by 1.1%, and MAPE by 5.3%. This represents a significant performance improvement, further validating the strong correlation between corn and soybean futures prices and demonstrating that using related agricultural futures prices is valuable for improving prediction performance of individual agricultural product futures models.

4 Conclusion

This study first analyzed the correlation between corn and soybean futures prices, then used the Attention-LSTM model to predict corn and soybean futures prices separately, and finally combined historical soybean futures prices with corn futures prices to predict corn futures prices. Specifically, the contributions of this study can be summarized as follows:

(1) Through correlation calculation and Granger causality testing, we verified that corn and soybean futures prices have a strong positive correlation, and that soybean futures prices are a Granger cause of corn futures prices —meaning changes in soybean futures prices cause changes in corn futures prices.

(2) We applied the Attention-LSTM model to predict corn and soybean futures prices and compared it with ARIMA, SVR, and LSTM models. Results show that adding Attention mechanisms improves prediction performance for both corn and soybean futures prices, validating the effectiveness of Attention mechanisms for agricultural futures price forecasting.

(3) We used historical soybean futures prices together with corn futures prices to predict corn futures prices. Compared with using only corn futures prices, MAE improved by 6.9%, RMSE by 1.1%, and MAPE by 5.3%. These results demonstrate that incorporating related agricultural futures price data has important value for improving the prediction performance of individual agricultural product futures models.

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