ISSN: 2710-0723

Prediction and Analysis of Cotton Futures Prices based on LSTM Model

Chencheng Wang*

School of Finance, Anhui University of Finance and Economics, Bengbu, China

*3106522988@qq.com

Abstract

In the context of global economic integration, the cotton futures market, as an important component of the agricultural futures market, not only affects the economic benefits of many enterprises in the cotton industry chain, but is also closely related to the macroeconomic situation due to price fluctuations. In view of the nonlinear and unstable characteristics of cotton futures prices, in order to better predict cotton futures prices accurately, this paper selects CCINDEX3128B as the basic model, collects relevant price data from Zhengzhou Stock Exchange from January 2, 2019 to December 18, 2024 as the in-depth research object, and innovatively uses Long Short Term Memory Network (LSTM) model for systematic analysis and prediction. In the research process, comprehensive data related to cotton futures prices was first collected, covering various influencing factors mentioned above, and strict data cleaning and preprocessing were carried out to ensure the accuracy and usability of the data. Subsequently, the processed data is inputted into the constructed LSTM model for prediction. In the process of model training and prediction, key indicators such as mean absolute error (MAE) and coefficient of determination were comprehensively analyzed to evaluate the predictive performance of the model. The results showed that the LSTM model exhibited good goodness of fit in cotton futures price prediction, with a MAE index of 117.45718 and an RMSE index of 153.78997, both of which were at a low level. This indicates that the error between the model's prediction results and actual values is small, and it can accurately capture the fluctuation trend of cotton futures prices, providing a high reference value for cotton futures market participants to make more scientific and reasonable decisions in market trading.

Keywords

Cotton Futures; LSTM Model; Price Prediction; Comparison of Indicators.

1. Introduction

Cotton, as the core raw material of the cotton textile industry, occupies a pivotal position in the textile industry and is also an extremely important economic crop. In the global market, cotton is widely used in the production of various textiles, from everyday clothing to comfortable bed sheets, beautiful curtains, etc., fully meeting people's daily needs. As a globally circulating commodity, cotton prices are influenced by a variety of complex factors such as international market demand, policy adjustments in various countries, and exchange rate fluctuations. Its price trend constantly affects the hearts of related industries and market participants. The price of cotton futures is influenced by a variety of complex factors, with climate conditions playing a decisive role in the yield and quality of cotton. Extreme weather conditions such as drought and floods may lead to reduced cotton production, thereby driving up prices; In terms of policy environment, government agricultural subsidies, import and export policies, etc. will directly or indirectly affect the market supply and demand relationship of cotton, thereby affecting price trends; The consumption index reflects the degree of market demand for cotton products, and fluctuations in consumer demand can drive fluctuations in cotton futures prices; The changes in gross domestic product will also affect the development and price level of the cotton industry at the macro level.

From a domestic perspective, in-depth research on cotton prices provides key data support for the government to formulate scientific and reasonable agricultural policies. By accurately grasping the dynamic changes in cotton prices, the government can gain a deep understanding of the supply and demand situation in the market, and thus formulate more targeted and adaptive policies, effectively promoting the healthy and stable development of the cotton industry. This not only helps maintain national food security, but also has significant implications for ensuring the smooth operation of the country's economy and society. Looking at the international market, studying cotton prices is an important basis for investors to seize market opportunities and make wise investment decisions; For international trade, accurate price analysis helps promote smooth trade processes and reduce trade risks caused by price fluctuations.

In recent years, with the rapid development of big data technology, the time series based cotton futures price prediction and analysis methods have been continuously optimized and improved. Many researchers use cutting-edge technologies such as deep learning algorithms and machine learning to improve the accuracy of prediction results. For example, Song Yulan et al. (2023) selected monthly cotton futures prices as sample data for in-depth analysis, and used the ARIMA model to predict the short-term trend of price fluctuations. The study found that the high volatility of cotton prices in the short term has a certain rationality, and its fluctuations are mainly influenced by factors such as liquidity trends and international prices. Based on this, it is expected that the cotton market will present a pattern of oversupply in the future, and cotton prices may show a downward trend. When studying cotton futures prices, Shi Lu (2023) used cotton prices from the Zhengzhou Commodity Exchange as a sample, preprocessed the data using SSA (Sparrow Algorithm), and then used LSTM model for prediction. The results show that the price prediction performance after data optimization is significantly better than the ARIMA model, with relatively lower errors. In addition, Wu Ye et al. (2018) used cotton futures prices of 3128B from January 2015 to December 2017 as the research sample, and systematically extracted 13 factors that have a significant impact on cotton prices, such as yield and consumption. They used a combination of mean influence value (MIV), genetic algorithm (GA), and BP neural network to screen variable factors and conduct predictive fitting. The results indicate that the fitting accuracy and prediction accuracy of the MIV-GA-BP neural network model are good. In the latest research, Xia, HS et al. (2025) proposed using big data to extract the main factors affecting prices, and combining artificial intelligence and data-driven approaches to enhance the reliability of the model. By combining CP with QR and using LSTM model for point estimation, the mechanism of interaction between feature variables and target variables was deeply explored, effectively improving the interpretability of the model. Liu Yang et al. (2024) used cotton futures price data from 2019 to 2024 in China to construct a multi-layer LSTM network prediction model for predicting cotton prices. By finely adjusting model parameters such as iteration times, window size, and network layers, LSTM networks exhibit higher prediction accuracy compared to traditional models such as multiple linear regression (MLR) and support vector regression (SVR), opening up new ideas for cotton futures price prediction.

However, despite some achievements in cotton price forecasting, there is still room for further improvement and refinement in existing forecasting methods. For example, the processing of time price series requires further exploration to fully grasp the key information hidden in the data, while more effectively utilizing the local features of the original sequence. In view of this, based on relevant data from January 2, 2019 to December 18, 2024, this article constructs an

ISSN: 2710-0723

LSTM model to predict cotton futures prices, aiming to further improve the accuracy and reliability of the prediction and provide more valuable references for the development of the cotton industry.

2. Model Related Theories

The LSTM model, also known as the Long Short Term Memory Network model, was innovatively proposed by Hochreiter and Schmidhuber in 1997 and has a milestone significance in the development of neural networks. In traditional recurrent neural networks (RNNs), there is a tricky problem of gradient vanishing or exploding. When dealing with long sequence data, as the time step increases, the gradient gradually approaches 0 (gradient disappearance) or increases sharply (gradient explosion) in the backpropagation process, which makes it difficult for the model to learn long-term dependencies and severely limits the performance of RNNs in handling complex time series tasks. The emergence of LSTM models has successfully broken this dilemma. LSTM effectively alleviates the gradient problem by introducing memory units and a series of sophisticated gating mechanisms, enabling the model to handle long sequence data excellently. Not only that, LSTM can also serve as a complex nonlinear unit and be widely used to build larger deep neural networks, providing powerful tools for solving various complex machine learning problems.

The core mechanism of LSTM lies in its unique cellular state and various "gate" structures. In long-term memory networks, there exists a data channel that runs through the entire sequence, which is the key to preserving long-term information in LSTM. In the initial stage, the forget gate takes the lead by reading input information and passing it to the sigmoid function. The sigmoid function is like an intelligent filter that determines which data should be retained and which data can be removed based on the characteristics of the input information. The filtered data then enters the input gate. The responsibility of the input gate is to determine which new information needs to be updated into the cellular state. Subsequently, the update gate will integrate the new information discovered by the neural network at the current time step into the cell state, thereby achieving dynamic updates of the cell state. Finally, the data enters the output gate. The output gate will transfer the previous hidden state and the current input to the sigmoid function. After being processed by the sigmoid function, the newly obtained cell state will be transferred to the tanh function, and the output result of the tanh function will be multiplied by the output result of the sigmoid function. Through this operation, the output gate can accurately determine the information that the hidden state should carry and output it. These output information will be passed on to the next time step, providing important basis for subsequent calculations. It is through this series of interlocking mechanisms that LSTM achieves effective memory and processing of key information in long sequence data.

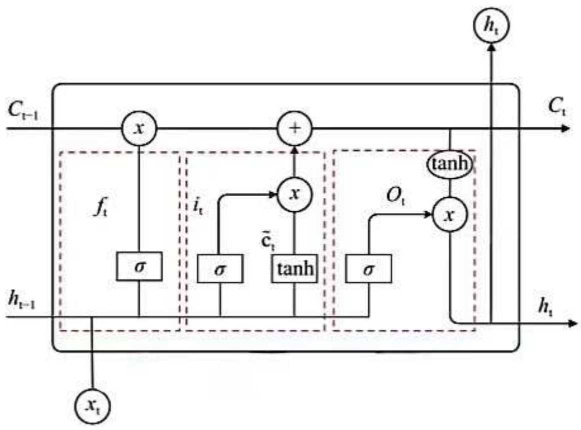

Figure 1. Flow Chart of LSTM Model

ISSN: 2710-0723

3. Empirical Analysis

3.1. Data Description

In the field of financial market research, cotton futures, as an important commodity futures variety, are affected by numerous factors in terms of price fluctuations. This study focuses on cotton futures 3128B, with its daily closing price as the core research object, aiming to deeply analyze the laws and driving factors behind the trend of cotton futures prices.

The study selected data from January 2019 to December 2024 as samples, with the price unit of yuan/ton. The included data not only includes daily closing prices, but also includes the highest and lowest prices, which can comprehensively reflect the price fluctuation range of cotton futures on each trading day. At the same time, in order to explore the impact of macroeconomic factors and international markets on cotton futures prices, the data also includes key indicators such as import volume, consumer price index, and international cotton prices. These data are all sourced from the authoritative Zhengzhou Stock Exchange, ensuring the reliability and accuracy of the data.

However, due to the fact that futures trading is not conducted daily, there are some missing values in the data. In order to ensure the scientific validity and effectiveness of the research results, we carefully processed the missing values. After a series of rigorous data cleaning and processing work, 1409 valid data were finally obtained.

Table 1. Experimental Part Data

transaction Date	variety Code	Open today	highest price	lowest price	Close today	settlement	volume	Position
2019-01-02	CF905	14835	14960	14835	14890	14900	72680	360612
2019-01-03	CF905	14860	14890	14750	14865	14810	122062	365672
2019-01-04	CF905	14875	14995	14855	14955	14920	176776	370916
2019-01-07	CF905	14995	15090	14940	15050	15020	144776	365992
2019-01-08	CF905	15090	15090	14960	15055	15025	131898	372034

3.2. Evaluation Criteria

The model is evaluated using RMSE, MAE, and R2, and the calculation formula is as follows:

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

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

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

Among them, yi represents the true value, y ^ i represents the predicted value, ȳ i represents the average of the true values, and n is the number of data points. RMSE is commonly used to represent the error between the predicted results of regression task models and the true values. For larger errors, the weight is higher, ranging from 0 to infinity, with smaller values being better; MAE represents the error between the predicted result and the absolute value of the true value. The weight of the error value is consistent, ranging from 0 to infinity, with smaller

ISSN: 2710-0723

values being better; R2 normalizes the square of the difference between the predicted result and the true value, making it easier to compare the differences between models. The value ranges from 0 to 1, with a closer value to 1 indicating a better model.

3.3. Model Prediction

3.3.1. Parameter Settings

Firstly, a comprehensive and detailed processing was carried out on the historical data collected from January 2019 to December 2024. In the data preprocessing stage, considering the dimensional differences of different feature variables, the maximum minimum normalization method is adopted to map various types of data (including daily closing prices, highest prices, lowest prices, import volumes, consumer price indices, and international cotton prices, etc.) to the [0,1] interval, ensuring that the model will not be biased during training due to differences in variable scales. After completing data normalization, divide the processed data into training and testing sets in a ratio of 80% and 20%. The LSTM model underwent high-intensity training on the training set, with a total of 200 training sessions. During the training process, by continuously adjusting the parameters of the model, such as learning rate, number of hidden layer neurons, etc., the model gradually fits the changing pattern of cotton futures prices.

After training, evaluate the performance of the model using the test set. The evaluation indicators include root mean square error (RMSE), mean absolute error (MAE), etc. These indicators can comprehensively measure the degree of deviation between the predicted and actual values of the model, thereby accurately judging the prediction accuracy of the model. The evaluation results are presented in a visual chart format (as shown in the following figure), clearly demonstrating the performance of the model on the test set.

This study is facing a larger and more complex dataset, and has optimized the model code settings to adapt to different market environments and data characteristics. At the same time, in the process of dividing and using the training and testing sets, some losses are inevitably generated due to overfitting or underfitting during the model training process. These losses are also presented in the form of charts, providing important basis for subsequent model improvement. Based on the changes in training loss and validation loss, the optimal number of training epochs can be determined. Generally, the optimal number of training rounds is chosen when the validation loss reaches its minimum value. At this point, the model performs best on the validation set and can ensure the accuracy of the model in actual prediction to a certain extent. In this experiment, as the number of training rounds increases, both the training loss and validation loss continue to decrease and stabilize after a certain number of rounds, indicating that the model gradually converges during the training process and can effectively learn the patterns in the data. For example, in the early stages of training, the loss value is relatively high, but after 50 rounds of training, the loss value remains basically unchanged, indicating that the model has reached a good learning state. Secondly, the line direction between the predicted value and the true value is basically consistent, such as maintaining the same trend of change during the price rise or fall stage, indicating that the LSTM model can accurately capture the long-term trend of cotton futures prices. For example, in 2023, cotton futures prices showed a significant decline due to policy adjustments, and the predicted value curve also decreased synchronously. This means that the model has a good response to price fluctuations caused by policy factors.

Figure 2. Data Trend Chart

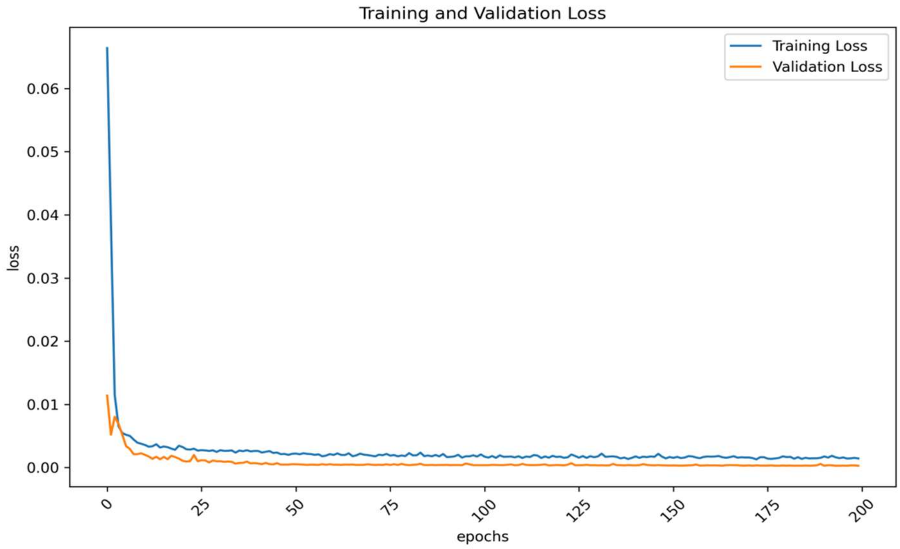

Figure 3. Fit between Training and Testing Sets

(1) Learning rate

The learning rate plays a crucial role in the model training process, as its size directly determines the speed of model parameter updates, which is closely related to the stability and final performance of the model. When the learning rate is too high, the model takes too big a step in the parameter update process, which can easily lead to missing the optimal solution during training, falling into the dilemma of local optima, and even overfitting, resulting in the model performing well on the training set but having poor generalization ability in the test set or practical applications. On the contrary, if the learning rate is too low and the model parameters are updated slowly, the training process will become extremely long, which may lead to insufficient model training and inability to effectively learn potential patterns in the data.

Liu Yang (2024) used a ten fold decreasing strategy between 0.1-0.0001 to explore the learning rate in his research on predicting relevant time series. By continuously trying different learning rates, the convergence and final performance of the model during training were observed. In this study, taking into account the characteristics of cotton futures data and the stability of model training, we kept the learning rate at the default value of 0.001. This value is in the middle range of Liu Yang's research. In the preliminary experiments, we compared multiple learning

ISSN: 2710-0723

rates and found that a learning rate of 0.001 can effectively avoid the model from falling into local optima or overfitting while ensuring the training speed of the model, and maintain a relatively stable convergence state during the training process.

(2) Time window length and dropout rate

Time window length is a key concept in time series analysis, which refers to a fixed time range selected from time series data. In the scenario of predicting the closing price of cotton futures in this study, the time window is used to select past historical data to predict the closing price of the next time point, or to sample, process, and observe market volatility signals. The choice of time window will significantly affect the accuracy of prediction and signal processing. If the time window is too short, the model cannot fully capture the long-term trend and cyclical characteristics of price changes; If the time window is too long, it may introduce too much noise data, which can also interfere with the predictive performance of the model.

This article sets the time window as the first five days, with a length of 5, and uses the closing price data of cotton futures in the first five days to predict the closing price of the next day. In the preliminary experiments, we tested the impact of different time window lengths (such as 3 days, 5 days, 7 days, etc.) on the predictive performance of the model. We found that when the time window was 5 days, the model could capture short-term price fluctuations while also taking into account long-term trends, resulting in ideal predictive performance.

Dropout rate is a regularization method used in the training process of neural networks. It refers to randomly discarding a portion of the activation values of neurons during the training process, so that the network does not overly rely on certain specific combinations of neurons, thereby enhancing the model's generalization ability. The dropout rate has a significant impact on the model's generalization ability and training speed. If the dropout rate is set too high, a large number of neurons may be discarded, and the model may not be able to learn enough effective information, resulting in slower training speed and decreased model performance; If the dropout rate is set too low, it cannot effectively prevent overfitting from occurring. This article ultimately sets the dropout rate to 0.25 for experimentation. Through multiple experiments comparing the performance of the model on the training and testing sets under different dropout rates, it was found that when the dropout rate is 0.25, the model can effectively prevent overfitting while maintaining good training speed and generalization ability, enabling the model to exhibit stable predictive performance on different datasets.

(3) Network layers and hidden layer nodes

The number of layers in a neural network determines its depth, which generally includes input layers, hidden layers, and output layers. In this experiment, the network layers of the model include input layer, hidden layer, regularization layer, and fully connected layer. The input layer is responsible for receiving external data, such as various price data of cotton futures, macroeconomic indicators, etc; The hidden layer is the core part of the model for feature learning and data transformation, which maps complex input data through nonlinear activation functions; Regularization layers (such as using dropout methods) are used to prevent overfitting of the model and enhance its generalization ability; The fully connected layer integrates the features output by the hidden layer and outputs the final prediction result. The selection of the number of hidden layer nodes usually depends on experience, experimentation, and cross validation. The insufficient number of nodes and limited expressive power of the model may lead to underfitting and inability to capture complex features in the data, resulting in unsatisfactory performance of the model on both the training and testing sets; However, with too many nodes, the complexity of the model increases significantly, which may lead to overfitting, sensitivity to training data, and poor generalization ability on the test set.

Due to the relatively small amount of data in this study, after multiple experiments and comparative analysis, the hidden layer nodes were set to 10. During the experiment, we

ISSN: 2710-0723

gradually increased the number of hidden layer nodes and observed the loss changes and prediction accuracy of the model on the training and testing sets. When the number of hidden layer nodes is 10, the model can fully learn data features while avoiding overfitting caused by too many nodes, achieving good prediction results under limited data conditions.

3.3.2. Model Prediction Results

After completing the model run based on the above parameters, the results are presented in the form of intuitive charts. From the figure, it can be clearly seen that the prediction curve of the LSTM model almost coincides with the true value curve, and its prediction results are extremely close to the true value. This high degree of fitting preliminarily demonstrates the excellent performance of the LSTM model in cotton futures price prediction. Further in-depth analysis of key indicators such as MAE, R^2, and RMSE can more accurately evaluate the performance of LSTM models and the accuracy of the experimental results. Mean Absolute Error (MAE), as a key indicator for measuring the average absolute difference between predicted and true values, plays an indispensable role in evaluating the accuracy of model predictions. The MAE value of the LSTM model is only 117.45718, which means that on average, the deviation between the predicted cotton futures price and the actual price is within a very small range. Compared to other traditional models, such a low MAE value fully demonstrates that the LSTM model can sensitively and accurately capture subtle changes in cotton futures prices, thus reflecting the true level of prices more accurately.

Root Mean Square Error (RMSE) takes into account both the magnitude and direction of prediction errors, and assigns greater weight to larger errors, making it uniquely valuable in evaluating model stability and reliability. The RMSE value of the LSTM model is 153.78997, which is at a relatively low level. This result indicates that throughout the entire prediction process, whether facing small normal price fluctuations or large abnormal price changes, the LSTM model can effectively control the error range with its unique algorithm and structure, greatly reducing the deviation between the predicted results and the actual values. Compared with traditional models such as SVR, LSTM models exhibit stronger adaptability and stability in dealing with complex price fluctuations.

The coefficient of determination (R^2) is used to evaluate the goodness of fit of a model to data, with a range of values between 0 and 1. The closer the value is to 1, the better the model's fit to the data. The R^2 value of the LSTM model is as high as 0.97107, which means that the model can successfully explain 97.107% of the cotton futures price changes. This outstanding performance fully demonstrates that the LSTM model almost perfectly captures the complex internal laws behind cotton futures price fluctuations, and can deeply explore key information in the data, thereby achieving a high degree of fitting to price trends. Compared with other models, the LSTM model has shown overwhelming advantages in data fitting and can provide more reliable basis for cotton futures price prediction.

Table 2. Prediction Results Indicators

index	MAE	RMSE	R^2
LSTM	117.45718	153.78997	0.97107

4. Model Comparison

In this cutting-edge exploration of cotton futures price prediction, we focus precisely on the in-depth comparative study between LSTM model and SVR (Support Vector Regression) model. MAE (Mean Absolute Error), RMSE (Root Mean Square Error), and R^2 (Coefficient of Determination) are key quantitative indicators for measuring the predictive ability of a model, and have become the core evaluation criteria throughout the entire study.

ISSN: 2710-0723

When building the experimental framework, the optimal parameter combination was set by repeatedly debugging different models, aiming to fully stimulate the maximum potential of each model. After detailed parameter optimization of the SVR model, actual measurements were conducted for cotton futures price prediction tasks. The results showed that the mean absolute error (MAE) of the SVR model remained stable at 145.9394, the root mean square error (RMSE) was 181.0056, and the coefficient of determination (R2) reached 0.9599. However, when these data are compared horizontally with the corresponding indicators of the LSTM model under the same conditions, the outstanding performance of the LSTM model becomes clear, far surpassing the SVR model in prediction accuracy, and all indicators show significant advantages.

In depth analysis of the root cause of the lower prediction accuracy of SVR model compared to LSTM model mainly lies in the fact that SVR, as a traditional model, has natural limitations when facing data such as cotton futures prices, which are full of complex fluctuations, highly nonlinear features, and dynamic time series changes, based on the principle of minimizing structural risk. The SVR model is difficult to effectively capture the complex nonlinear relationships between data points when processing data, and is less sensitive to long-term dependency features in time series, resulting in bias in predicting complex trends. The LSTM model, with its unique gating mechanism, can effectively remember and process long-term dependency information in time series, flexibly learn complex patterns in data, and have stronger adaptability and predictive ability for dynamic changes in cotton futures prices, thus standing out in prediction tasks and achieving more accurate prediction results.

5. Conclusion

In the field of cotton futures market research, accurate prediction of cotton futures closing prices is of crucial importance for investors to grasp trading opportunities and effectively manage risks. This study aims to accurately predict the closing price of cotton futures by constructing a Long Short Term Memory (LSTM) model. For this purpose, we extensively collected historical data on cotton futures, covering multiple key indicators such as closing price, highest price, lowest price, trading volume, and open interest. These data provide rich information dimensions for model training. During the model construction phase, we carefully set and debugged multiple key parameters. The learning rate, as an important factor affecting the speed of parameter updates during model training, directly affects the convergence speed and final performance of the model. After multiple experimental comparisons, we have determined an appropriate learning rate to ensure that the model does not miss the optimal solution, get stuck in local optima, or overfit during training due to a high learning rate, nor does it experience slow training or insufficient model training due to a low learning rate.

The setting of the number of network layers and hidden layer nodes is equally crucial. The number of network layers determines the abstraction level of data features in the model, while the number of hidden layer nodes affects the expression ability of the model. By continuously adjusting the number of network layers and hidden layer nodes, and combining cross validation methods, we ultimately determined a parameter combination that can balance model complexity and prediction accuracy. In addition, to prevent overfitting of the model, we introduced dropout rate as a regularization method, which randomly discards the activation values of some neurons to enhance the generalization ability of the model. After repeated experimentation, a suitable dropout rate has been determined, which enables the model to effectively avoid excessive dependence on certain specific combinations of neurons during training. Through the above series of parameter settings and model construction, we use the LSTM model to predict the closing price of cotton futures. The results show that setting the dropout rate reasonably while increasing the influencing factors of variables and adjusting parameter values can significantly affect the prediction accuracy of the model. The LSTM model

ISSN: 2710-0723

has demonstrated good predictive performance and can predict the closing price of cotton futures with small errors, providing important reference and inspiration for subsequent related research. It can be clearly seen from the experimental process that appropriate parameter settings and model optimization play a decisive role in improving the prediction accuracy of LSTM models.

However, it should be noted that cotton prices are influenced by numerous complex factors both domestically and internationally. As Zhu Yan (2018) conducted in-depth research on cotton prediction and analysis by selecting variables from three dimensions: supply, demand, and policy. If analysis is based solely on historical price data, there are obvious limitations. In addition to considering micro level factors such as price and trading volume, it is also necessary to comprehensively consider multiple macro level factors. For example, fluctuations in international cotton prices directly affect the pricing of the domestic cotton market; The import and export situation reflects the supply and demand relationship in the domestic and international cotton markets, and has a significant impact on prices; Natural factors such as climate conditions can affect the yield and quality of cotton, which in turn affects cotton prices. So future research should further incorporate these macro and micro factors on the basis of existing models, comprehensively optimize the model structure and parameter settings, in order to improve the prediction accuracy of cotton futures prices, reduce the volatility of prediction results, and provide more reliable decision-making basis for participants in the cotton futures market.

Acknowledgments

This work is supported by the school level scientific research project of Anhui University of Finance and Economics "Prediction and Analysis of Cotton Futures Prices Based on LSTM Model" (Grant No: XSKY25085).

References

[1] Liu Yang, Li Yuhan, Dou Baoming Cotton futures price prediction method based on LSTM [J]. Software, 2024, 45 (07): 8-12+86.

[2] Shi Lu Cotton futures price prediction based on improved LSTM model [J]. Journal of Henan University of Animal Husbandry and Economics, 2023, 36 (03): 28-34.

[3] Song Yulan, Qian Kun Analysis and Prediction of Cotton Prices in China [J]. Price Monthly, 2023, (06): 29-35.

[4] Jiang Zhihang Research on Cotton Price Prediction Based on BILSTM Neural Network [D]. Chongqing Normal University, 2021.

[5] Wu Ye, Liu Tingting, Fang Shaoyong Research on Cotton Price Prediction in China Based on MIV-GA-BP Neural Network [J]. Cotton Textile Technology, 2018, 46 (07): 77-80.

[6] Zhu Yan Analysis of Factors Influencing Cotton Prices in China and Price Prediction [D]. Donghua University, two thousand and eighteen

[7] Wang Weiguo, Zhao Xinmin Research on the Prediction Method of Cotton Futures Prices in China Based on EMD-BP Neural Network [J]. Journal of Shihezi University (Philosophy and Social Sciences Edition), 2013, 27 (01): 78-80.