Soybean Futures Price Prediction Based on CNN-LSTM Model of Bayesian Optimization Algorithm

Yulan Luo

School of Finance, Guangdong University of Foreign Studies, Guangzhou, China, 510006

2603132744@qq.com

Abstract. In recent years, the complex international environment and economic situation have made soybean futures prices increasingly unstable, which is not conducive to financial stability. Therefore, this paper uses a BO-CNN-LSTM model to accurately predict soybean futures prices and to manage price fluctuations for investors and governments. Firstly, LSTM network is employed to predict soybean futures prices using the local features extracted by CNN network. In addition, CNN-LSTM hyperparameters are optimally solved using Bayesian optimization algorithms. Finally, the constructed model is compared with BP neural network, LSTM model and CNN-LSTM model. This paper selects the basic daily data of the soybean futures contract No.1 of Dalian Commodity Exchange from 2014 to 2021 for research. According to the results, CNN-LSTM models based on Bayesian optimization algorithms perform best. Compared with the basic CNN-LSTM model, MAPE increased by 44.17%, RMSE increased by 24.61%, MAE increased by 41.48%, and R2 increased by 0.06%, which demonstrates Bayesian optimization's superiority.

Keywords: BO-CNN-LSTM, Time series prediction, Soybean futures.

1. Introduction

China 's soybean futures contract was listed on the Dalian Commodity Exchange in December 1993. With the gradual improvement of China's futures market, its price discovery, risk control and other functions have been gradually valued [1]. Despite being the world's largest soybean consumer, China has a low soybean self-sufficiency level, and is reliant mostly on imports. In recent years, the complex environment and severe economic situation at home and abroad have made soybean futures prices more and more unstable [2]. Therefore, in-depth analysis of the fluctuation law of soybean futures prices and accurate prediction of the trend of soybean futures prices will help soybean futures hedgers to reasonably avoid price risks, futures speculators to invest rationally [3], and help the government to formulate relevant price control policies, strengthen market supervision, and promote the stable development of financial markets.

Traditional statistical methods and artificial intelligence methods are the two main categories of financial time series prediction methods [4]. Statistical methods mainly use moving average autoregressive model [5], exponential smoothing model [6] and so on for modeling and prediction. In September 1927, Yule first published the literature on the basic model of autoregressive, and in 1931, he proposed the basic model of moving average. Robert G. Brown (1960) expected to solve the defect that the moving average can not reflect the long-term trend. Therefore, the exponential smoothing method was proposed to obtain the future trend value by weighting the past data with different weights. This method is very practical for the prediction of financial time series [7]. Zhang Yanyu (2017) established a VAR model of gold futures series, pointing out that the price of gold futures contracts on the Shanghai Futures Exchange is affected by factors such as the Shanghai Composite Index, DJI, and crude oil prices. These factors can be included in the influencing factors when predicting trends [8]. Wen et al. compared the predictive ability of moving average models such as ARIMA, ARCH and (GARCH) and exponential smoothing models for commodity futures such as cocoa beans and corn, indicating that the exponential smoothing model is more suitable for daily data, while the moving average model is very effective at predicting weekly data [6]. There are certain limitations to the statistical model because futures market prices fluctuate irregularly.

In recent years, with the extensive improvement of computer capabilities, machine learning has received extensive attention from academia because of its excellent learning effect, and it has been applied to financial time series prediction [9]. Traditional ANN algorithms include: Back Propagation (BP), Bayesian Learning (BL), Random Decision Forests (RDF), Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), etc. Yang Jianhui et al. (2011) proposed a nonparametric method SVR and an improved futures price prediction model, which is superior to the traditional parameter method in prediction accuracy [10]. Dhar S.et al. used decision tree and random forest ensemble algorithm to predict the return of stocks in order to reduce investment risk [11]. Wei Wenxuan used the improved radial basis function (RBF) to predict the Chinese stock market. Based on the comparative experiments, it can be shown that the model converges quickly and predicts accurately at high levels [12]. The machine learning model can solve the nonlinear problem well, but most of the algorithms have high requirements for sample distribution. In the calculation process, there will be problems such as low generalization ability, over-fitting, and only local optimum.

Further in-depth research shows that deep learning pays more attention to the overall centralized solution in financial time series prediction, which can well consider long-term problems. Deep learning models mainly include convolutional neural network (CNN), deep belief network (DBN), recurrent neural network (RNN) and variant models. Fan Junming et al. constructed a multi-layer LSTM network price prediction model to predict soybean futures prices. According to the results, LSTM network model provides better prediction results than ARIMA model, MLP model, and SVR model [13]. Zhang Jie et al. proposed the MAN model under the LSTM encoder-decoder framework, using the multi-level attention mechanism to extract the potential characteristics of domestic and foreign soybean futures historical transaction information, and integrating external factors such as weather and investor attention to achieve the prediction of the closing price of Chinese soybean futures [14]. Jing Nan et al. proposed the CNN-LSTM model, which introduced the attention mechanism at the end of the LSTM to improve the prediction of Shanghai copper prices at high frequencies. Compared with CNN, LSTM, CNN-LSTM and other benchmark models, the CNN-LSTM hybrid model with attention mechanism improves the accuracy of prediction [15]. Prediction results, however, are highly influenced by hyperparameter setting. The deep learning model needs to spend a lot of time on experiments to find the optimal hyperparameter, which is inefficient.

Therefore, aiming at the problem of soybean futures price prediction, this paper combines two deep learning methods of convolutional neural network (CNN) and long short-term memory network (LSTM), and uses Bayesian optimization method to select the hyperparameters of CNN and LSTM, and constructs a convolutional neural network model based on Bayesian optimization algorithm (BO-CNN-LSTM). In the empirical study, the soybean No.1 trading data of Dalian Futures Exchange from 2014 to 2021 were selected for prediction, and compared with the prediction results of CNN-LSTM model without Bayesian algorithm and traditional BP and LSTM models to evaluate the model's effectiveness and feasibility. The innovation of this paper is:

(1) From the microscopic point of view, select the basic market indicators of soybean futures as influencing factors, the basic market and soybean futures prices associated, therefore, can better predict soybean futures prices.

(2) Financial time series are processed using the CNN and LSTM algorithms combined to maximize their advantages. In CNN, local features are extracted from data and combined to form high-level features. The LSTM can extend the time dimension and retain the influence of long-term memory on the present moment. In the task of soybean futures price forecasting, it is necessary to consider the multi-dimensional correlation of time series data. Therefore, the CNN-LSTM model is more suitable for soybean futures price analysis and prediction.

(3) CNN-LSTM model parameters are adjusted using the Bayesian optimization algorithm. Bayesian parameter adjustment has fewer iterations and faster speed, which can reduce the calculation cost. It is still robust to non-convex problems, thus improving the accuracy of soybean futures price prediction.

The paper consists of four parts, each of which includes the following information: The first chapter is an introduction that explains the background and significance of this topic. In the second chapter, the basic principles of convolutional neural network (CNN) feature extraction, long short-term memory network (LSTM) time series prediction and Bayesian optimization algorithm hyperparameter optimization are described. The third chapter, the empirical research of soybean futures price forecast. The fourth chapter, summary and outlook.

2. Model introduction

2.1. CNN

The construction of soybean futures price prediction model needs to consider the relationship between multi-dimensional samples. Convolutional neural network can abstract basic features from space and generalize them dynamically. With convolution calculations and deep structure, the convolutional neural network (CNN) is a kind of feedforward neural network. As a representative algorithm of deep learning, it can effectively extract the features of two-dimensional images and high-dimensional data. Generally, neural networks consist of input, hidden, and output layers, with convolutions as well as poolings and fully connected layers in the hidden layer. As shown in Figure 1, the structure is as follows.

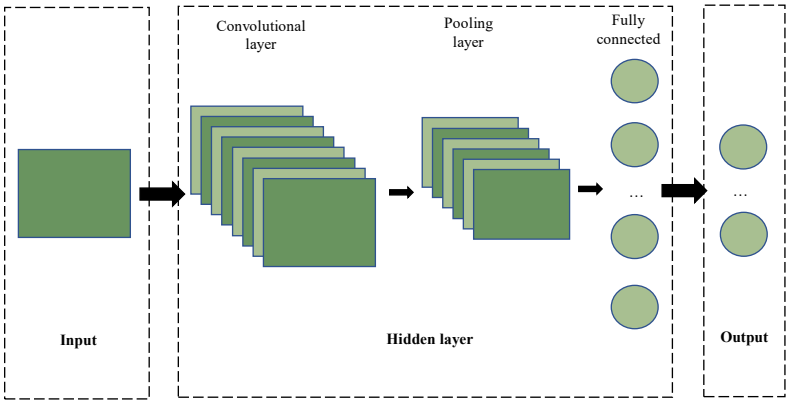

Figure 1. Convolutional neural network structure

(1) Input layer

A main purpose of the input layer is to preprocess the data and reduce the influence of the data dimension difference on the model, so as to facilitate the subsequent processing of each layer and improve the learning efficiency of the model. The input of CNN is composed of continuous M time-step feature vectors. Let x_t denote the eigenvectors of the t_{th} time step, then the sequence constructed in this section is

$$X_i = [x_{(t-M+1)}, x_{(t-M+2)}, \cdots, x_t]^T \tag{1}$$

(2) Hidden layer

(a) Convolution layer

In the convolution layer, multiple convolution kernels are used to extract the features of the input data. Weight coefficients and deviations are assigned to each element of the convolution kernel. In order to adapt to the feature extraction of financial time series, the convolution layer is improved. Feature surfaces are formed by the output of the improved convolution layer, and the neurons are filled with these surfaces. In the improvement process, we use the M×N (N is the number of influencing factors mentioned above) dimension area as the connection between the upper and lower layers of neurons. Additionally, by using the convolution kernel associated with each feature surface, the value of each neuron is calculated. For the first convolution layer, the operation formula is:

$$y_{k,j}^{(1)} = f\left(\sum_{s=1}^{N}\sum_{t=1}^{M}\omega_{k,s,t}^{(1)} y_{s,j+t-1}^{(0)} + b_k^{(1)}\right) \tag{2}$$

Among them, $y_{k,j}^{(1)}$ is the output value of the j_{th} neuron of the k_{th} feature plane in the first convolution layer, f is the activation function, default to Relu, $w_{k,s,t}^{(1)}$ is the weight of the s_{th} row and t_{th} column in the k_{th} convolution kernel, $y_{s,j+t-1}^{(0)}$ is the input data, $b_k^{(1)}$ is the bias value corresponding to the k_{th} convolution kernel.

(b) Pooling layer

In the convolutional layer, after features are extracted, feature selection and information filtering will be performed on the output feature map, and the feature matrix will be generated after dimensionality reduction. There are a variety of pooling functions, such as average and maximum pooling. After pooling, the parameters are simplified, the model size is reduced, the calculation speed is accelerated, and the robustness and goodness of fit of the model are improved.

(c) Fully connected layer

A convolutional neural network's fully connected layer is located at the end of the hidden layer. To obtain more discriminative features, it can combine the convolutional layer and the pooling layer nonlinearly.

Assuming that a total of K compressed feature surfaces are obtained after pooling, the S_{th} neuron is taken as an example, which is derived in the fully connected layer as follows:

$$y_s^{FC} = f\left(\sum_i x_i^* \times k_{i,s}^{(1)} + b_s^{FC}\right), s = 1, 2, \cdots, h \tag{3}$$

Here, x_i^* is the feature vector obtained in series, $k_{i,s}^{(1)}$ is the connection weight between the s_{th} neuron of the fully connected layer and the i_{th} element of the input vector, b_s^{FC} is the bias value of the s_{th} fully connected neuron, f is the ReLU activation function, and h is the number of neurons in the fully connected layer.

(3) Output layer

The output layer is fully connected with the full connection layer, and the output value y_j of the j output layer nodes can be calculated as follows:

$$y_j = \sum_{s=1}^{h} y_s^{FC} \times k_{s,j}^{(2)} + b_j^{Output}, j = 1, \cdots, T \tag{4}$$

Among them, $k_{s,j}^{(2)}$ is the connection weight between the j_{th} neuron in the output layer and the s_{th} neuron in the fully connected layer, and b_j^{Output} is the bias value of the j_{th} output layer neuron; t is the number of output categories, T=2.

Calculating the probability of an input sequence belonging to a particular quality mode is done by applying the softmax function:

$$S_j = soft\ \max(y_j) = \frac{e^{y_j}}{\sum_{t=1}^{2} e^{y_t}}, j = 1, 2 \tag{5}$$

Here, S_j is the probability value of the input data belonging to the type j abnormal pattern, and e is the natural constant.

The soybean futures price prediction data set in this paper is a multi-dimensional time series, and there is coupling between different features and factors. Therefore, one-dimensional convolution kernel is used to input multivariate time series through different channels to retain more information.

The information of each influencing factor is extracted after processing by convolutional neural network.

2.2. LSTM

The data selected for soybean futures price prediction is the daily data from 2014 to 2021, and the data volume is relatively large. LSTM can provide a solution to long-term memory problems and huge data volumes when predicting soybean futures. As a special type of RNN, LSTMs are mostly implemented through three gating logics, namely the forgetting gate, input gate, and output gate. They determine the memory and forgetting degree of past information and instant information, and have long-term memory function. The proposed method is intended to solve the problems of gradient disappearance and gradient explosion that occur during long sequence training. Figure 2 shows the specific three gate structures.

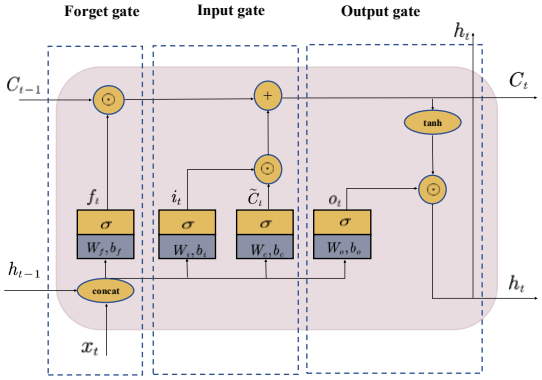

Figure 2. LSTM schematic diagram

(1) Forget gate

The main role is to decide whether to discard some information from memory cell c. The information that the input X_t of the t_{th} layer and the output h_{t-1} of the previous layer remain in the long-term state c_t of the current layer after the forgetting gate is filtered out. The activation function σ is used to process the information obtained from h_{t-1} and X_t to obtain the value of 0 to 1, 1 means all retained, 0 means all forgotten. The calculation formula of forgetting gate is as follows:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{6}$$

Where w_f is the weight matrix of h_{t-1} and x_t to the forgetting gate, b_f is the bias, and σ is the sigmoid function.

(2) Input gate

This mainly determines what new information is added to the state of a cell. It includes two parts: first, h_{t-1} and x_t are passed through the sigmoid layer to obtain i_t, which determines what values need to be updated. At the same time, the information creates a new candidate cell state vector $\tilde{C}_t$ through the tanh layer, and the state will be updated with the new vector. Next, the memory block will use these two information to update the state, add the updated value to the current memory cell, and generate a new memory state C_t through these two parts. The formula is as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{7}$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{8}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{9}$$

Among them, W_i and W_c are weight matrices, b_i and b_t are corresponding biases, and $\odot$ represents element multiplication.

(3) Output gate

In the output gate, the information to be output is automatically determined, and the degree of output is calculated. First, the information and hidden layer state at the previous moment are input into the sigmoid layer to calculate the part of the cell state that can be output. Afterward, the current state of the cell enters the Tanh layer for processing to determine a value between [-1, 1]. The above two parts of the results are multiplied to obtain the part that determines the final output. Here is the calculation formula:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{10}$$

$$h_t = O_t \odot \tanh(C_t) \tag{11}$$

Where W_o is the weight matrix, b_o is the corresponding bias, and $\odot$ represents the element multiplication.

2.3. Bayesian optimization algorithm

When using the CNN-LSTM model to predict soybean futures prices, Selecting the appropriate hyperparameters is essential, therefore, the model hyperparameters are optimized using the Bayesian optimization algorithm. In Bayesian optimization, the Bayesian theorem guides the search for the minimum and maximum values of the objective function. Grid search and random search do not use the information of the searched points, while Bayesian optimization uses the historical information observed before to perform the next optimization at each iteration. The computational cost of some model objective functions is very large, such as convolutional neural networks. Optimization and evaluation may take one day or several days at a time, so using Bayesian optimization algorithms can greatly improve search efficiency. Bayesian optimization problem consists of four parts: objective function, domain space, probabilistic surrogate model and collection function.

2.4. Framework of this article

CNN has the advantage of spatial dimension, which can extract the local features between multi-dimensional samples, and integrate the proposed fragment feature vectors. The LSTM can extend the time dimension and retain the influence of long-term memory on the present moment. Combining the characteristics of the two types of models, this paper first concatenates the settlement price and other seven basic market shadow factors into a vector representation, uses CNN 's short sequence feature abstraction to extract high-dimensional features, and then uses LSTM to synthesize short sequence high-dimensional features for time series prediction. Following are the specific steps:

Step 1: Obtain the soybean futures price data, divide the training set and the test set, normalize the training set and input it into the CNN network for training.

Step 2: Influence variables and predictive variables enter the CNN network for feature extraction. The convolution neural module includes convolution layer, pooling layer and fully connected layer. After optimizing the model parameters by Bayesian algorithm, the hierarchical structure of abstract features is gradually extracted through convolution layer, the pooling layer is sampled and merged, the fully connected layer is reorganized, and the feature sequence is output.

Step 3: The feature vector enters the LSTM layer after the Bayesian algorithm optimizes the parameters to learn the characteristics of the soybean No.1 futures price sequence to obtain the prediction sequence.

Step 4: Using the softmax function to calculate, the output data is inversely normalized, and finally the predicted value of the settlement price of soybean No.1 futures is obtained.

As shown in Figure 3, the overall hybrid model is operated as follows:

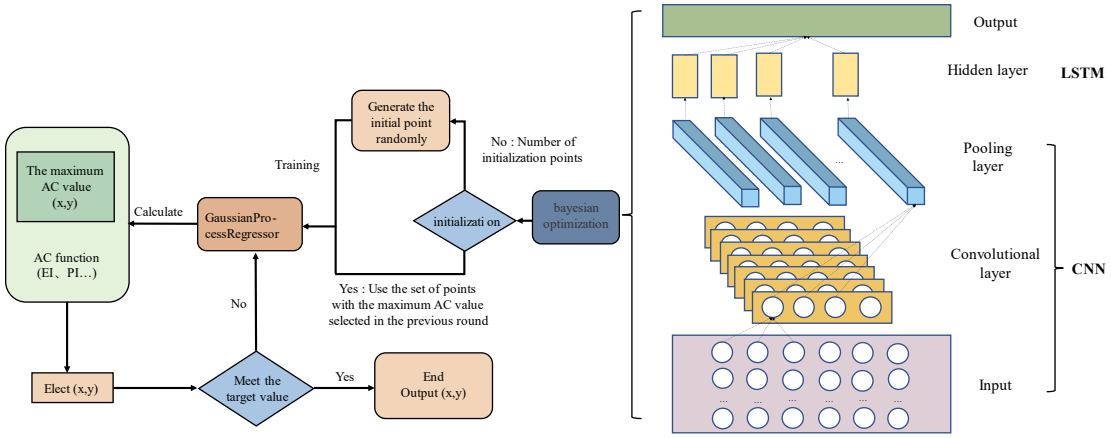

Figure 3. Principle of mixed model

3. Empirical study

3.1. Data selection and preprocessing

(1) Soybean futures data selection

Since China officially canceled the controversial temporary storage mechanism of soybeans in 2014, the market then determines the price of soybeans. Therefore, this paper selects the basic daily data of the yellow soybean No.1 futures contract listed on the Dalian Commodity Exchange from January 2014 to December 2021 for research, with a total of 1950 observation samples. Among them, opening price, highest price, lowest price, closing price, trading volume, transaction amount and open interest are used as input characteristics, and the settlement price is the prediction result. The data come from Dalian Commodity Exchange.

(2) Data preprocessing.

Using the maximum and minimum normalization method, the data is normalized before training to eliminate the effect of different dimensions. Following that, the training set and the test set are divided 9: 1. The normalization is shown in Formula 12:

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{12}$$

Where x is the specific value of the input feature, $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the corresponding feature.

3.2. Modeling Settings

(1) Evaluation index settings

For a comprehensive evaluation of the model's performance, this paper will choose four evaluation indicators, RMSE, MAE, MAPE and R^2, to build an evaluation system to measure its predictions. The calculation method is shown by the formula 13~17:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - p_i)^2} \tag{13}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - p_i| \tag{14}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - p_i|}{y_i} \times 100\% \tag{15}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - p_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{16}$$

$$\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i \tag{17}$$

Where y is the true value, p is the predicted value, i is the number of samples, and $\bar{y}$ is the average of n samples.

(2) Baseline model settings

For better evaluation of CNN-LSTM model based on Bayesian optimization, we construct BP neural network, LSTM model, and basic CNN-LSTM model as baselines.

Table 1. Interpretation and parameter setting of baseline model

Model	Interpretation	Parameter setting
BP neural network	Based on the error back propagation algorithm, BP is a multilayer feedforward neural network. It is a supervised learning neural network. A gradient descent method is used to approximate the minimum value in this method. [16].	Hidden layer: 9 Learning rate: 0.01 Permissible error: 0.001 Epochs: 100
LSTM model	A time-recurrent neural network, the LSTM, solves the issue of gradient explosion and gradient disappearance, which has plagued RNNs for years. [17].	BatchSize: 256 Iterations: 100 Learning rate: 0.01 HiddenUnits1=128 HiddenUnits2=128
CNN-LSTM model	The CNN-LSTM model combines the best features of CNN and LSTM. To retain historical information in long sequences, the LSTM model retains the characteristics, and the CNN model extracts the local features.	NoFilter1=64 FilterSize=3 BatchSize: 256 Iterations: 100 Learning rate: 0.01

(3) Model parameter settings

Prediction results are influenced greatly by hyperparameter settings in the experiment. The hyperparameters that need to be set in the model constructed in this paper are the number of convolution kernels, the size of convolution kernels, the number of hidden layer units, the size of batch processing, the learning rate and the number of iterations. According to the loss curve and a series of experiments, some hyperparameters are obtained: the number of iterations is 100, the batch size is 256, and the learning rate is 0.01. The representative network hyperparameters are optimized by Bayesian optimization algorithm. The optimized parameters are: the number and size of CNN convolution kernels; the number and size of hidden layers in the first layer of LSTM; and the number of hidden layers in the second layer. According to Table 2, hyperparameter selection and Bayesian optimization results are shown.

Table 2. Bayesian optimization hyperparameter range and selection results

Hyperparameter	Hyperparameter range	Hyperparameter value
FilterSize	[2, 16]	5
NoFilter	[2, 512]	76
HiddenUnits1	[10, 300]	273
HiddenUnits2	[10, 300]	136

3.3. Experimental result analysis

In this paper, the BO-CNN-LSTM prediction model is constructed to predict the price of China 's soybean futures. For the purpose of verifying the superiority of the model proposed in this paper, the model is compared with BP neural network and LSTM benchmark model, and the established evaluation index system is used to measure the effect of different models. The results are shown in table 3, and the comparison results of prediction accuracy of different models are shown in figure 5 ~ figure 8.

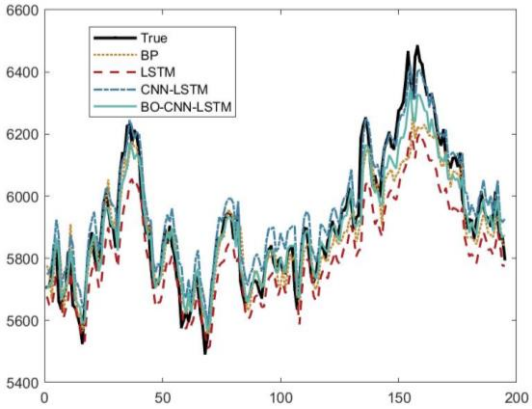

Figure 4. Comparison of prediction sets of different models

Table 3. Comparison of prediction accuracy between different models

Model	MAPE (%)	RMSE	MAE	R^2
BP neural network	4.35%	273.0575	259.9014	0.96657
LSTM model	1.25%	92.1162	75.8463	0.9895
CNN-LSTM model	1.20%	75.1851	69.7185	0.9940
BO-CNN-LSTM model	0.67%	56.6818	40.7992	0.9946

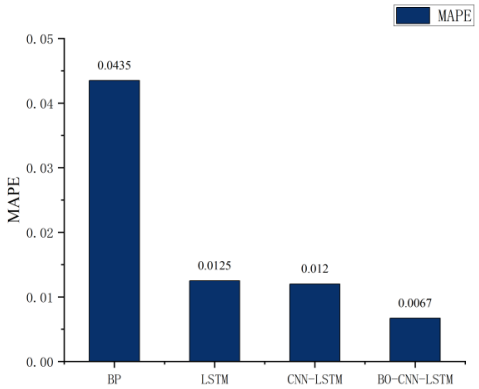

Figure 5. Comparison of MAPE values of different models

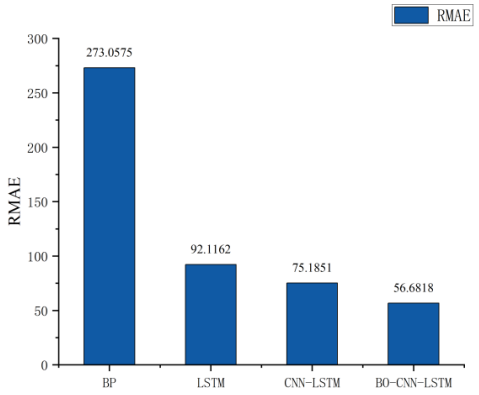

Figure 6. Comparison of RMAE values of different models

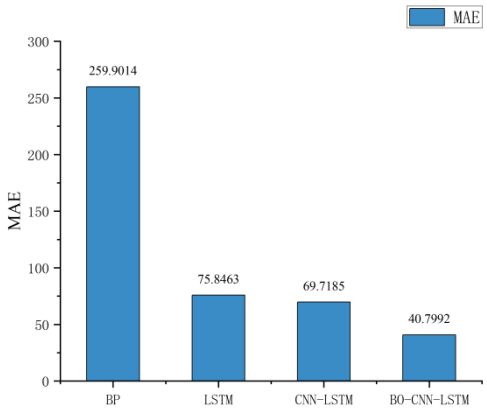

Figure 7. Comparison of MAE values of different models

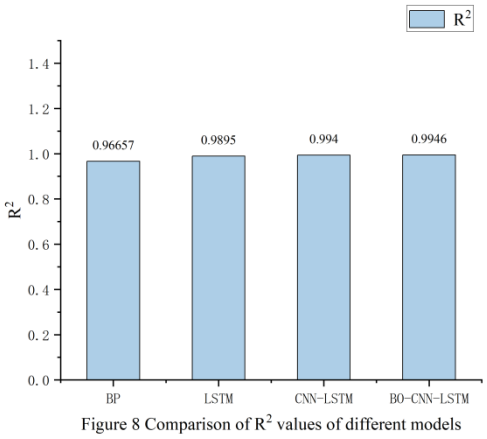

Figure 8. Comparison of R^2 values of different models

Based on the experimental results, the following can be concluded:

(1) There is significant improvement in prediction accuracy between LSTM, CNN-LSTM, and BO-CNN-LSTM models, compared to BP, because the deep learning model has stronger layer-by-layer adaptive feature extraction ability than machine learning [18]. After using the basic neural network LSTM, the evaluation index has been greatly improved. Among them, MAPE is increased by 71.26%, RMSE is increased by 66.26%, MAE is increased by 70.82%, and R^2 is increased by 2.37%.

(2) Compared to LSTM models alone, the CNN-LSTM hybrid model offers better evaluation index values. Among them, MAPE is increased by 4%, RMSE is increased by 18.38%, MAE is increased by 8.08% and R^2 is increased by 0.45%. The hybrid model proposed in this paper is found to improve goodness of fit and produce more reliable and accurate predictions. Due to the complexity and uncertainty of futures price fluctuations, the CNN-LSTM model can use a hybrid model to decompose complex prediction tasks. Firstly, the CNN model is used to extract local features between multi-dimensional samples, and then the LSTM model is constructed to predict specific values.

(3) BO-CNN-LSTM model performance has drastically improved with Bayesian optimization algorithms. Compared with the CNN-LSTM model, the evaluation indicators have been greatly improved. Among them, MAPE is increased by 44.17%, RMSE is increased by 24.61%, MAE is increased by 41.48%, and R^2 is increased by 0.06%. As can be seen, Bayesian optimization algorithm has great potential for deep learning time series prediction.

4. Conclusions and prospect

In this paper, a BO-CNN-LSTM neural network based on Bayesian optimization is proposed in order to predict soybean futures prices. To extract local features, CNN is used, which is then input into the LSTM model to predict time series, making the fusion network able to retain long-term

historical information. Additionally, the Bayesian optimization algorithm utilizes the historical tuning information throughout the whole process, improving the efficiency of parameter searching. Based on the results of the experiment, the following conclusions can be drawn:

(1) The basic market information of soybean futures is closely related to the price change of soybean futures, which can reflect the macro market, micro market and investors' psychological expectations, and can be used as a better predictor of soybean futures prices.

(2) The CNN-LSTM model makes full use of CNN to extract local features and LSTM for time expansion. As a result, it is more suitable for time series processing owing to its long-term memory function.

(3) Using Bayesian optimization algorithm to optimize the hyperparameters can not only improve the prediction accuracy but also improve the operation efficiency.

However, this paper does not consider the influencing factors of soybean futures prices comprehensively enough, and only predicts from the basic market. Therefore, in order to predict soybean futures prices more accurately, it is not only necessary to study from internal factors, but also to consider external factors affecting soybean futures prices.

References

[1] Zhou Dapeng, Mu Yueying. Decomposition of influencing factors of soybean futures market price in China based on VAR model [J]. Contemporary rural finance and economics, 2022, No.308(05): 55-59.

[2] Du Rong, Zhu Lijuan. Analysis of factors affecting soybean price changes in China [J]. China Oil, 2017,42 (06): 1-4 + 24.

[3] Xiong Tao, Bao Yukun. Research on soybean futures price prediction based on dynamic model average [J]. China Management Science, 2020, 28 (05): 79-88. DOI: 10.16381/j.cnki.issn1003-207x.2020.05.008.

[4] Xu Yulin, Kang Mengzhen, Wang Xiujuan, etc. Intelligent prediction of corn and soybean futures prices based on deep learning [J]. Smart Agriculture, 2022, 4 (04): 156-163.

[5] Ziegel E R. Tie series analysis, forecasting, and control [J]. 1995.

[6] Weng Y C, Shy J W. The comparison of the forecasting models of the raw material futures' prices [J]. Journal of Information and Optimization Sciences, 2010, 31(1): 129-145.

[7] Brown R G, Meyer R F. The fundamental theorem of exponential smoothing [J]. Operations Research, 1961, 9(5): 673-685.

[8] Zhang Yanyu. Empirical study on the influencing factors of gold futures price in China [D]. Central China Normal University, 2017.

[9] Xu Jiali. CNN-LSTM Shanghai gold futures price prediction based on attention mechanism [D]. Chengdu University of Technology, 2021. DOI: 10.26986/d.cnki.gcdlc.2021.000876.

[10] Yang Jianhui, Li Long. Option price forecasting model based on SVR [J]. System engineering theory and practice, 2011, 31 (05): 848-854.

[11] Dhar S, Mukherjee T, Ghoshal A K. Performance evaluation of Neural Network approach in financial prediction: Evidence from Indian Market [C] // 2010 International Conference on Communication and Computational Intelligence (INCOCCI). IEEE, 2010: 597-602.

[12] Wei Wenxuan. Application of Improved RBF Neural Network in Stock Market Forecasting [J]. Statistics and Decision Making, 2013, No.387 (15): 70-72. DOI: 10.13546/j.cnki.tjyjc.2013.15.035.

[13] Fan Junming, Liu Hongjiu, Hu Yanrong. Soybean futures price prediction based on LSTM deep learning [J]. Price Monthly, 2021, No.525 (02): 7-15. DOI: 0.14076/j.issn.1006-2025.2021.02.02.

[14] Zhang Jie, Zhen Liulin, Zhai Dongsheng. Soybean futures forecasting based on multi-level attention mechanism [J/OL]. System engineering: 1-11 [2023-03-13]. http://kns.cnki.net/kcms/detail/43.1115. N.20220718.1135.002.html.

[15] Jing Nan, Shi Zijing, Shu Yumin. High-frequency price prediction of Shanghai copper futures based on attention mechanism and CNN-LSTM model [J/OL]. China Management Science: 1-13 [2023-03-13]. https://doi.org/10.16381/j.cnki.issn1003-207x.2020.0342.

[16] Zhang Y, Wu L. Stock market prediction of S&P 500 via combination of improved BCO approach and BP neural network [J]. Expert systems with applications, 2009, 36(5): 8849-8854.

[17] Ta V D, Liu C M, Tadesse D A. Portfolio optimization-based stock prediction using long-short term memory network in quantitative trading [J]. Applied Sciences, 2020, 10(2): 437.

[18] Geng Jingjing, Liu Yumin, Li Yang, etc. Stock index prediction model based on CNN-LSTM [J]. Statistics and decision-making, 2021, 37 (05): 134-138. DOI: 10.13546/j.cnki.tjyjc.2021.05.029.