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Research Article

Prediction and Analysis of Artwork Price Based on Deep Neural Network

Chen Liu

College of Art, Tianjin University of Commerce, Tianjin, China

Correspondence should be addressed to Chen Liu; yqsdsmm@tjcu.edu.cn

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The use of deep learning methods to solve problems in the field of artwork prices has attracted widespread attention, especially the superiority of long short-term memory network (LSTM) in dealing with time series problems. However, the potential for deep learning in the prediction of artwork price has not been fully explored. This paper proposes a deep prediction network structure that considers the correlation between time series data and the combination of two-way LSTM as well as one-way LSTM networks to predict the price of artworks. This paper proposes a deep-level two-way and one-way LSTM to predict the price of artworks in the art market. Taking into account the potential reverse dependence of the time series, the bidirectional LSTM layer is used to obtain bidirectional time correlation from historical data. This research uses a matrix to represent the artwork price data and fully considers the spatial correlation characteristics of the artwork price. Simultaneously, this paper uses the two-way LSTM network to correlate the potential contextual information of the historical data of the artwork price stream and fully perform feature learning. This study applies the two-way LSTM network layer to the building blocks of the deep architecture to measure the inverse dependence of the price fluctuation data. The comparison with other prediction models shows that the LSTM neural network fused with one-way and two-way proposed in this paper is superior to other neural networks for predicting price of artworks in terms of prediction accuracy.

1. Introduction

The art market has never been a static market, and risks often coexist with benefits. In the art market, investors often use price fluctuations to measure price risk. No matter what kind of external shock the investment target receives, its risk is reflected in the price, which is the price fluctuation [1, 2]. Price fluctuations bring challenges to not only market participants, but also opportunities. Therefore, the reasonable estimation of the price of art has attracted more and more attention. There are many factors that affect price fluctuations, which may be political factors, the corresponding policy changes, or the creation of a certain art tool in the market [3]. In addition to the above factors in the commodity market, there may also be extreme weather or a game between supply and demand companies. Different market participants have different expectations of the market conditions based on their own different information. Transactions are conducted in different markets to find the optimal allocation of assets, which also makes it more difficult to capture the price of an asset. It is precisely because of price uncertainty that a reasonable quantitative estimate of price has become the basis for more and more risk management strategies [4]. At present, market participants have many methods for risk management, such as risk warning or calculating the value of assets at risk. However, no matter which method is adopted and what period it is in, the study of forecasting price is an important basis for formulating risk management strategies [5].

So far, the relevant research on predicting the price of artworks in the art market has not yet been developed [6]. In the previous literature on the price fluctuation of artworks in my country, most of them used the modeling of price time series. However, traditional analysis models have certain prerequisites for the characteristics of price time series [7, 8]. The characteristics of price time series themselves also lead to the limitations of traditional analysis models. First, the traditional analysis model requires that the price time series itself be stable; that is, the mean and variance of the data itself cannot change with time [9]. But in many cases, price time series often fail to meet this requirement. Second, price time series have limited explanations for their own volatility. This is difficult to effectively characterize the volatility characteristics and often requires more price factors to model, so as to enhance the interpretation [10].

The deep neural network can improve the traditional price time series analysis model and effectively enhance the interpretation [11–13]. Deep learning belongs to the field of artificial intelligence [14, 15]. Computer algorithms are used to simulate human learning behaviors, so as to continuously improve its own performance structure and make correct judgments in continuous learning [16]. At present, machine learning has made great progress in image recognition. For example, machine learning can effectively extract the characteristics of a picture through dimensions such as color, brightness, and size [17, 18]. In the field of art price fluctuation prediction, we can also use the learning ability of deep learning models to effectively extract the features of price time series, so as to achieve the purpose of feature extraction and prediction [19, 20].

Based on the deep neural network, this work designs a new method for predicting the price fluctuation of artworks. The contributions are as follows: this paper proposes a neural network for predicting the price of artworks in the art market, taking into account the characteristics of time series of art price data, makes use of forward as well as backward dependence of spatiotemporal data in time and the correlation in space, and adopts the most popular deep learning method to fully learn the price fluctuation of artwork to predict. Extensive experiments verify the effectiveness and reliability of the method.

2. Related Work

Price prediction refers to the prediction behavior of dynamic analysis of future price changes of commodities based on the historical value of commodities and price trends. Since commodity prices had played an extremely important role in the rational allocation of resources since ancient times, therefore, domestic and foreign scholars had always regarded the research and prediction of commodity price trends as an important topic. Currently, commonly used price prediction algorithms were divided into two categories: algorithm with simple time series and algorithm with machine learning.

With the continuous deepening of the research on simple time series algorithms, the application fields of simple time series analysis had gradually expanded. At present, simple time series analysis algorithms had been utilized in many fields like agricultural product price prediction, industrial commodity price prediction, and financial stock price prediction [21]. Because less data information was used in the analysis, at the same time, the effective information analysis of the history was insufficient. The predicted results still could not meet the needs of social development. Literature [22] analyzed the influence of seasonality on future changes in electricity prices based on the periodicity and seasonality of electricity price fluctuations. It used the autoregressive integral moving average model to predict the price of electricity to obtain better results. Literature [23] was based on the characteristics of the problem that the concentration of aero engine lubricants was affected by many complex factors, and its changing trend was difficult to predict. An ARIMA model based on nonstationary time series was proposed, and the prediction results were satisfactory. It showed that this method had better accuracy of fitting and predicting ability. Literature [24] predicted the future price of AWS EC2 by using several forecasting methods such as linear regression and ARIMA. It found that the SARIMA model that adjusts the training data set by distinguishing the modeling period performs better than the simple model. Literature [25] and others evaluated and compared ARIMA, ARNN, XGBoost, support vector machine, hybrid ARIMA-ARNN, ARIMA-XGBoost, and ARIMA-SVM. Experimental results showed that ARIMA cannot accurately capture nonlinear data. However, the neural network had an excellent performance, and it was found that the combined model has the best prediction effect. Literature [26] used a comparison based on the normal distribution and the T distribution. It was found that the fluctuation of food prices was evenly distributed.

With the vigorous development of machine learning in recent years, researchers had proposed many extremely effective commodity prediction algorithms because deep learning algorithms had the characteristics of small errors between the prediction results and the real values, and strong generalization capabilities. In recent years, the algorithms had aroused extensive research and application of scholars for price forecasting. Literature [27] used the BP neural network combination algorithm based on the particle swarm optimization algorithm to overcome the initial weight sensitivity problem according to the diversity of factors affecting the price of vegetables. This well simulated the relationship between the nonlinear vegetable price and related factors and had achieved a good forecasting effect. However, this combination forecasting method was complicated to calculate, and it was difficult to obtain the optimal solution. Literature [28] used the AdaBoost algorithm to predict road traffic flow, which could better predict the congestion on the road at a specific time in a scene with many complex influencing factors. Literature [29] used the XGBoost integrated algorithm to predict oil prices, and the prediction results of the three oil prices were relatively accurate. This showed that the gradient boosting algorithm could get good results in oil price prediction. Literature [30] compared the performance of the gradient boosting decision algorithm with the neighboring algorithm, SVM, random forest, and other commonly used machine learning algorithms. The results verified that the gradient boosting decision tree algorithm was better than other algorithms, but it also showed that the existing gradient boosting algorithm was not ideal for large amounts of data. Literature [31] researched on machine learning algorithms in financial stock time series forecasting. A combined algorithm based on support vector regression and HP filtering was proposed to predict the stock price of Moroccan Telecom Company. Experiments showed that the model could obtain better results for stock prices based on time series. Literature [32] analyzed the nonlinear time series problem of agricultural product prices and used the nonlinear regression network to predict price for agricultural products. The results showed that the algorithm has good forecasting effects than traditional ARIMA algorithm in terms of nonlinear time series forecasting. However, the nonlinearity was caused by the instability of the prediction results of the regression neural network algorithm. Literature [33] and others proposed to use the three deep learning frameworks CNN, RNN, and LSTM to predict and compare the stock prices of NSE listed companies. The results verified that the deep learning architecture could capture hidden changes in the data and can make predictions. The comparison showed that the LSTM algorithm had better performance for data with time series.

3. Method

This section will introduce in detail the overall architecture of the converged one-way and two-way LSTM network and each network component. The main research object of this thesis is the forecast of fluctuations in the price of art in the art market in the future, in order to provide some predictive information. Here, we define price fluctuation prediction as predicting price in a period of time in the future based on historical price information.

3.1. Problem Definition. Time series have characteristics such as trend, seasonality, or periodicity. The main purpose of studying time series is to make predictions, that is, to infer some future changes based on the existing time series data. For the time series forecasting problem, the most critical point is to determine the change pattern of the existing time series. And it is assumed that this model will continue to influence future changes.

Art price flow data refers to fluctuations in prices within a certain period of time. It also changes continuously with time, and from a macro perspective, it has certain characteristics such as periodicity and regularity. Therefore, we can regard price information as time series information. In the dissemination of price information, as the time goes by, price data at a later moment will be affected to a certain extent by data fluctuations at the previous moment.

The goal of this experiment is to predict the serial value of future prices using price values over multiple historical times. Suppose that $A_T = [a_1, a_2, \ldots, a_T]$ is the historical input data extracted from the historical transaction price stream sequence signal, and $B_T = [b_1, b_2, \ldots, b_T]$ represents the future price prediction sequence. Then, the conditional probability that the predicted value is B_T under the condition that the historical information is A_T can be expressed as

$$p(B_T \mid A_T) = \prod_{t=1}^{T} p(b_t \mid c_t), \tag{1}$$

where c_t can be interpreted as the hidden state of the dynamic system of price propagation. It is generated from the previous hidden state c_{t-1} and the current price input a_t, shown as follows:

$$c_t = f(c_{t-1}, a_t). \tag{2}$$

The purpose of this article is to hope that a good function expression f can be learned through the network to describe the prediction of future price.

The price fluctuation prediction of an artwork usually uses historical price information for a period of time. Among them, n historical time steps are input:

$$A_T = [a_{T-n}, a_{T-n+1}, \ldots, a_{T-1}]. \tag{3}$$

In the process of art price forecasting, time-space correlation is a factor that must be considered. Time correlation refers to the correlation between current and past prices and the time span (time domain). The spatial correlation refers to the price correlation between the artwork and different markets, that is, the same time interval (spatial domain). In a certain market, the price of an artwork may be affected by the price of artwork in other markets. In order to enhance the temporal and spatial correlation, the price impact of other art markets is taken into consideration. This study uses price data in different markets as input. Assuming that the price markets consists of p categories, we need to use n historical time steps to predict the price at time T. The entered price data matrix can be characterized as

$$A_T^p = \begin{bmatrix} a_{T-n}^1 & \cdots & a_{T-1}^1 \\ \cdots & \cdots & \cdots \\ a_{T-n}^p & \cdots & a_{T-1}^1 \end{bmatrix}, \tag{4}$$

where a_t^p represents the price of the p-th art market at time t.

To reflect the time attribute for the flow data, price matrix is illustrated by $A_T^p = [a_{T-n}, a_{T-n+1}, \ldots, a_{T-1}]$. Each element a_t is a vector of market prices.

3.2. Two-Way LSTM Art Price Prediction Model. The two-way LSTM network is also a variation of the two-way recurrent neural network structure. Therefore, this article first introduces the two-way recurrent neural network.

For the traditional recurrent neural network in the learning of time series problems, generally, only simply consider the impact of historical time series on future time series. However, this ignores some of the contextual influence factors that may be implicit in the process of network dissemination on the future time series. If, in the training process, the network can not only learn from the historical moment input and the current input, but also merge the nearby future information input and perform the network modeling process, then, it will provide great reference value for time series forecasting problems. If we can know some contextual information, then we can have some contextual judgments about the price situation at the previous moment. Then, this forecast of the current moment can be more accurate.

Because the traditional recurrent neural network generally adds a time step lag between the input and the target when solving the sequence problem, it can give the network some context information. The future information for T-step is added to predict the output. T can be large to learn more future available feature. However, it if T is too large, the accuracy of the prediction result may decrease. Because the model concentrates its energy on learning and memorizing massive input information, and there is no reasonable learning of the input information, ss a result, the joint modeling ability of the predictive model decreases. The bidirectional recurrent neural network can realize modeling by processing forward and backward data propagation. This two-way transmission not only provides historical knowledge for each neuron node in the network, but also virtually learns the trend of subsequent changes.

In the forward propagation layer, the input data is nonlinearly transformed according to following formula, and a forward hidden layer output is obtained:

$$c_t^f = \sigma\left(W_{cc}^f c_{t-1}^f + W_{ac}^f a_t + d_f\right). \tag{5}$$

In the backward propagation layer, the input data is nonlinearly transformed according to following formula, and a backward hidden layer output is obtained:

$$c_t^e = \sigma\left(W_{cc}^e c_{t+1}^e + W_{ac}^e a_t + d_e\right). \tag{6}$$

Train two hidden layers of recurrent neural network, and the two independent hidden layers pass through a connecting layer. Combine the output of forward pass layer and output of reverse pass layer:

$$c_t = W^f c_t^f + W^e c_t^e + d_c. \tag{7}$$

For the dependence of the forecasting problem, all the information should be used. Generally, the data input to the LSTM is arranged in chronological order, and the result is that the information for LSTM is passed from time step $t-1$ to t in a positive direction. Therefore, the LSTM structure only uses forward dependencies, but very likely useful information is filtered out. Therefore, it can be beneficial to consider inverse dependencies. Because counterdependence transmits information for the negative direction, another reason why counterdependence is included in our research is the periodicity of prices. The price of artworks has strong periodicity and regularity. Analyzing the periodicity of data from the perspective of forward and backward, especially for recurring price patterns, will improve forecasting performance. However, on the basis of literature review, price analysis studies rarely use backward dependence. In order to fill this gap, this study added a two-way LSTM layer as an integral part of the network structure. The two-way LSTM (TWLSTM) network layer has the ability to handle the forward and the backward dependencies.

The TWLSTM network framework used in this experiment is essentially a variant of the TWRNN network. Different from the traditional LSTM network, TWLSTM not only considers the forward dependence of the time series, but also considers the backward dependence. TWLSTM uses two independent hidden layers to process forward and backward sequence data, connecting two hidden layers to the same output. Facts have proved that two-way network is significantly better than the one-way network in many fields such as sentiment classification and speech recognition. However, according to our review of the literature, TWLSTM has not been used for art price prediction. For the price prediction problem, we usually only consider that the previous moment may have a certain impact on the price. But we can think about it in the reverse direction. In the forecasting process, whether the price at the next moment will also adversely affect the price at the previous moment, and whether it will also have a certain impact on our forecast results, the expanded TWLSTM layer structure including the forward propagation LSTM as well as the backward propagation LSTM is shown in Figure 1.

The output sequence for the forward layer is generated with the positive sequence input. The output sequence of reverse layer is generated with the reverse input. Use standard LSTM updated equations to calculate forward and reverse layer outputs.

3.3. Mask Layer Model. For LSTM-based model, if input time series includes vacancies, then the prediction network must have a certain deviation in the predicted value of the result, because it is impossible to perform network learning and calculation of missing values during training. But if the vacancies are set to a fixed value that we have predefined in advance, it will have a great impact on our training and test results. Therefore, we adopted a mask layer in front of the overall network to overcome the potential problem of missing values. For a given input sequence value, this experiment first passes the Mask layer to perform a function similar to data masking. Use this to locate the time steps that need to be skipped during the experiment. Figure 2 shows the details of the Mask mechanism.

The mask value μ is predefined, usually zero or empty. Vacancies in the time series are fixed to μ. In the input time series, if it is a vacancy, it is equal to μ, and the training pipeline of step t is skipped. Thus, the state of the computing unit at step $t-1$ is directly input to step $t+1$, which is equivalent to making a skip input. The output of step t is equal to μ, which can be regarded as a missing value. Similarly, we can use the masking mechanism to deal with input data that continuously loses values.

3.4. Converged LSTM Network. According to previous experimental research, the LSTM network architecture with multiple hidden layers can gradually establish higher-level sequence data representation. Thereby, the more the effective modeling, the more accurate the prediction results. The deep LSTM architecture is to superimpose a network of multiple LSTM layers, and the output for the previous LSTM layer can be used as the input of next LSTM layer. Similar to convolutional neural networks, within a certain range, the more the layers of LSTM are, the better the high-level features of the input data can be learned. However, the LSTM network structure itself is more complex than other

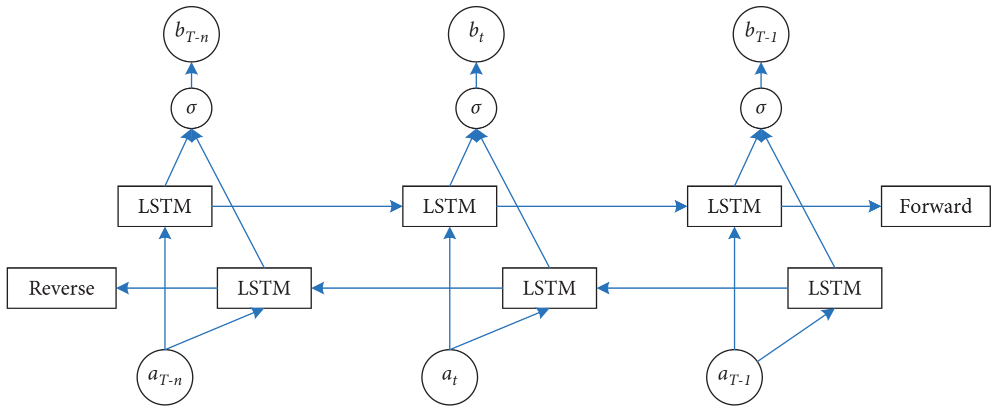

FIGURE 1: The structure of TWLSTM.

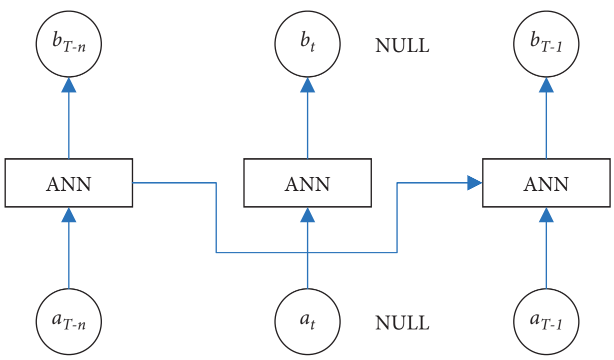

FIGURE 2: The structure of Mask layer.

neural networks and has more learning parameters. In the training process, the more the layers, the longer the training time.

Considering both the prediction accuracy and training time, this study uses a two-layer LSTM network to improve the effectiveness of the neural network. A TWLSTM network can utilize forward as well as backward dependencies. When spatiotemporal information is input into the TWLSTM network, the spatial and temporal correlations of different market prices can be extracted in process of feature learning. TWLSTM is suitable as the first layer to extract more important information. As for predicting future prices, the top layer needs to use the extracted feature, the output from the previous layer, to iteratively generate prediction values in the forward direction. Therefore, we choose the LSTM layer as the last layer of the entire prediction network. In our research, we propose a new network architecture that combines two-way and one-way LSTM network layer structure (CLSTM) to predict the price of art. The overall architecture is illustrated in Figure 3.

The CLSTM model includes a TWLSTM layer and a LSTM layer. In order to make full use of data and learn complex characteristics, the fused unidirectional and bidirectional LSTM network can include one or more optional intermediate hidden layers. It can be a unidirectional LSTM network or a TWLSTM network. The LSTM network can also predict the value of multiple future time steps.

3.5. Structural Optimization of the Predictive Model. For the network framework that has been built, it is necessary to keep improving the predicted results. Predecessors have also tried various methods in this regard to optimize the overall model. In this paper, we use the dropout and early-stop methods to tune the overall framework of the model to make its prediction accuracy more accurate.

In the neural network learning process, a large number of parameters are required. However, if the proportion of the number of training samples is much smaller than the number of training parameters, the model obtained at this time will be prone to overfitting. At this point, the generalization ability of the model is very poor. That is to say, it is not suitable for the model we have learned to change a data set, so this model is actually not a good model for us. The dropout method can effectively reduce the occurrence of overfitting, which is equivalent to adding a regularization constraint to the model. Combining multiple models can generally improve the performance of machine learning methods. However, for large neural networks, averaging the output of many individually trained networks is obviously a very expensive thing. When the single models are different, it is most helpful to combine multiple models. To make networks different, they either have different architectures or receive training. It is difficult to train many different network structures, because it is very difficult to learn a set of optimal hyperparameters for each network structure, and training each neural network requires a lot of calculations. In addition, the pretraining of each network usually requires a lot of data, there are not enough data available to train network. Dropout is a way to solve these two problems. It prevents overfitting and temporarily removes the unit from the network during training, as well as all its incoming and outgoing connections; let us assume for the time being that these hidden units do not exist in the neural network.

For deep learning problems, the final model is obtained through continuous training. The training process is what is learned by constantly updating and iterating each parameter in the model. But in the process of constant iteration, the model may also reach a kind of overfitting. Therefore, we use the early-stop method to cut off the number of iterations to prevent training overfitting. The early-stop method generally

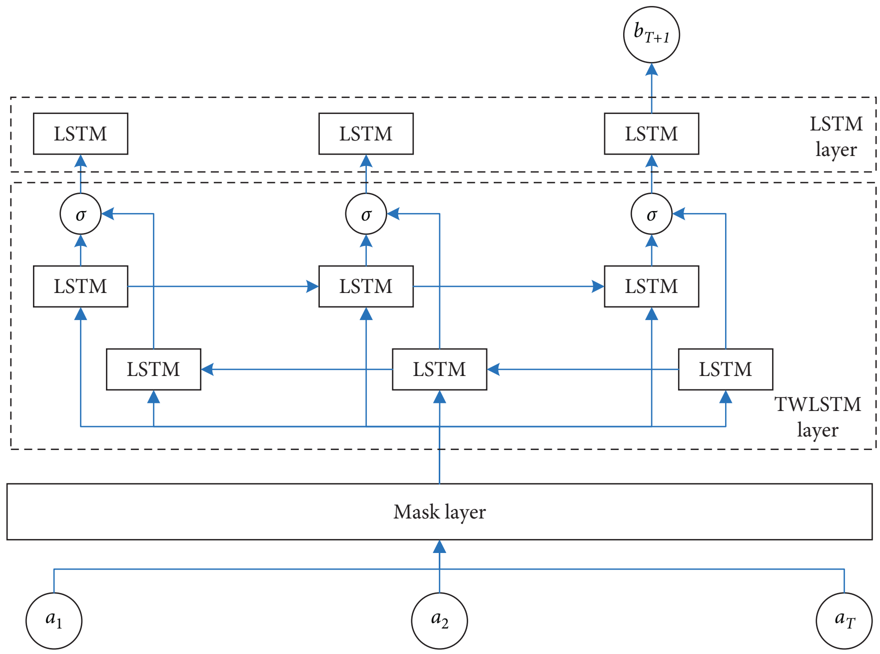

Figure 3: The structure of proposed CLSTM prediction network.

first divides the data set into the training set as well as the validation set and then set each complete iteration to an epoch. At the end of each epoch, the accuracy of the verification data set is calculated. When the accuracy does not continue to increase, the network automatically stops training in advance. So, how to define that the accuracy of a validation set no longer improves is a question worth discussing. It is not to say that once the accuracy of the verification data set drops, it is considered that it will no longer improve. Because it is possible that, after this epoch, the accuracy rate temporarily decreases, and the accuracy rate may rebound as the network training progresses. Therefore, it cannot be judged that the accuracy rate will not increase simply because of a temporary decrease. According to previous experimental experience, the general approach is to record the accuracy of the highest validation set during the training process. If epoch fails to reach the highest accuracy rate before 10 times, we can assume that the training accuracy of the network will not increase anymore. At this point, we can stop the iteration in advance to end the training process.

4. Experiment and Discussion

4.1. Experimental Set. This experiment is implemented based on the Ubuntu 18.04 platform. The main deep learning tool is the PyTorch learning framework to build and implement the model. PyTorch is a relatively advanced neural network framework, a deep learning library written based on the python language. There are some basic network frameworks commonly used in deep learning modeling in PyTorch, such as convolutional layer neural network, recurrent neural network, and fully connected layer. Using the network framework functions written at the bottom of PyTorch can easily support us to implement some experimental models and reduce the inconvenience caused by writing a lot of lengthy code. Table 1 shows the specific experimental environment.

This work also considers the availability of data and the effectiveness of analysis and self-made a time series data set of artwork prices. The data and selected data from January 2010 to December 2019 in my country, which include a relatively complete period of art price fluctuations, are used for research and analysis.

In this paper, RMSE and MAE are used as the basis of model tuning and the evaluation index of the final prediction result. The following is the detailed calculation formula:

$$\begin{aligned} \mathrm{RMSE} &= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - x_i\right)^2}, \\ \mathrm{MAE} &= \frac{1}{N}\sum_{i=1}^{N}\left|y_i - x_i\right|, \end{aligned} \tag{8}$$

where N is the number of samples, y_i is the predicted value, and x_i is the true value.

4.2. Comparison with Other Methods. To verify the effectiveness of the model, this experiment compares the performance of the proposed method with SVR, RF, SAE, and LSTM neural network. In these baseline models, the self-encoding network model is equivalent to a multilayer fully connected neural network. RF and SVR are prediction algorithms often used in machine learning, and they have excellent applications in dealing with price prediction problems. For SVR, RBF core is used. For RF, the experiment chooses to build 10 decision trees, and for each decision tree, the maximum depth of decision tree learning is not limited.

Table 1: Experiment environment.

Item	Name
Operating system	Ubuntu 18.04
CPU	Intel core i7-6700
Memory	64 GB
Development language	*Python*
Deep learning framework	PyTorch 1.6

For the SAE network, three self-encoding neural network layers are used in the experiment. For the LSTM network, the three-layer LSTM network is used as the main core to predict the network structure in the experiment. The result is illustrated in Table 2.

To facilitate the comparison of the results of various experimental methods, we made the experimental results of Table 2 into a histogram as shown in Figure 4.

It can be seen that, compared with other methods, the method designed in this paper obtains the best performance. Compared with the best-performing LSTM method in Table 2, the method in this paper reduces the RMSE index by 1.9 and the MAE index by 1.4. Obviously, the method in this article is effective and reliable.

4.3. Evaluation on the Number of Network Layers. The main neural network frameworks used in this experiment are LSTM and TWLSTM networks. Therefore, the performance of the entire network is not only closely related to the number of LSTM and TWLSTM layers taken. This section mainly discusses the selection of LSTM and TWLSTM network layers in the experiment. For the experimental network framework, we first input the input data into the TWLSTM network, so we first fix the number of LSTM network layers to compare and discuss different TWLSTM layers. The results are shown in Table 3.

It can be clearly seen that when the number of TWLSTM network layers is two, the best performance can be obtained. Next, with the best experimental results in the previous step, this article fixes the number of TWLSTM layers to experiment and compare the influence of different LSTM layers on prediction performance. Table 4 shows the influence of adding different layers for LSTM networks to the prediction network architecture on the prediction performance.

It can be seen that when the number of TWLTSM layers is fixed, the RMSE and MAE values of the predicted network reach the lowest point at the third layer. So, in the end, the main body of our overall network prediction framework is a two-layer TWLSTM network plus a three-layer LSTM network.

4.4. Evaluation on Time Lag Length. For price forecasting, the general method used is to compare price data to time series data for time series forecasting. Usually, a piece of historical data is used to predict the data value at a certain point in the future. Then, how many historical moments of data are selected naturally becomes a question worthy of experimental discussion. Here, the selected historical time data is generally called the time lag. For choosing different lag time steps, the model behaves differently. Figure 5 shows the RMSE and MAE values of the predicted results under different lag time steps.

It can be found that when the time lag step is 15, the experimental prediction results are more accurate. Therefore, the length of the input sequence chosen by our final network is 15. As the lag step increases, network performance first rises to the peak and then drops.

Table 2: Comparison with other methods.

Method	RMSE	MAE
SVR	22.7	17.4
RF	19.2	15.2
SAE	16.4	13.6
LSTM	13.8	10.7
CLSTM	11.9	9.3

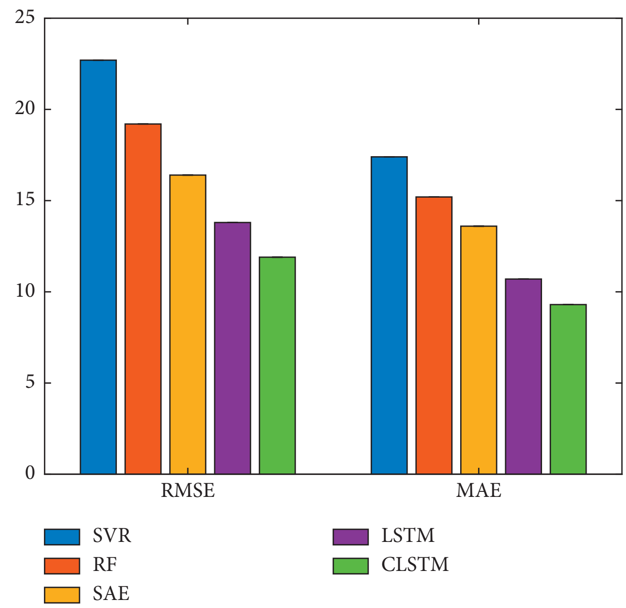

Figure 4: Comparison with other methods.

Table 3: Experimental results of different TWLSTM layers.

TWLSTM layers	RMSE	MAE
1	13.2	11.4
2	12.4	10.3
3	13.7	10.8
4	14.6	12.3

Table 4: Experimental results of different LSTM layers.

LSTM layers	RMSE	MAE
1	13.5	10.4
2	12.8	9.7
3	11.9	9.3
4	13.7	11.5

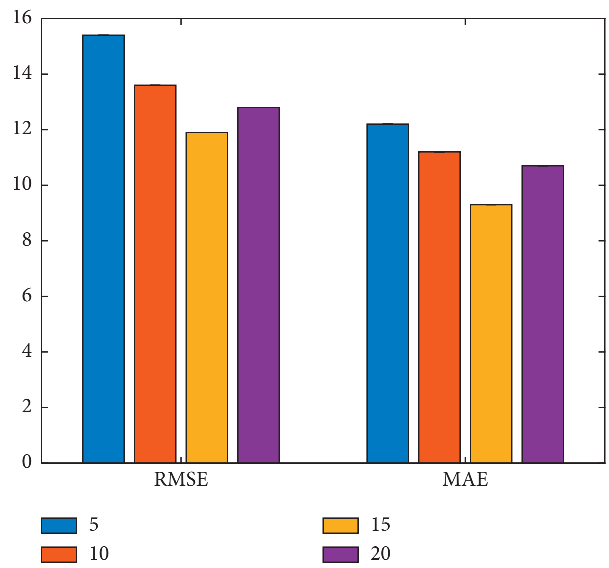

Figure 5: Experimental results of different time lag lengths.

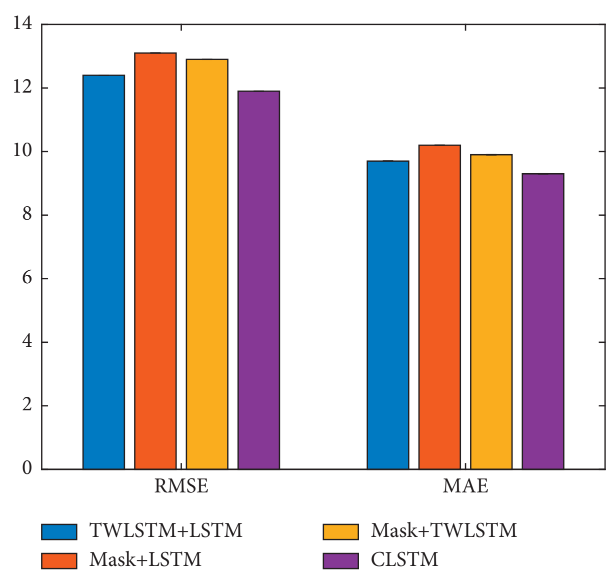

Figure 6: Comparison of the importance of different modules.

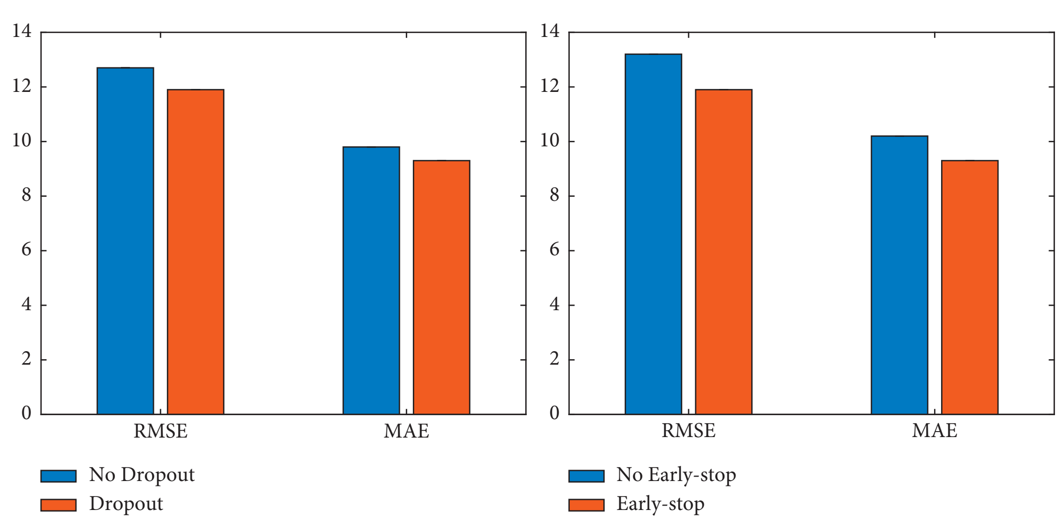

Figure 7: Evaluation on structural optimization.

4.5. Evaluation on Module Importance. To verify that each module of the model is an indispensable part, this article also conducts an experimental comparison. Under the original network structure, we removed the Mask layer, TWLSTM layer, and LSTM layer, respectively. The three new models and the network model are trained and tested for many times, the experimental results obtained are averaged and compared. The experimental results are illustrated in Figure 6.

It can be seen that no matter which module is missing, it will affect the prediction accuracy of the network. When all three modules are combined together, the RMSE and MAE values are the lowest. Therefore, each module is extremely important to our prediction network.

4.6. Evaluation on Structural Optimization. In this work, the strategies of dropout and early-stop are utilized to optimize the structure, to verify that these methods can promote the performance of prediction. A comparative experiment was carried out, and the results are shown in Figure 7.

It can be seen that, after the introduction of the dropout and B optimization strategies, the RMSE and MAE warranty of the network has been reduced to a certain extent. Obviously, these two methods can improve the prediction performance for the model. This further proves the effectiveness and correctness of this method.

5. Conclusion

In the price prediction problem, the LSTM neural network structure can capture the dynamic characteristics of price fluctuations. But at the same time, when predicting the price of art in a certain market, the influence of upstream and downstream prices on the price of art should not be ignored. With the use of the forward and backward dependence for spatiotemporal data, the extracted feature will be more comprehensive. This work proposes a neural network for price prediction of various artworks in the art market. It uses price data to have the characteristics of time series, considers the temporal and backward dependence of spatiotemporal data and spatial correlation, and uses the most popular deep learning methods to fully learn prices to make predictions. First, this work expands the field of price prediction to the entire market network and closely links the impact of the spatial and temporal correlation of price data on the prediction results. Second, this work proposes a deep-level fusion one-way two-way LSTM network architecture that considers the correlation of time series. Third, we add mask layer to skip the processing of missing data, which is helpful to the improvement of prediction results. The experimental results show that the neural network structure with the two-way LSTM layer and the one-way LSTM layer can learn the temporal and spatial features from the data set more effectively. In future work, we will devote ourselves to designing more efficient and lighter deep neural networks to predict the price of artworks.

Data Availability

The datasets used during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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