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A Prediction Model of Gold Price Change Against US Dollar Based on BP Neural Network

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Abstract. This project predicts the trend of gold price change against the US dollar and provides a more scientific and effective basis for investment decisions. The whole system is divided into two aspects: data visualization and BP neural network model application. For visualization and analysis, the powerful drawing function of Matlab was used for perspective drawing, and line graphs were created to show the degree of fit of the predicted values with the accurate values and the trend of change. For the BP neural network, the price prediction code based on the BP neural network was written using Matlab, and a prediction accuracy of 0.92230 was achieved by calculating the mean square error. The research results of this project provide a powerful price prediction tool based on neural network modeling, which will bring investors more accurate and objective information about price trends and provide more reliable and clearer prediction results to improve the success rate of investment.

Keywords: Price prediction model, BP neural network, MATLAB pivot charts.

1. Introduction

Gold is one of the rarer, more precious, and valued metals. The ounce is generally the international unit of gold, while the "tail" is the ancient Chinese unit. Gold is also an important metal in many areas, not only as a special currency for reserves and investment but also as an important material in the jewelry industry, electronics, modern communications, aerospace, and aviation industries. Its price changes reflect the world and North American economic changes.

The United States of America, the Republic of El Salvador, the Republic of Panama, and several other countries use the United States dollar as their legal tender. Gold and the United States dollar are important currencies whose price changes reflect changes in the world and North American economies, and the price of gold is closely linked to the exchange rate of the United States dollar. Therefore, it is very important to forecast the price of gold against the US dollar.

In finance, where change is extremely rapid, BP neural networks can model nonlinear relationships between input and output data, enabling the solving of complex problems, the handling of large amounts of data, and the improvement of accuracy in forecasting tasks. This allows for an efficient presentation of projections of exchange rates. In the investment industry price changes have a crucial impact on investors' decisions.

Yuqing Luo et al. Predicting the price of carbon quotas using BP neural networks. They sorted out the influence mechanisms of macroeconomics, domestic and foreign energy, and international factors on the price of carbon allowances, and extracted seven proxy variables from these three aspects to study their relationship with the national price of carbon emission rights in China. It is found that the BP neural network performs well in short-term carbon price prediction, the error rate can be less than 5%, and its data fitting degree is high. It can effectively utilize historical data to capture the trend of the national carbon price, providing a reliable reference for carbon market trading enterprises and investors for their management and decision-making [1].

Hanshen Mao et al. used BP neural networks to predict the price of carbon emission rights. They used the grey correlation model to screen out the influencing factors of carbon emission right price and introduced the cuckoo algorithm to optimize the initial weights and thresholds of the BP neural network. From the experimental results, it is analyzed that the cuckoo algorithm has a stronger optimization ability than the particle swarm algorithm, which more significantly improves the prediction ability of the BP neural network. In the process of establishing the optimized neural network model of the cuckoo algorithm, the generalized mapping ability of the neural network and the global search ability of the cuckoo algorithm are integrated to further improve the prediction effect [2].

Anle Cui et al. used neural networks to predict the price of liquor In this study, the micro components of 64 liquor samples of six brands were analyzed by GC-MS technology to obtain the characteristic profiles of liquor samples. They reduced the original baijiu mapping data from high-dimensional to low-dimensional by PCA and KPCA and then built PCA-BP neural network and KPCA-BP neural network models to realize baijiu price prediction. The method using GC-MS combined with KPCA-BP was found to be useful for price prediction of baijiu [3].

Shuai Chen predicts the closing price of a stock based on the GA-BP neural network and finds that the GA-BP neural network model overcomes the drawbacks of the standard BP neural network, which is easy to falls into the local optimum and has a slow convergence speed. This makes the model effective in improving the accuracy of short-term forecasts of stock closing prices. The introduction of an input parameter handicap can reduce the error of GA-BP neural network prediction and improve prediction accuracy. The method has high application in stock prediction [4].

Lijuan Wu and Zeyuan Meng evaluate the green credit risk of banking institutions based on the BP neural network. The results show that BP neural networks have good price prediction performance. Through the indicator system design, model construction, and model simulation training. The results show that the BP neural network can well predict the green credit risk of banking institutions. Moreover, the BP neural network method is used to analyze and evaluate the green credit risk, which is more objective than the traditional method, and has higher fault tolerance, self-learning, and self-adaptive ability [5].

Although the BP algorithm has many advantages and is widely used. However, it has many drawbacks, such as easy falling into the local optimum, slower convergence, and difficulty in determining the number of input neurons, the number of hidden layers, and the number of neuron nodes per layer. In addition, BP neural networks are mostly used only to predict a particular product, and studies related to exchange rate prediction do not have a wealth of relevant information in the field of BP neural network usage. To improve the above shortcomings, this paper designs a BP neural network-based prediction model for the price change of gold against the U.S. dollar. Combining BP neural network, data visualization, and big data analytics, the model will provide in-depth financial data insights and forecasting capabilities.

Therefore, in this paper, through the BP neural network, we carry out the prediction of the change of gold to the US dollar. First of all, this paper carried out a smoothness test on the selected gold against the dollar data and then carried out a smoothness treatment on the exchange rate data. Then the exchange rate volatility series was tested for normality and BDS to verify the nonlinearity of the exchange rate volatility series. Finally, this paper addresses the above shortcomings of BP neural networks and puts forward the corresponding solutions in a targeted manner. To solve the problem that the BP algorithm tends to fall into local optimization, the additional momentum method is proposed. To solve the problem that the number of neuron inputs is difficult to determine, the Autocorrelation Criterion (AC) is chosen to determine the number of input neurons. The sample mean turning point test (MCPT method) was utilized to select the optimal sample size for the sample set. The improved BP neural network algorithm is applied to the forecasting of the exchange rate of RMB against the US dollar, and the forecasting effect is examined using the set difference test index. This paper aims to improve the prediction accuracy of the model.

2. Introduction to the Dataset

In terms of visualization of relevant financial data, this paper relies on the published data on the official website of the World Gold Council, including the opening price of gold and the US dollar exchange rate. Closing price, high price, low price, and date and time. Collected from June 11, 2004, to March 1, 2024, the data collected at hourly intervals a total of 114,557 groups, each piece of data to explore the exchange price at that time.

2.1. Matlab Perspective Analysis

This project is based on data plotting pivot charts for a large number of gold-to-dollar exchange prices. Pivot charting complements the summarized data in a pivot table by adding visual effects to it so that comparisons, patterns and trends can be easily viewed. This method allows for quick aggregation and an interactive way to analyze large amounts of data. By aggregating and visualizing the data, the researcher can intuitively determine the trend of price fluctuations and the magnitude of the deviation of the predicted value from the true value, which is more conducive to reacting to the predictive accuracy of the constructed neural network. This project uses Matlab to create a big data statistics table, a line statistics chart of exchange price versus prediction sample, and relative error versus prediction sample, and also distributes to visualize the regression, training state, and performance of the neural network during the operation. The charts allow for better detection and analysis of data.

2.2. BP Neural Network

BP (Back Propagation) neural network, or error back propagation neural network, was proposed in 1986 by a team of scientists led by David Rumelhart and James McClelland. This neural network model is a multi-layer feed-forward network structure trained according to the error backpropagation algorithm and has become one of the most widely used neural network models due to its powerful function approximation ability, self-learning, and self-adaptation properties.

BP neural network simulates the information processing of the human brain's nervous system, which is a highly nonlinear dynamical system. Its core advantage lies in its ability to realize distributed storage and parallel collaborative processing of information. Although the structure and function of a single neuron are relatively simple when a large number of such neurons are interconnected to form a complex network system, the behaviors, and functions it exhibits become extremely diverse and powerful.

Structurally, BP neural networks are characterized by a clear hierarchy: each layer of neurons in the network is fully connected to the neurons in the layer above it and to the neurons in the layer below it, while no connections are established between neurons within the same layer. This structure forms a feed-forward neural network system without feedback, where each layer of neurons receives only the output of the neurons in the previous layer and passes it on to the next layer.

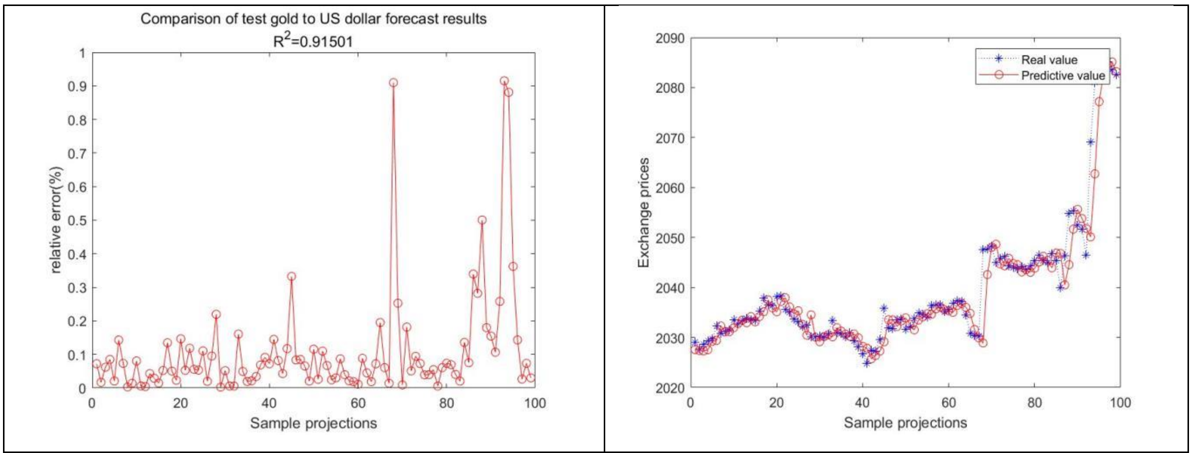
Functionally, feedforward neural networks with only a single computational layer can only solve linearly differentiable problems, whereas, for a large number of nonlinear problems in the real world, it is necessary to construct multilayer neural networks by introducing at least one hidden layer. The hidden layer and its neurons can help the network learn the complex and nonlinear relationships in the input data, thus allowing the multilayer neural network to handle and solve more complex nonlinear problems. At the same time, the neural network contains a smoothness test as well as autocorrelation criterion, sample mean turning point test (MCPT method), smoothness test is the basis of time series analysis, and its basic theory mainly includes sample autocorrelation function and autoregressive model. The autocorrelation function is an important tool for time series preprocessing, and the smoothness of time series data is assessed by calculating the sample autocorrelation function. The autoregressive model is a commonly used time series modeling method, based on the historical data of the time series itself for forecasting, and according to the model residual analysis to achieve the test of smoothness.

Overall, BP neural networks provide a powerful tool for solving problems such as complex function approximation, pattern recognition, classification, and prediction through their unique structure and learning algorithms. It has a wide range of applications in many fields such as image recognition, speech processing, natural language understanding, etc. With the continuous development of deep learning theory and the improvement of computational power, BP neural networks and their variants have become increasingly significant in the field of artificial intelligence.

3. Analysis of Results

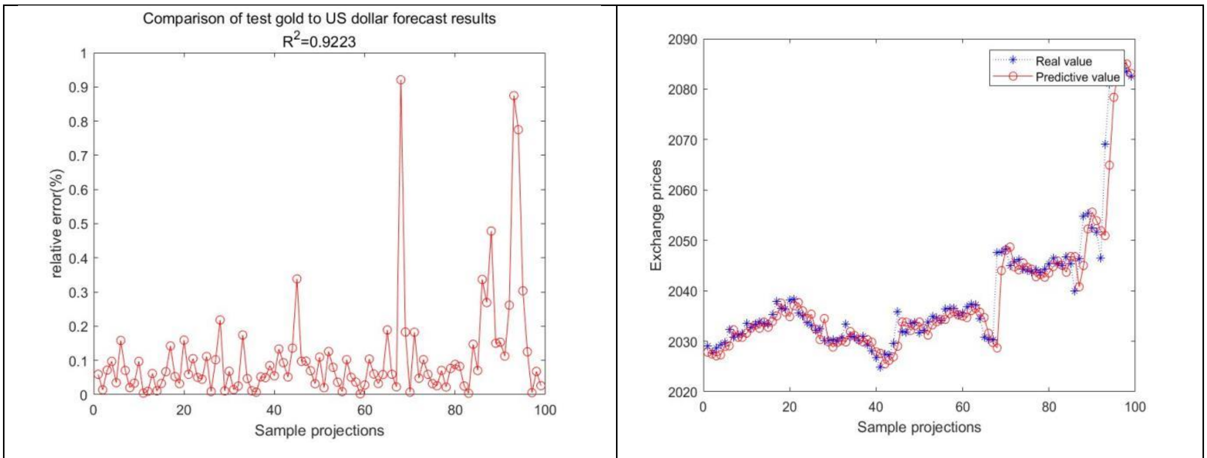
3.1. Results

The Figs. 1-4 of comparison of prediction results and the trend of real and predicted values were plotted using Matlab, respectively. In the comparison Figs 1-4 of prediction results, the horizontal coordinate represents the prediction sample, and the vertical coordinate represents the relative error. In the true value vs. predicted value chart, the horizontal coordinate represents the predicted sample, the vertical coordinate represents the exchange price, the blue asterisk represents the true value, and the red circle represents the predicted value.



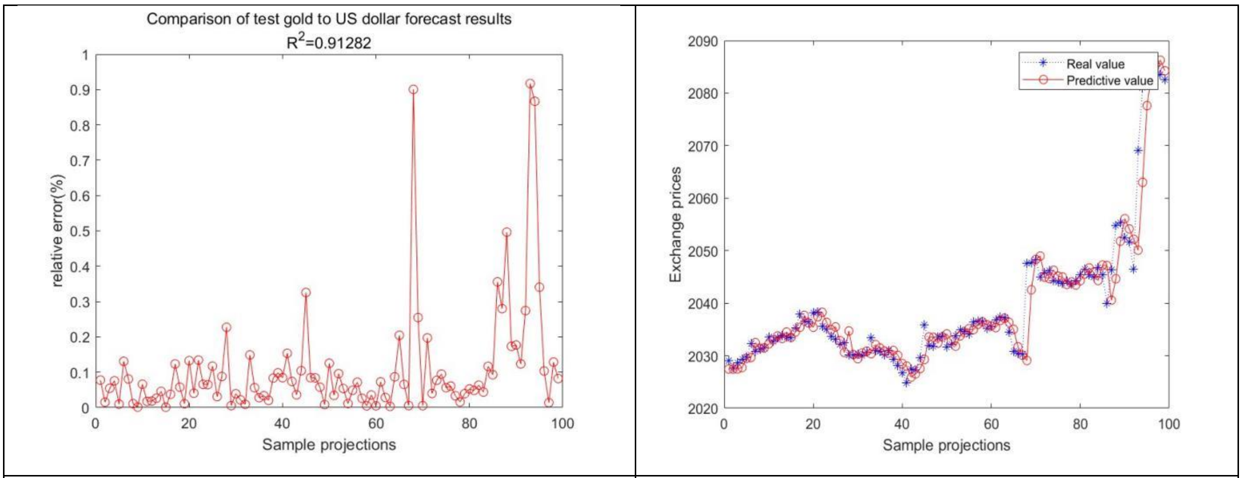
(a) (b)

Fig. 1 The results of the first prediction, (a)Comparison of the predicted results of the first prediction; (b)Trend of the true value of the first prediction versus the predicted value (Original).



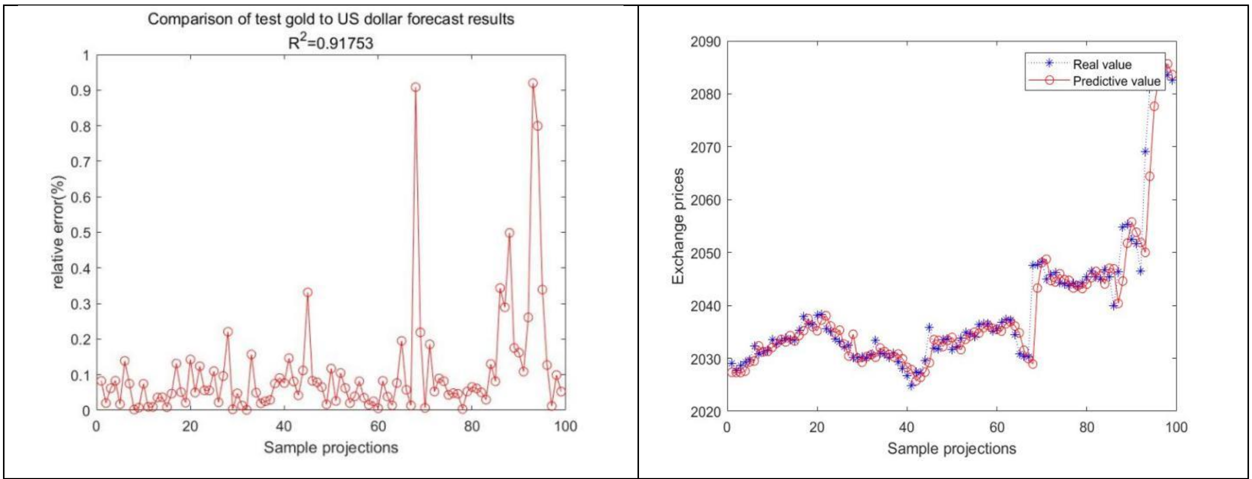
(a) (b)

Fig. 2 The results of the second projection, (a)Comparison of prediction results with modified hidden layer;(b)Modifying the true value vs. predicted value chart of the hidden layer (Original).



(a) (b)

Fig. 3 The results of the third projection, (a)Comparison of prediction results for modified training rounds;(b)Modifying the true vs. predicted trend of training rounds (Original).



(a) (b)

Fig. 4 The results of the fourth projection, (a) Comparison of prediction results after modifying the learning rate; (b)Trend of true and predicted values after modifying the learning rate (Original).

3.2. Analysis and Discussion

The text is currently based on the BP neural network to realize the prediction model of the price change of gold against the US dollar, and the first prediction result shows that the trend of the real value and the predicted value is the same, and the mean square error is 0.91501 (as shown in Fig. 1 (a) and (b)). To make the neural network further optimized, the group chose to achieve the purpose by modifying the data such as hidden layers, number of training rounds, learning rate, and hidden nodes.

By modifying the hidden layers several times, the test results show that the neural network works best when the number of hidden layers is 9. The following is the result after modifying the hidden layers, and the mean square error is improved to 0.9223 (as shown in Fig. 2 (a) and (b)).

By modifying the number of training rounds several times, the test results show that the effect of modifying the training discourse on the change of data is not obvious (as shown in Fig. 3(a) and (b)).

By integrating the previous articles, this paper analyzes two possible potential influencing factors, one is the insufficient amount of data, and the other is the inappropriate size of the target value. If you want more training rounds, you need to get a solution by lowering the target value, by the lower the target value, making the neural network more sensitive to the change of training rounds. Improve the quality of data to improve the degree of effect obvious.

Ultimately, data from multiple experiments show that the target value of -3 works better, and the prediction accuracy improves somewhat as the number of training rounds increases.

In the original basis for the modification of the learning rate found that the learning rate adjusted too high would affect the performance of the neural network, the group finally decided on a 0.01 for the learning rate (as shown in Fig. 4(a) and (b)).

The relative error of the final result is kept within 0.9, and the mean square error reaches about 0.92000, this better prediction accuracy highlights the efficiency and effectiveness of AI BP neural networks in data analysis in the financial field.

4. Conclusion

Finally, this paper will be the least square error by calculating the mean value of the difference between the predicted value and the true value of the sum of squares to get the mean square error, through the size of the number to measure the degree of fit of the model, and came to the conclusion that based on the BP neural network prediction model of the price change of gold against the U.S. dollar the system in the practical application of the system shows a very high degree of accuracy of this conclusion, embodied in the prediction of the value of the real value of the trend of the trend of the basically the same, the high degree of fit, the value of mean square error reached 0.92230. The mean square error value reaches 0.92230, which not only demonstrates the powerful performance of the BP neural network in forecasting research but also verifies and demonstrates the effectiveness and broad prospect of the application of big data and forecasting tools in the financial field. The research in this project provides investors with a powerful tool to help them better understand the price trends of financial products and adjust their investment strategies accordingly, thus enhancing the return effect.

In the future, this neural network can also be added to the prediction of the relevant influencing factors, combined with the data comprehensive analysis and prediction of the results to achieve better prediction results.

This application of neural networks in the financial industry demonstrates the great potential of artificial intelligence in predicting and determining the direction of trends.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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