Quantitative trading decision model based on LSTM neural network

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Abstract. As trading markets are vulnerable to national policies and economies, some investors choose to leave their assets in the hands of market traders for management. To help market traders find the best portfolio, the best trading strategies were dynamized to obtained by predicting the daily price movements of gold and bitcoin. BP neural network, time series analysis, and LSTM neural network were chosen for modeling quantitative trading decisions and modify the dynamic model of optimal trading. The LSTM neural network was used to indicate the time series because of the best fit of 0.991. And the investment weights for gold and bitcoin were calculated based on the particle swarm algorithm to be 0.09:0.91 and over the five-year trading period an initial $1,000 investment would yield $66,588.987. In addition, the optimal daily trades dynamically were re-solved by changing the values of the investment weights by 2:3, 2:1, 3:2, and 1:2 and obtained that the total number of assets of gold and bitcoin is smaller than the total number of assets with an allocation ratio of 0.09:0.91 for either allocation ratio. Thus, the model in the present paper provides the optimal strategy.

Keywords: LSTM neural network, particle swarm algorithm, hierarchical analysis.

1. Introduction

With the advent of the information age, the Internet has promoted disseminating information over long distances. The electronic trading market is gradually becoming mature worldwide, and more and more people realize the importance of reasonable investment. Quantitative trading, as an emerging trading transaction method, has attracted the attention of investors [1]. Through the Internet, many people have achieved wealth appreciation. Currency is one of the financial management methods with high liquidity, stable price, and low risk.

says Warren Buffett. Some investors hand over their assets to market traders for investment to increase returns. Market traders maximize their total return by buying and selling volatile assets frequently. A commission usually accompanies each purchase or sale. Gold and bitcoin are among the primary forms of investments. To hedge the risk of investments, it becomes essential for market traders to decide whether to buy, hold or sell the assets in their portfolios.

So, the main aim of this paper is to develop a model that gives the best daily trading strategy based only on price data up to that day [2] which would help market traders to choose a sound portfolio approach to investing to ensure that they do not lose money.

2. Methods and models

2.1. Three methods for prediction

The gold and bitcoin markets are highly volatile and liquid. Therefore, two aspects were needed to consider: first, predict the daily trading prices of gold and bitcoin; second, based on the prediction

results, dynamically plan to get the best daily portfolio approach. The best daily trading strategy can be obtained by combining the two aspects.

BP neural network, time series analysis, and LSTM neural network for forecasting were chosen. By comparing the goodness of fit of the three methods, the optimal method is selected to forecast the time series of gold and bitcoin markets.

2.1.1. BP neural network

The BP neural network consists of an input layer, an implicit layer, and an output layer. First, past price data of gold and bitcoin are input in the input layer. The information and errors are propagated forward and backward through the learning process in the implicit layer. After several iterations, the errors are brought to a predetermined accuracy. Finally, the output completes the training of the gold and bitcoin value prediction model. the principle of the BP neural network is shown in the Fig.1[3].

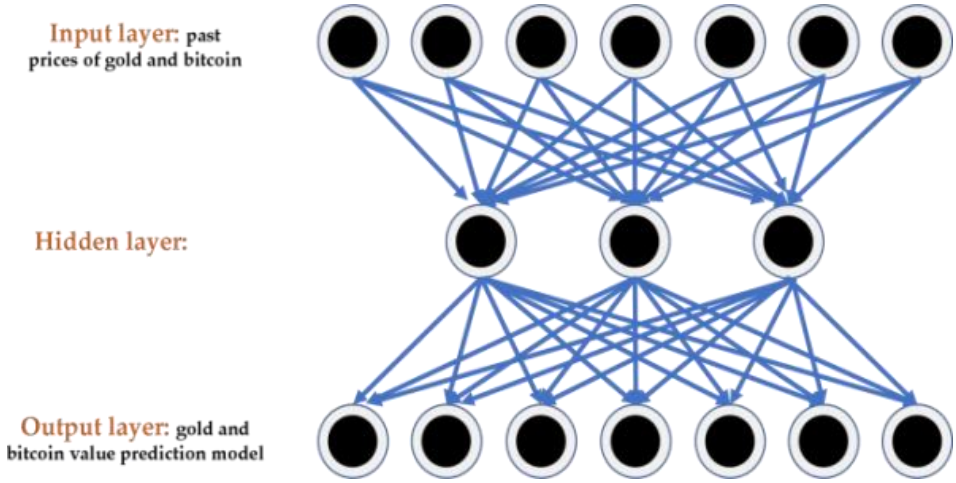

Figure 1. Principle of BP Neural Network

Step (1): since the values of gold and bitcoin show non-linear variation, in order to simplify the training process and prevent the training time from being too long, the historical data was normalized up to a certain date. Then, the error of the transmission was set to Eq. (1):

$$e = \frac{1}{2}\sum_{i=1}^{q}(d_i - y_i)^2 \tag{1}$$

Where, d_i is the value of the output, q is the number of output layers, and y_i is the completed training model for gold and bitcoin value prediction [4].

Step (1): The iterative formula was set as Eq. (2):

$$W^{n+1} = W^n - \eta\frac{\partial e}{\partial W} \tag{2}$$

Where, W is the weight and η is the learning rate.

Step (3): The future value trends of the two currencies are predicted based on the obtained prediction functions for gold and bitcoin. The mean square error (MSE, Eq. (3)) was introduced in order to evaluate the prediction effectiveness of BP neural networks.

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \tag{3}$$

2.1.2. Time series analysis

The prices of gold and bitcoin are often volatile and non-stationary due to economic and policy influences. Therefore, when the ARIMA model was used to forecast the time series of gold and bitcoin, stability processing of the raw data is required [5].

Firstly, the raw data was processed with first-order difference to transform all data into stable ones. Then, the differenced data was used to create an autocorrelation plot (ACF, Fig. 2A) and a partial autocorrelation plot (PACF, Fig. 2B).

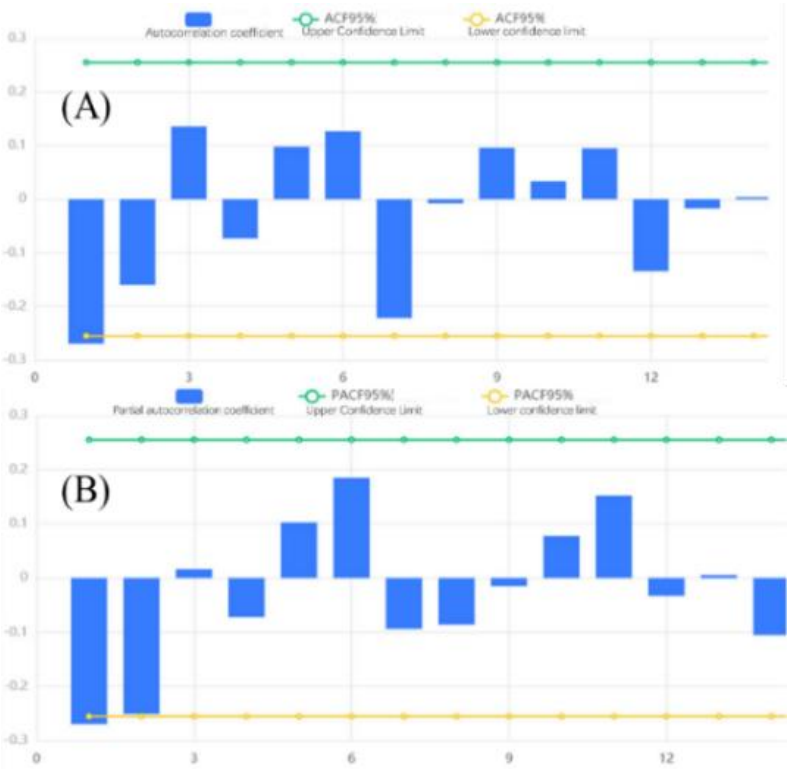

Figure 2. ACF (A) and PACF (B)

It can be seen that a part of the data series appears in the ACF with PACF in the 95% confidence interval. Therefore, the model was built as ARIMA. For the *i*-th time series, the model is as Eq. (4) follows.

$$z_t = \mu + \sum_{i=1}^{p} r_i \, z_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{4}$$

Where, μ is the constant term, p is the order of the differential treatment, r_i is the autocorrelation coefficient, and $\varepsilon_t$is error [6]. All known parameters are brought into the model and further calculated to obtain (Eq. (5)):

$$z_t = 1.719 - 0.395\varepsilon_{t-1} \tag{5}$$

R^2 was introduced in order to evaluate the time series forecasting effect of the ARIMA model (Eq. (6)).

$$R^2 = 1 - \frac{\sum_i (z_i - \hat{z}_i)^2}{\sum_i (z_i - \bar{z}_i)^2} \tag{6}$$

2.1.3. LSTM neural network

LSTM neural network is commonly used in processing some serial information. Since it can find some longtime dependence problems, the daily price of gold and bitcoin could be predicted.

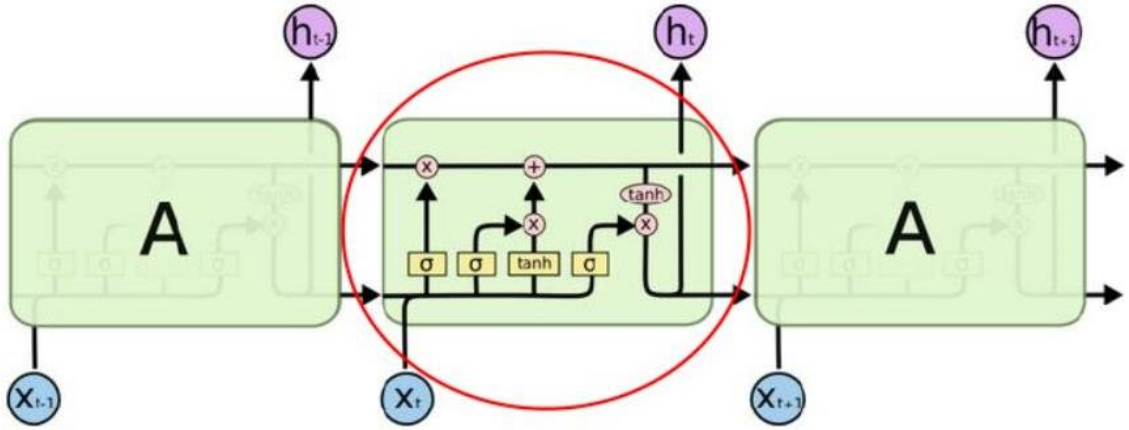

Figure 3. Principle of LSTM neural network

The LSTM neural network mainly consists of an input layer, an output layer, and a hidden layer. Internally, it includes a memory store (Cell) and three gatings (Gates) settings. The schematic diagram is shown in Fig. 3.

Firstly, when predicting the time series of gold and bitcoin, the LSTM neural network can control the transmission state by gating the state. The data that is not important to the prediction results are eliminated. At the same time, the data that are relevant to the prediction results are applied over a long distance. Then, the information state in the cell is updated [7].

Finally, the function of the predicted gold and bitcoin time series is obtained by outputting the gate output.

The following is a partial description of our application of the LSTM neural network to predict the gold and bitcoin time series:

(1) All the prices of gold and bitcoin were normalized. This makes the network converge quickly to avoid saturating the neurons and further increase the speed of the algorithm. When the algorithm is done processing the data, it performs a reverse normalization to bring the processed data back to the original data range.

(2) The backward value of the external parameter in the model was set to 5, indicating that each data is predicted from the previous 5 data. This is used to improve the accuracy of the prediction.

(3) The total number of training parameters used in the model was 943001, and eight types of neural network layers were built. All data from September 11, 2016, to September 10, 2021 was used. The process of forwarding computation with backpropagation was performed 50 times each time with 1715 data as the training set for the prediction of 100 data.

(4) This model selects 10% of the training set as the validation set in order to correct the weights and parameters of the optimized model in time. Also, the generalization ability of the model can be better verified. By metabolizing the data, the earliest 100 data are removed, and 100 new data are updated [8]. The relu function was used as the activation function. The values of other hyperparameters are shown in the table 1.

Table 1. Value of other hyperparameters

Parameter	Value
Number of hidden	1,50,100,200
Number of hidden layer nodes	1,50,100,200
Learning rate	0.0001,0.001,0.01,0.1
Batch size	1815
Dropout Ratio	0.2
Loss function	Mean absolute error
Optimizer	SGD, RMSprop, Adam

Since both LSTM neural networks and BP neural networks are part of neural networks. Therefore, the time series prediction effectiveness of the LSTM neural network for gold and bitcoin is evaluated in combination with Eq. (3).

2.2. Dynamic model of optimal transaction

To develop the best trading strategy for a given day, the total amount of gold and bitcoin held on that day were needed to translate into dollars for measurement purposes. In addition to this, market traders pay a commission each time they buy or sell a certain amount of gold or bitcoin. Therefore, the daily best trade dynamics was modeled as Eq. (7).

$$f_{n+1} = C_{n+1} + G_{n+1}x_n + B_{n+1}y_n - f \tag{7}$$

Where C_n is the total number of dollars on day n, G_n is the price of gold on day n, B_n is the price of bitcoin on day n, x_n is the number of gold purchases on day n, and y_n is the number of bitcoin purchases on day n. The number of dollars and bitcoins purchased is related to the ratio of the money spent to buy them on day n-1 to the price on that day, as shown in the Eq. (8) and (9).

$$x_n = \frac{C_{n-1} \times G_{nz}}{G_n} \tag{8}$$

$$y_n = \frac{C_{n-1} \times B_{nz}}{B_n} \tag{9}$$

Where, G_{nz} is the investment weight of gold on day n, and B_{nz} is the investment weight of bitcoin on day n. Both are fixed values.

The market trader's commission is related to the number of times gold or bitcoin is bought or sold and is α% of the amount of each transaction. Therefore, the expression for the commission is as Eq. (10) follows.

$$f = |\bar{G}_{n+1} - \bar{G}_n| \times \alpha_{gold} + |\bar{B}_{n+1} - \bar{B}_n| \times \alpha_{bitcion} \tag{10}$$

Where, suppose α_{gold} = 1%, $\alpha_{bitcion}$ = 2%, $\bar{G}_n$ is the total value of gold on day n, $\bar{B}_n$ is the total value of gold on day n. The total value of gold and bitcoin is calculated by Eq. (11) and (12).

$$\bar{G}_n = G_n x_n \tag{11}$$

$$\bar{B}_n = B_n y_n \tag{12}$$

After several iterations, the total dollar amount for a given day is calculated. When the total dollar amount is the largest, the best trading strategy for that day could be determined.

To calculate G_nz and B_nz, the Sharpe ratio was defined. Based on the data predicted with the LSTM model, to quantify the daily bitcoin to gold investment ratio, the Sharpe ratio formula was improved by constructing the formula containing two unknown quantities for the investment ratio. By solving the Sharpe ratio, a portfolio of gold and bitcoin with high returns and low risk could be obtained. The expression for the Sharpe ratio is as Eq. (13) shown.

$$sharpratio = \frac{r_p - r_f}{\sigma_p} \tag{13}$$

Where, $r_p$is the annualized portfolio profit rate, r_f is the annualized risk-free rate, and σ_p is the standard deviation of the annualized portfolio risk rate. r_f was set as 0.03 ($r_f = 0.03$) and then the Sharpe ratio could be simplified (Eq. (14)).

$$sharpratio = \frac{0.827109x_1 + 0.041444x_2 - 0.03}{\sqrt{0.192906x_1^2 + 0.0046x_1x_2 + 0.0047x_2^2}} \quad (14)$$

Where, x_1 is the percentage of bitcoin investment, and x_2 is the percentage of gold investment.

Next, to obtain the optimal Sharpe ratio index, a particle swarm algorithm was used to make day-by-day predictions of the investment percentages [12]. The investment ratio of bitcoin and gold was calculated by bringing in the particle swarm algorithm. The main formula of the particle swarm algorithm is shown as Eq. (15) and (16).

$$v_i^d = wv_i^d + c_q r_q\left(pbest_i^d - x_i^d\right) + c_2 r_2\left(pbest^d - x_i^d\right) \quad (15)$$

$$x_i^{d+1} = x_i^d + v_i^d \quad (16)$$

Finally, the Sharpe ratio and particle swarm algorithm were combined to get the best investment strategy that gives investors the highest returns.

3. Results

3.1. The goodness-of-fit of the three models

Combining equations (3) and (6), we solve to obtain the goodness-of-fit of the BP neural network, time series analysis, and LSTM neural network predictions (Fig. 4).

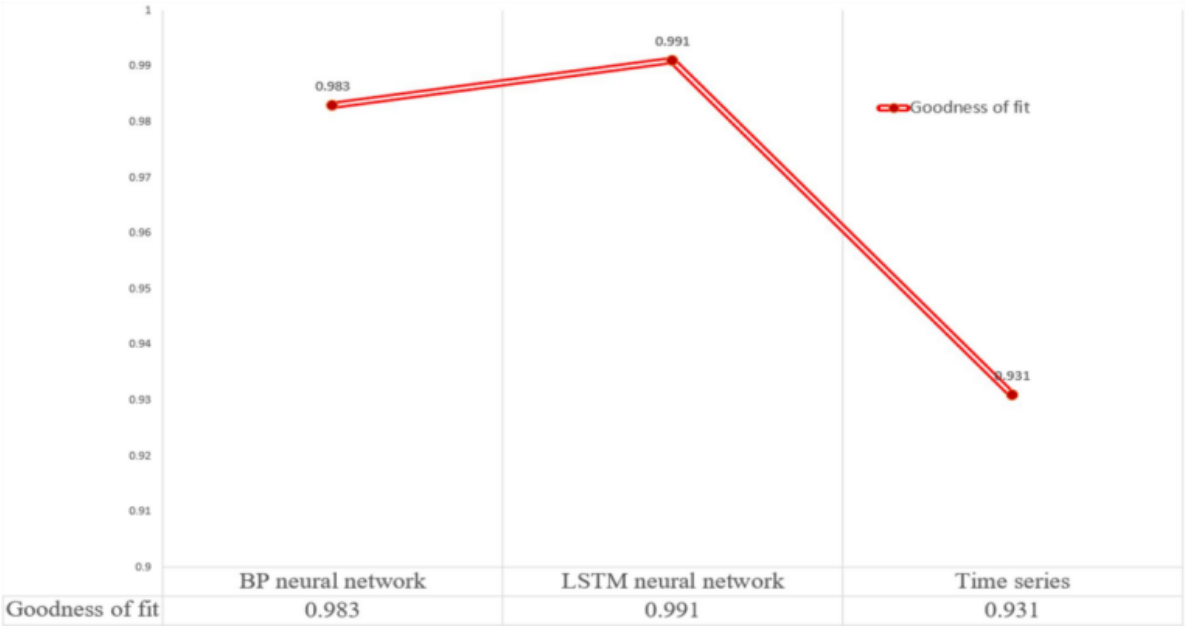

Figure 4. the goodness-of-fit of the BP neural network, time series analysis, and LSTM neural network predictions

In addition, these three methods were utilized to predict the time series of Bitcoin from November 10, 2016, to November 19, 2016. Fig. 5 showed the expected results for Bitcoin over ten days [9]. The bitcoin time series obtained from the LSTM neural network prediction is closest to the actual value according to Fig. 5. Therefore, combining the goodness-of-fit of the three methods, it is accepted that the LSTM neural network is the most accurate for predicting the time series of gold and bitcoin and has the best prediction effect. In practical applications, LSTM neural networks should predict financial time series.

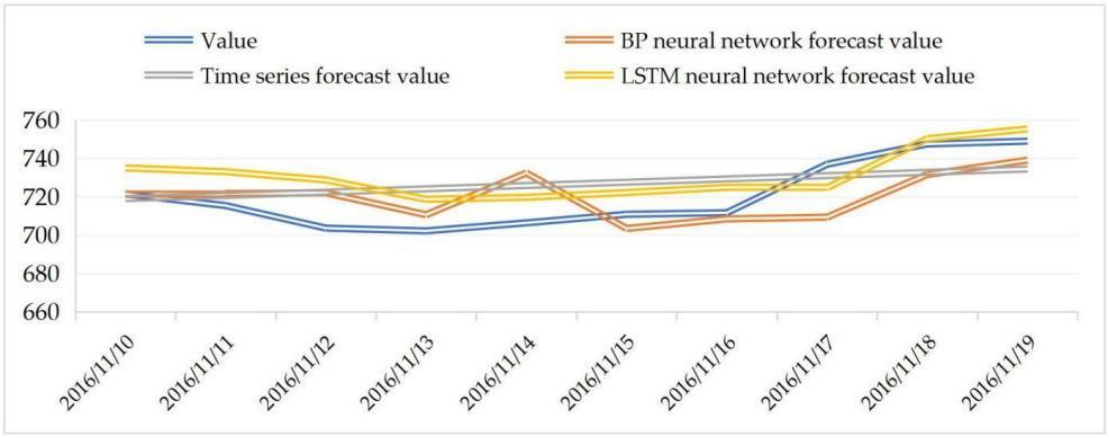

Figure 5. Expected results for Bitcoin over ten days

3.2. Gold and Bitcoin Daily Best Trades

3.2.1. The growth rate prediction

Gold and Bitcoin are traded for five years. We can only get the best trading strategy based on the price data at a specific date. Therefore, the LSTM neural network was use to predict the prices of gold and bitcoin after a particular date by choosing the prices between the five-year trading periods [10]. The time series obtained from the forecasts are then calculated to get gold and bitcoin's growth and decline rates. The volatility of gold and bitcoin from September 12, 2016 to September 10, 2021 is shown in Fig. 6.

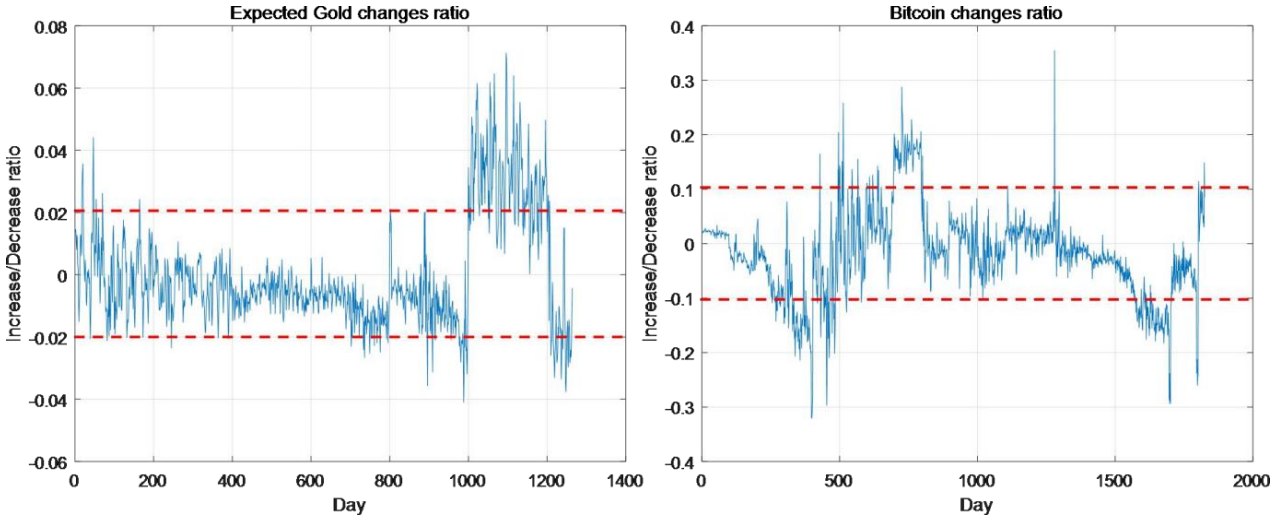

Figure 6. The daily price growth rate of gold and bitcoin

As can be seen from Fig. 6, the price growth rate of gold is mostly concentrated between ±0.02% and the price growth rate of bitcoin is mostly concentrated between ±0.1%. Theoretically, you can sell when the price goes up and buy when the price goes down. However, as the growth rates of gold and bitcoin fluctuate within this range, the degree of price change is not very large. Therefore, we set the price growth rate of gold and bitcoin to buy within this range.

In addition, to simplify the calculation, we set: when the price growth rate of either gold or bitcoin does not satisfy one of the ranges, then neither is purchased; when the price growth rate of both gold and bitcoin exceeds the specified range, then they are sold when the price goes up and bought when the price goes down [11].

3.2.2. Dynamic model of optimal transaction

By calculation according to 2.2, the investment weight of gold and bitcoin is 0.09:0.91. An analysis of the results shows that when we invest in both gold and bitcoin, we can support close to a third of our money in gold and the other two-thirds in bitcoin. This shows that Bitcoin has a higher rate of

return and higher risk; gold has a lower rate of return and lower risk. The best daily returns can be obtained when the investment ratio of gold to bitcoin is 0.09:0.91. The total value of gold and bitcoin over the five-year trading period is brought in for iterative calculation using our model and strategy. Ultimately, this yields an initial $1,000 investment that would be worth $66,588.987 on September 10, 2021.

3.3. Modify the dynamic model of optimal transaction

To prove that our model provides the best strategy, a solution process is analyzed for 3.1, which utilizes hierarchical analysis to calculate the investment weights of gold and bitcoin, i.e., the sizes of G_{nz} and B_{nz}. Then, the optional portfolio is obtained based on the size of the investment weights. Since G_{nz} and B_{nz} are fixed values, this inspires us to solve the dynamic model by varying the G_{nz} and B_{nz} fetching values and then observing the dynamic model results for optimal trading at different fetching values. Finally, the correctness of the model is further demonstrated by observing the solution results without taking the values.

Firstly, set parameters β_1 and β_2 and $\beta_1\beta_2$, is replaced with G_{nz} and B_{nz}. Combining with Equation (7), the daily optimal dynamic model is modified as Eq (17) follows:

$$f_{n+1} = C_{n+1} + \frac{G_{n+1}G_{n-1}}{G_n}\beta_1 + B_{n+1}y_n\frac{B_{n+1}G_{n-1}}{B_n}\beta_2 - f \tag{17}$$

Combining equation (10), the daily prices of gold and bitcoin are brought into the modified model. Through iterative calculations, the impact of different portfolio approaches on returns is compared (Fig.7), which shows that the market has the highest returns when the portfolio of gold and bitcoin is 0.09: 0.91. Hence, our model provides the best strategy for investing in gold and bitcoin.

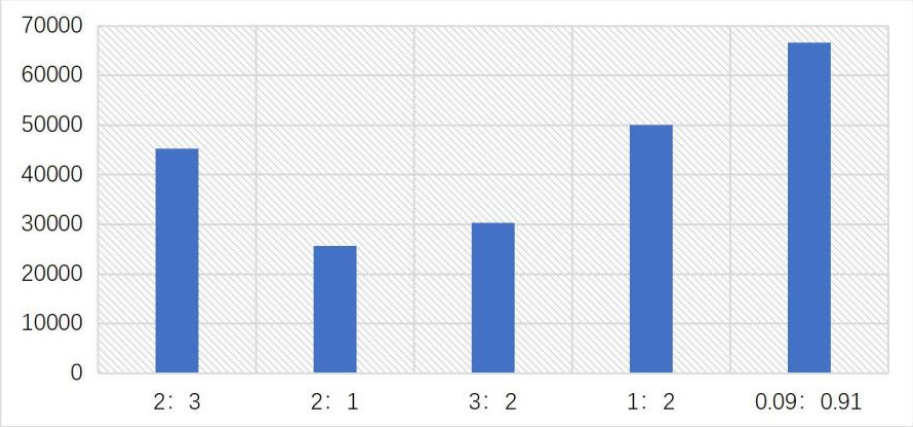

Figure 7. Returns under different portfolio approaches

4. Conclusion

Many investors who do not have professional knowledge are easily influenced by the Internet and lose their money. Therefore, it becomes essential to apply intelligent algorithms in predicting financial time series to reduce investment risk. Based on this, we first applied BP neural network, LSTM neural network, and time series analysis method to predict the daily price trend of gold and bitcoin based on the data provided in this project and the LSTM neural network has the best accuracy in predicting the financial time series. Based on the data predicted with the LSTM model, we proposed the optimal daily trading strategy, enabling investors to obtain the highest return. The ratio of gold to bitcoin investment is 0.09:0.91 and over the five-year trading period an initial $1,000 investment would yield $66,588.987.

References

[1] Li Yi. Research on the application of quantitative trading strategy model [D]. Yunnan University of Finance and Economics.

[2] Li Xudong. Application of Machine Learning in Financial Data Forecasting [D]. Hangzhou University of Electronic Science and Technology.

[3] Gsn, A., Apsk, B., & Ck, C. Dropout technique for image classification based on extreme learning machine. *Global Transitions Proceedings*, 2021, 2 (1): 111 - 116.

[4] Yang Qing, & Wang Chenwei. Research on global stock index prediction based on deep learning LSTM neural network Statistical research, 2019, 36 (3), 13.

[5] Luo Hongpen. Research on Intelligent Hybrid Forecasting of Financial Time Series Based on Gray-ARIMA.

[6] Xu Hui. Research on portfolio optimization based on improved particle swarm algorithm [D]. Tianjin University of Commerce.

[7] Lai Hongjie. Bitcoin - a new type of "gold" in the digital era [J]. China Business Theory, 2018 (2): 2.

[8] Wang Qian, Du Zhuo Ya. A study on the difference between bitcoin and gold hedging function - based on VAR-BEKK-GARCH mode [J]. Management Science, 2022, 35 (2): 13.

[9] Hao Ryin, Chen Xiangguang. A Marxist analysis of bitcoin and its development trend [J]. The Economist, 2018 (7): 8.

[10] Bai Jiancheng, Huang Yunfei, Gao Zengen, et al. A study on the impact of economic policy uncertainty and digital currency market volatility--an empirpcal analysis based on the bitcoin market [J]. Operations Research and Management, 2022, 31 (5): 183 - 189.

[11] Guo Peng. Bitcoin: The new generation of electronic gold [J]. Talent, 2013 (26): 2.

[12] Wang Changqing, Huang Jing. Energy-efficient optimized coverage algorithm for wireless sensor networks based on co-evolutionary particle swarm algorithm [J]. Journal of Henan Normal University: natural science edition, 2016 (1): 5.