Bitcoin Trading using LSTM

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Abstract. Bitcoin is a high-risk and high-yield investment, and in recent years, more and more investors have begun to pay attention to Bitcoin, but its riskiness has deterred many. However, the data over the past few years has continued to show that Bitcoin is exceptionally profitable, and holding Bitcoin for a long time is an investment option. This paper analyzes how to use Bitcoin and gold for venture capital and uses LSTM neural network to demonstrate its capability in trading. Furthermore, this paper delineates the novel strategy making combined with LSTM and a traditional technical indicator which yield more winning rate.

Keywords: Bitcoin; LSTM; Neural network; Machine learning

1 Introduction

BITCOIN, the largest cryptocurrency in the world, is growing with its popularity among investors. Nevertheless, there have few quantitative methodologies to make the best strategies. Its intrinsic value is unpredictable. However, based on the historical data of Bitcoin and other investments, Bitcoin has had over 100% annualized return for over 5 years. Therefore, this paper aims to demonstrate how to apply LSTM neural network, known for its ability in time-series forecasting, in Bitcoin trading.

In this paper, setting the back-testing environment in a trading environment with only gold and Bitcoin, simulating other assets through gold, and the change rate of gold can be replaced, just as in the framework proposed in this paper.

First, setting up a trading system based on the requirements of the proposed problem and the capabilities of the trading system include a daily update of assets, asset buying and selling, and ensuring that only data before the trading date is provided for model training.

Secondly, constructing a baseline based on the types of regular traders: (1) Trend Follower; (2) Contrarian; (3) Hybrid type (with Moving average), and (4) the traders who have always held Bitcoin and gold, which allows us to compare and illustrate the advantages of our model. Then, technical indicators, including MACD and RSI trading strategies, simulate the actual market.

Next, this paper proposed using BI-LSTM for time series forecasting. LSTM's long short-term memory characteristics make it a tremendous advantage in predicting time series. Compared to ANN, MLP, ARMIAX, or other machine learning algorithms, LSTM outperformed them in predicting financial time series. BI-LSTM has been

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shown in recent papers to have better predictive performance than LSTM. Since back-testing of financial sequences can only use data before the back-testing transaction date, it cannot use the global data to determine the specific architecture and hyperparameters of BI-LSTM. This paper proposed using grid-search for real-time optimization and completed this trading strategy. Here, we recorded transactions for assets in back-testing and found that our model, while not high in forecast accuracy and precision, was significantly smaller in predicting true negatives.

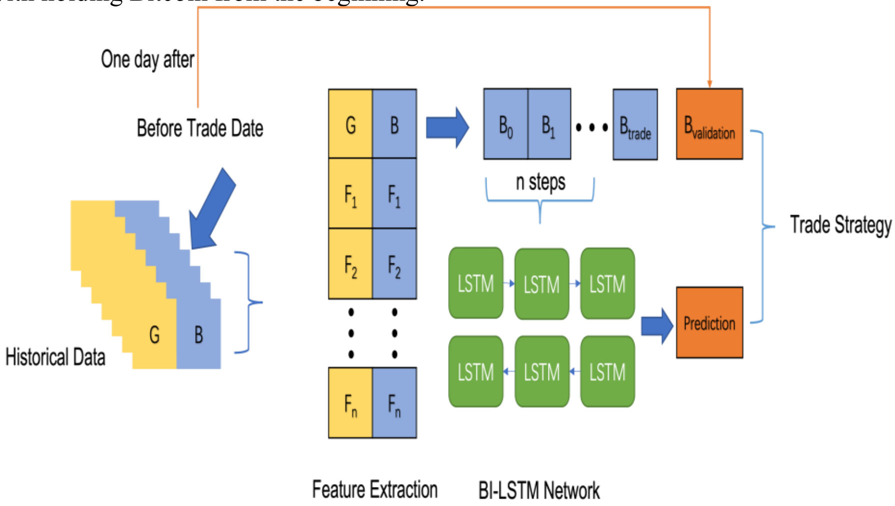
Based on the characteristics of our model, combined with the fact that holding Bitcoin always brings higher returns, this paper proposes the idea of 'HODL THE COIN' (The term HODL derives from the misspelling of HOLD by early Bitcoin traders. It implies that Bitcoin assets should always been held, even under the influence of market changes, they should not be sold. Because the high yield of return of this idea, which is market-proven, the term HODL is growing its popularity among Bitcoin traders.) Moreover, integrate it into the basic trading strategy. The empirical results show that the strategy significantly increases the yield and reduces the maximum drawdown. The maximum drawdown value is 23.6%, at 0.02 Bitcoin transaction fee, can get a return of 34219$, and in the absence of transaction fees, can get a 118925$ gain.

Finally, this paper proposes whether the machine learning model can be combined with technical indicators to improve the model even further. They are combining MACD with our decision model to form a hierarchical structure that allows MACD to assist in decision-making. Experiments have shown that such a method can increase the winning rate of the trading strategy.

2 Problem Statement

First, this paper applies covariance analysis to gold and Bitcoin to show their consistency and calculate the average annual return and volatility. Estimating covariance matrices of each year's price allows us to understand the inner mechanism of gold and Bitcoin. The use of standard error, because it does not protect against heterogeneity, can lead to significant errors in the model. In this article, the variance-covariance matrix is used, thus avoiding this problem.

Then, the study analyzed the basic trading strategies with Moving Average (MA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) and constructed their return as a baseline to show the performance of our strategy. From the perspective of actual returns, if investors have been holding Bitcoin, they can get at least 4000% of the total return, no matter which trading strategies will cause the return to decline. The main reasons for the decline are: 1. The excessive frequency transaction rate leads to a gradual increase in transaction costs, which leads to a significant decline in the final return. 2, Bitcoin's Volatility is too high accurately predict the future trend in a short period is impossible, resulting in missing some of the time where Bitcoin skyrocketed. For example, September 2020 to April 2021. Further, this paper builds a modified Bi-LSTM model utilizing the Thomas Fischer approach [1]. To predict the portfolio of assets that investors should hold given the data up to that trading day. The result is promising, though the average return is still low compared with holding Bitcoin from the beginning.



Note: Data obtained before simulated trade-day, taken as input with feature extraction, training Bi-LSTM network to predict trade-day. Validating with the actual move of buying or selling according to trade-day actual price.

Fig. 1. BI-LSTM network.

The trading framework proposed in this article is described in Figure 1, and on the left is the presentation of the historical data extracted in this paper. The model is constructed using only the data before the simulated trading day. After obtaining the data, this paper extracts n features, the panel data that constitutes Bitcoin and gold, and their features were constructed. Entering the data into the BI-LSTM network to obtain the prediction results and calculates the winning rate according to the actual result of the simulated trading day.

Finally, this paper presents a trading model based on assets' risk and future expectations, where we try to hold Bitcoin as much as possible. Except for the predicted colossal drop in the future, our strategy will not change the assets. Assets' risk is calculated with RSI and Volatility. The future expectation is based on modified BI-LSTM, which predicts future gold and Bitcoin prices. Then this paper proposes a grid-search framework for each Date, building a grid according to the input step, an input unit, according to the value of each grid, using all the data of the Date for back-testing, that is, train the Date (A parameter defined in this paper. Here indicating the number of dates before trading date.) model, train $n \times Date$ model in total and analyze which of these models can bring the highest return. Every day, the model performs such optimizations to ensure that it can adapt to changes in market behavior, as reflected from October 2017 to May 2018 and October 2020 to June 2021.

The structure of this paper is as follows. Section 3 investigates the context of Bitcoin and the situation of quantifying Bitcoin, and Section 4 reviews the previous works. Next, Section 5 gives some critical assumptions to solve the problem in this article.

Section 6 describes the prime Notation used in this paper in advance and the method in Section 7. Sensitivity analysis of transaction costs is reported and discussed in Section 8. In Section 9, this paper gives some of the improvements to the proposed model and some innovative ideas, which are summarized in Section 10 and provide some direction for future research.

3 Literature Review

It is well known that the forecasting task of financial time series is arduous, mainly driven by high noise and the generally accepted form of semi-strong market efficiency. The financial models that establish relationships between these return prediction signals and future returns are often transparent and fail to capture complex nonlinear dependencies. Over the past decade, machine learning methods have shown remarkable developments in financial time series forecasting [2]. Evidence has been established that machine learning techniques can identify (nonlinear) structures in financial market data.

Fernandes uses artificial neural networks, support vector machines, and integrated algorithms to predict the direction of Bitcoin and the maximum, minimum, and closing prices [3]. Harikrishnan et al. point out the application of various machine learning algorithms in predicting stock prices [4]. Siami-Namini and Namin compared LSTM to the Autoregressive Integral Moving Average (ARIMA) model [5]. Their empirical results applied to financial data show that LSTM outperforms ARIMA regarding lower forecast errors and higher accuracy. Basak et al. apply stochastic forests, gradient boosting decision trees (XGBoost), and a range of technical indicators to analyze the performance of predicted stock returns in the medium to long term [6]. In our work, using the Bi-LSTM network with an attention mechanism. According to Siami-Namini, Bi-LSTM models provide better predictions than ARIMA and LSTM models. This paper introduces a technique for selecting a period of data and aims to enhance the prediction performance [7,8].

Most predictive models operate by training using global (all) data and bringing the calculated hyperparameters directly into the back-testing process [9-12]. For example, LSTM has multiple steps predicting one step, where it is difficult to determine how many steps of data are needed to enter to optimize the prediction value. However, if the investor used enough computing power, optimizing the model training parameters in each back-test is possible. From the literature alone, LSTM has a neural network model with a back propagation class with excellent predictive power for Bitcoin [13-16]. When modeling BTC/USD returns, the nonlinearities observed in BTC/USD returns need to be considered. Among them, BTC/USD returns exhibit periodic local trends (or bubbles) that can be predicted using technical indicators.

4 Assumptions & Rationales

Following the request from the Problem, this paper made the following assumptions:

1. Bitcoin and gold trading usually involve the opening and closing prices of the day's high and the lowest of the day. However, according to the data set, only one value

is provided for the daily data, so this paper assumes that this value is the closing price to facilitate the back-testing of the transaction.

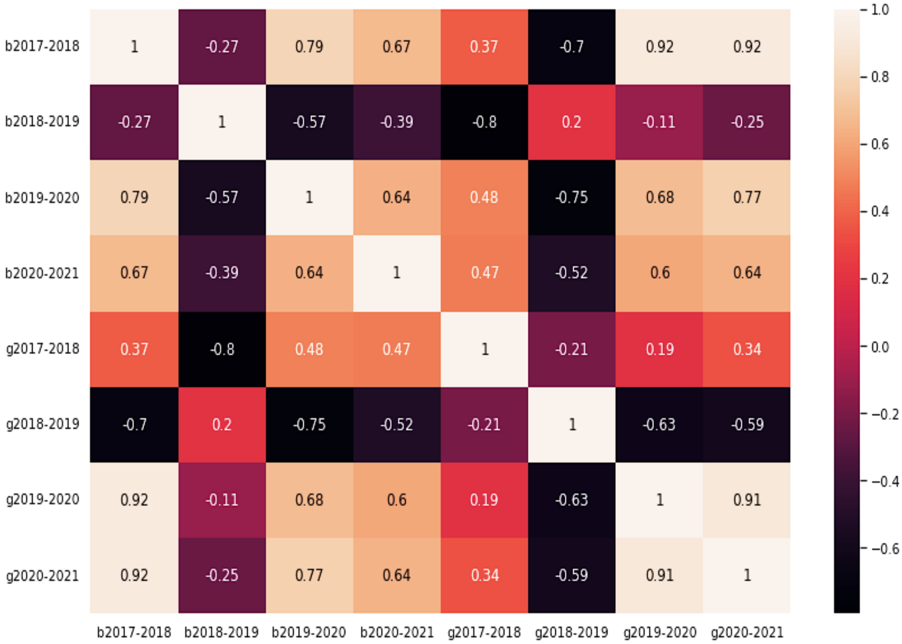
2. To simplify the calculation, we believe that cash does not have a minimum current yield, i.e., cash does not appreciate or depreciate.

3. This paper believes that there are no delays and failures in trading and that the asset can be successfully purchased every time an order is placed

4. This paper remains unknown about the data after the trading day, i.e., every training of the model and the adjustment of hyperparameters only depend on the data before the trading day. Using this hypothesis to divide the dataset, including the training set (training, testing, validation) and the out-of-sample test set.

5 Strategies

Testing the correlation between Bitcoin and gold, where gold represents the assets that can be purchased regularly, is a common intuition. Bitcoin is an investment product with high risk, and gold is an investment product used for hedging. Figure 2 looks at the correlation between Bitcoin and gold each year.



Note: B: Bitcoin; G: gold

Fig. 2. Correlations between gold and Bitcoin over different years and intra-years.

On the lower left corner's diagonal, it can be seen that Bitcoin and gold are positively correlated. This counter-intuition result helped us develop the trading strategy, which in order to maximize the returns (obviously, holding cash is not as good as holding gold, yet holding gold does not have as much as average return compared to holding bitcoin), so as mentioned above, the idea is to hold Bitcoin as much as possible to maximize the returns, take gold as a safe-haven asset, if and only if Bitcoin's prediction is uncertain. The gold forecast value will rise in the future.

5.1 Trading Simulation and Back testing Method

Bitcoin and gold trading system for back-testing is required in order to estimate the final value of 1000$. First, by setting the date parameter to control the data the model can access, that is, to prevent the model from acquiring future data. The trading module is based on the transaction cost and bought/sold assets based on the portfolio ($[CBG]$) information returned by the strategy module. This paper also designed a time-lapse module, which updates the information in $[CBG]$ based on the growth rates of Bitcoin and gold in the actual data at each date change. The specific algorithm for portfolio determination is as follows:

Algorithm 1 CBG trading moddule

```
Require: input [C,B,G], gold trading data as GOLD, bitcoin trading data as
  BIT, Date, tradeDate, goldtradeDate
                                  ▷ [C,B,G] is the combination of protfolio
  if Date < tradeDate then C=1,B=0,G=0
                            ▷ tradeDate stands for beginning of trading
  else
     Determine the buy/sell signal for bitcoin BITsignal
     if Date in goldtradeDate then
        Determine the buy/sell signal for gold GOLDsignal
        if BITsignal == 1 and GOLDsignal == 1 then
           C=0,B=1,G=0
         ▷ The ratio of bitcoin and gold may change depending on strategies
        else if BITsignal == 1 and GOLDsignal == 0 then
           C=0,B=1,G=0
        else if BITsignal == 0 and GOLDsignal == 1 then
           C=0,B=0,G=1
        else if BITsignal == 0 and GOLDsignal == 0 then
           C=1,B=0,G=0
        end if
     else
        if BITsignal == 1 then C=0,B=1,G=0
        else
           C=1,B=0,G=0
        end if
     end if
  end ifreturn [C,B,G]
```

5.2 Construction of Baseline

Immediately after, this paper built several baselines, first of all, naturally holding Bitcoin or gold to bring benefits, and secondly, according to the Stefano Rossi paper, in equilibrium of market, the optimal quantitative trading depends on the number of different types of traders in that market. Usually when there are few fundamental traders, the best quantitative strategy is to follow the trend after a small price change. But for many fundamental traders, the best strategy is often to follow the trend in reverse after a small price change. Therefore, traditional traders are generally divided into three categories:

1.Trend-following (e.g., buying after prices have gone up).

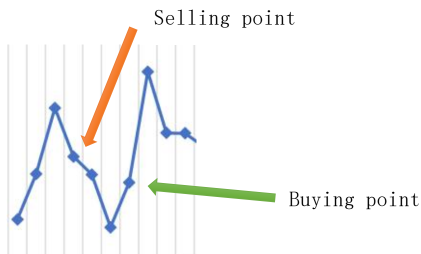
Observe the changes in Bitcoin and gold, buy immediately when the price rises after falling, and sell immediately after the price falls. When both assets have a buying signal simultaneously, analyze which asset has the most significant increase in the previous two days and choose the asset with the most significant increase to buy.

2.Contrarian (e.g., buying after prices have gone down).

Observe the changes in Bitcoin and gold, buy immediately when the price starts to fall, and sell immediately when the price starts to rise. (The strategy is not profitable; this baseline is removed)

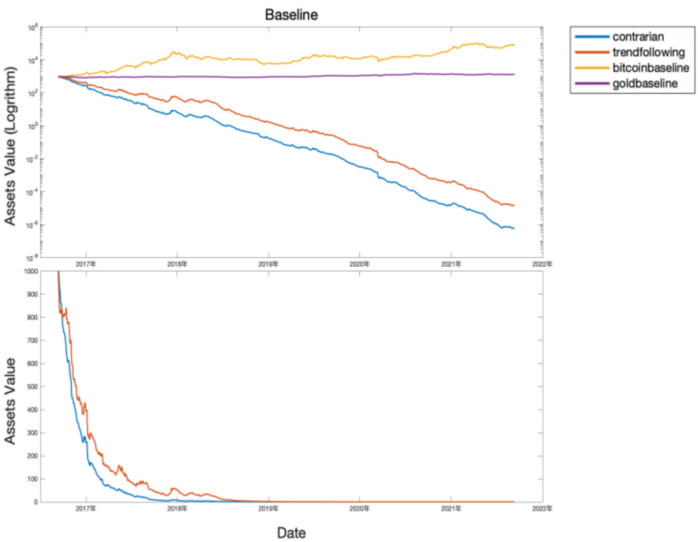
3.Hybrid forms where the direction of price-contingent trading varies across time horizons, magnitudes of past price changes, instruments, and market structures.

The specific mechanism of accurate simulation for 1 and 2 types of traders is as Figure 3.



Note: Selling the assets after the highest price and buying the assets after the lowest price.

Fig. 3. Trend Followers' Strategy.



Note: Blue: Contrarian; Red: Trend Follower

Purple: Hold Gold (since beginning); Yellow: Hold Bitcoin (since beginning)

Fig. 4. Baseline Comparison.

In the experiment in Figure 4, the result shows that when the transaction cost is more than 1%, if investors consider the above baseline, they will eventually lose all the capital, which might be high-frequency transactions. Actual income is lower than transaction costs.

To reduce the frequency of trades, this paper use moving averages instead of raw data for trading decisions, MA5, MA10, MA20, MA30, MA60, and MA250, respectively.

The daily price for BTC/USD will be denoted by $P_{Bt}, t = 1,2,3,\ldots,T$, similarly, price for gold will be denoted by $P_{Gt}, t = 1,2,3,\ldots,T$, and the return series for each asset is $r_{Bt} = P_{Bt}/P_{Bt-1}$; $r_{Gt} = P_{Gt}/P_{Gt-1}$. To calculate the moving averages, here denote the length of the average as n, and let m_t^n be the moving average at time t, where:

$$m_t^n = \left(\frac{1}{n}\right) \sum_{i=0}^{n-1} P_{t-i} \tag{1}$$

the test results show that more considerable gain can be obtained when the moving average window is 30. Furthermore, this paper applies quantitative indicators that can be used well to help with investment decisions. However, some indicators require more dimensional data. Here we only selected two more widely used indicators: RSI and MACD, as a reference for investment decisions.

The MACD indicator, called Moving Average Convergence / Divergence, belongs to the general trend indicator. It consists of long-term moving average DEA and short-term line DIF. It uses short-term moving average DIF and long-term line DEA crossover as signals. DIF is the core, and DEA is the auxiliary. Its role is to identify investment opportunities in the stock market and, secondly to protect the investment income in the stock market from loss.

The MACD (DIF, DEA) is calculated as follows:

$$EMA(P,N)_{\mathrm{t}} = \frac{2}{N+1} * P + \left(1 - \frac{2}{N+1}\right) * EMA_{\mathrm{t-1}} \tag{2}$$

$$\text{set } \alpha = \frac{2}{N+1}, EMA(1) = P_1 \tag{3}$$

$$EMA(1) = P_1 \tag{4}$$

$$EMA(2) = \alpha P_2 + (1-\alpha)P_1 \tag{5}$$

$$EMA(3) = \alpha P_3 + \alpha(1-\alpha)P_2 + (1-\alpha)^2 P_1 \tag{6}$$

$$EMA(4) = \alpha P_4 + \alpha(1-\alpha)P_3 + \alpha(1-\alpha)^2 P_2 + (1-\alpha)^3 P_1 \tag{7}$$

$$\cdots\cdots$$

$$EMA(t) = \alpha P_t + \alpha(1-\alpha)P_{t-1} + \alpha(1-\alpha)^2 P_{t-2} + \cdots$$

$$+ \alpha(1-\alpha)^{t-2} P_2 + (1-\alpha)^{t-1} P_1 \tag{8}$$

Where EMA is Exponential Moving Average

$$DIF_t = EMA(P_t, 12) - EMA(P_t, 26) \quad (9)$$

$$DEA = EMA(DIF_t, 9) \quad (10)$$

$$MACD = 2 \times (DIF - DEA) \quad (11)$$

The relative strength indicator RSI, created by Welles Wilder, is currently a commonly used short-term indicator in stock market technical analysis.

The relative strength index RSI is a technical indicator that judges the future market trend by comparing the amplitude of the rise and fall of a single stock price or the size of the index of the entire market according to the principle of the balance between supply and demand in the stock market, to judge the future market trend.

From the principle of its construction, the same as the MACD, TRIX, and other trend indicators, the RSI indicator analyzes the primary change trend of a single stock or the entire market index. Nevertheless, unlike the MACD, TRIX, etc., the RSI indicator is to find the closing price of a single stock at a certain time or the strength of the closing index of the entire index at a certain time, rather than directly smoothing the closing price of the stock or the stock market index.

The relative strength indicator RSI is the ratio of the market's increase to the increase plus the decline over a certain period. It is a quantitative and graphical embodiment of the buying and selling power, and investors can predict future stock price trends according to their market movements and trajectories. In practice, it is often used in conjunction with moving averages to improve the accuracy of market forecasts.

The RSI is calculated as follows:

$$RSI = 100 - 100 / (1 + RS) \quad (12)$$

$$RS = Relative\ Strength = AvgU / AvgD \quad (13)$$

Where, $AvgU$ is the Average of Up Move for the past N prices, $AvgD$ is the Average of Down Move of the past N prices, N is the period of RSI.

The methods of using MACD and RSI to assist investment decisions are:

1. DIF > 0, DIF cross upwards DEA, MACD>0. Indicates that the stock is in a rising state and accelerating.

DIF>0, DIF cross downwards DEA, MACD <0. Indicates that the stock is in a rising state, but the upward rate is slowing down, the upward trend may change, and the stock price may turn down.

DIF < 0, DIF cross upwards DEA, MACD>0. Indicates that the stock is in a downward state, but the downward rate is slowing down, the downtrend may change, and the stock price may turn upward.

DIF<0, DIF below DEA, MACD<0.Indicates that the stock is in a downward state, and the decline is accelerating, and the downward trend continues.

2. RSI changes in the range between 0 and 100, with 50 as the boundary, greater than 50 for the strong market; less than 50 for the weak market, above 80 or more into the overbought zone, easy to form a short-term retracement, below 20 below the oversold zone, easy to form a short-term rebound.

The back-testing result of using these strategies are shown below:

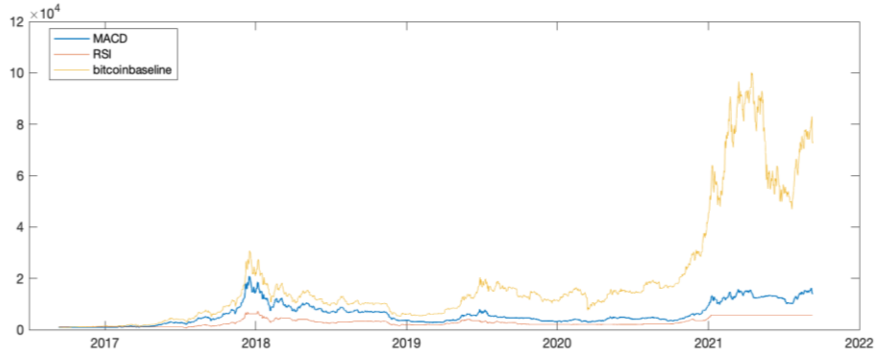


Fig. 5. MACD, RSI strategies.

As can be seen from Figure 6, the overall level of MACD is higher than that of USING MA30 alone but still not as profitable as holding Bitcoin all the time. Considering that RSI and MACD are lagging indicators, they might be that they are not good indicators for crypto. Investors should focus on price action instead.

5.3 Forecasting with Bi-LSTM

In this section, this paper delineates the structure of using Bi-LSTM in forecasting bitcoin and developing a strategy. First, process the data and divide it into training data and trading data based on the data obtained before the transaction date. Because the Bi-LSTM model uses a multi-step calculation, our trading date data and training dates data have an inevitable overlap. Among them, the accessible data is divided into training date, test date, and verification date data. The training date data helps us train models and optimize parameters using existing data, and the trading part is to use data outside the sample for predictions. Secondly, introduced our model's framework, compared LSTM with Bi-LSTM, and compared it with the method of using technical indicators, highlighting the advantages of Bi-LSTM. Finally, analyzing the flaws of Bi-LSTM and adopting the idea of "HODL" improved our decision-making model and demonstrated it.

The model uses simple technical indicators to produce a feedforward neural network with a cost of density forecasts of Bitcoin return. By running several models from September 2017 to September 2021, the results find that backpropagation neural networks dominate various competing models in terms of their forecast accuracy. Concluding that the dynamics of Bitcoin returns are characterized by predictive local nonlinear trends that reflect the speculative nature of cryptocurrency trading. Therefore, based on Thomas Fischer, we construct a nonlinear Bi-LSTM prediction model based on LSTMs [1]. The CUDA Deep Neural Network Library (cuDNN) is a GPU-accelerated library for deep neural networks. The created model with 25 LSTM cells, followed by a 0.1 drop layer, and then a dense layer with ReLU activation functions consisting of 1 output node. Our loss function is MSE, with adam optimizer. Considering the relatively small sample of data, we choose batch size to be 128, with up to 400 epochs for training and early stopping. The experiment splits 0.1 training data for validation.

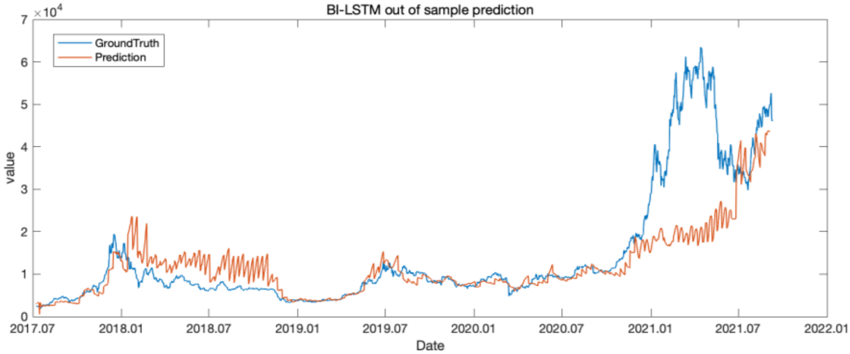


Fig. 6. BI-LSTM out of sample prediction (with first 90 days as input).

In Figure 7, the experiment analyzes all transaction records for transactions made using this model. Treating the profitable trades as the winning ones.

The accuracy of the proposed model forecasts for the BTC/USD can be demonstrated as follow:

$$Accuracy = (TP + FN)/(TP + TN + FP + FN) \tag{14}$$

$$Precision = TP/(TP + FP) \quad Recall = TP/(TP + FN) \tag{15}$$

$$F1 - score = (2 \times Precision \times Recall)/(Precision + Recall) \tag{16}$$

$$True\ negative\ ratio = 1 - FN/(TP + TN + FP + FN) \tag{17}$$

Table 1. BI-LSTM performance

True positive	True negative	False positive	False negative
44	31	49	28

Table 2. BI-LSTM performance

Accuracy	Precision	Recall	F1-score	False negative ratio
0.49342105	0.47311828	0.58666667	0.52380952	0.81578947

It can be seen from Table 2 and Table 3 that the Accuracy of the model is not very high. However, it is significant that it has a significant advantage in avoiding the prediction of true negatives. Then by giving two models, one based on Bi-LSTM only, the other is trying to hold as many Bitcoin as possible (Figure 8). In the first model, Accuracy is vital to the final return since investors do not want to miss appreciation and want to avoid depreciation. However, in the second model, the expectation is to decrease the True negative, which means that if Bitcoin will appreciate in the future, our model mistakenly judges this stage as depreciating. This will cause investors to sell Bitcoin at the wrong time, thus missing the stage of Bitcoin appreciation. At first glance, the logic of the two models is the same. Both are for the sake of buying low and selling high. Nevertheless, because of the long-term holding of Bitcoin, the second model first reduced many transaction costs, and the second successfully dodged some major plunges, thus increasing the final income. Based on this strategy, the final return of 1000$ in the 4th year is 34219, which max 23.6% drawback, and the improved model has a 53.7 percent win rate.

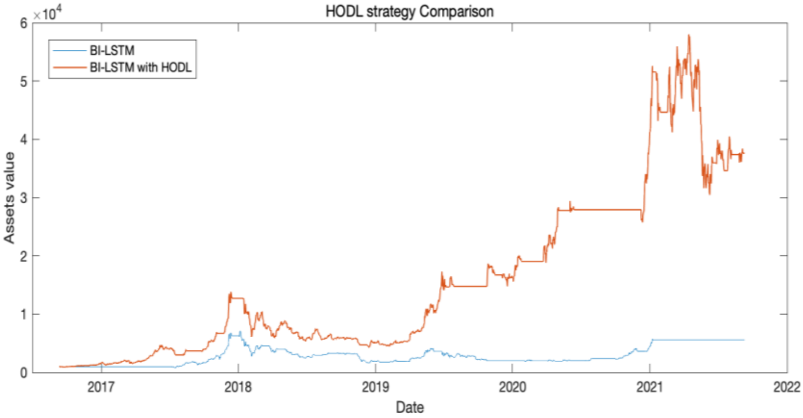


Fig. 7. HODL strategy comparison.

After this, according to the hyperparameter characteristics of the model. This paper carried out a Grid-searching Bi-LSTM model, whereby using multi-step prediction, one is to reduce the amount of calculation, the other is to reduce the frequency of transactions, can better get the future trend. In evaluating the proposed model, this paper compared LSTM and BI-LSTM (Figure 9), and BI-LSTM provided statistically significant improvements in prediction accuracy. However, in some stages, BI-LSTM is significantly inferior to LSTM models and technical analysis in terms of out-of-sample prediction accuracy.

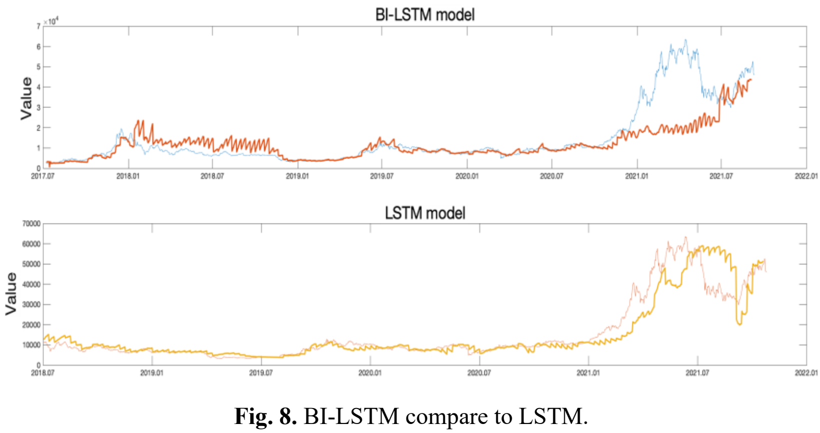


Fig. 8. BI-LSTM compare to LSTM.

This paper speculates that the long-term memory type of BI-LSTM leads to a lack of awareness of changes in market behavior and a lack of valid information because the input is one-dimensional data.

6 Improvement & Innovation

Using simple technical indicators, this paper makes further secondary decisions based on Bi-LSTM decisions. We introduce the MACD indicator for the secondary judgment detection of the period when Bi-LSTM is judged to be falling. If the MACD judges that Bitcoin may appreciate during this period, we choose to hold Bitcoin. We run several models from September 2017 to September 2021 and found that adding a model of technical indicators dominates various competing models in terms of their final return. The conclusion is that the dynamics of Bitcoin returns are characterized by predictive local non-linear trends that reflect the speculative nature of cryptocurrency trading. The dynamic nature of Bitcoin's returns allows for better predictions when combined with neural networks and technical metrics.

7 Conclusion

Under the 0.02 and 0.01 transaction fees for Bitcoin and Gold, the framework proposed in this paper can achieve 34129 final returns with a max drawback of 23.6%. The annualized return is 2.419, which is still profitable even considering the risk. The results of this paper show that the return on BTC/USD can be predicted by using past returns and BI-LSTM using simple technical trading rules. BI-LSTM, with the best predictive power, combined with big ideas "HODL THE COIN", tries to hold Bitcoin as much as possible. There is high profitability and robustness. However, the predicted performance dropped over time, possibly due to Bitcoin's volatility. It can be concluded that the dynamics of daily BTC/USD returns exhibit local trends that the speculative nature of cryptocurrency trading may trigger. Further research should expand the inputs, perhaps considering the number of daily blocks added to the chain or other measurements.At the same time, to be able to simulate Bitcoin transactions more realistically, investors should consider intra-day trade instead and use the intraday trading records, that is, the opening price, the closing price, the highest point, and the lowest point as inputs to obtain a more robust model.

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