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Research on the applicability of time series models for bitcoin price prediction: taking ARIMA and LSTM as examples

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Abstract. This paper takes the prediction of Bitcoin price as the research goal and comparatively analyzes the applicability of two types of time series models, autoregressive integrated moving average model (ARIMA) and long short-term memory (LSTM). Based on the daily closing price data of Bitcoin from October 2013 to December 2021, the ARIMA model and the LSTM model were constructed respectively, and the performance of the models was verified through stationarity tests, parameter optimization and prediction error analysis. The research results show that the ARIMA model performs stably in the short-term prediction of linear trends, but it is difficult to capture the nonlinear fluctuations of Bitcoin prices. Due to its long-term memory ability, the LSTM model has more advantages in nonlinear feature extraction and long-term dependency processing, and its prediction accuracy is significantly higher than that of the ARIMA model (MAPE is reduced by approximately 60%). Furthermore, this paper explores the potential of the hybrid model and finds that the method combining wavelet decomposition and model fusion can further improve the prediction effect and provide a direction for future research.

1 Introduction

With the rapid development of blockchain technology, since its birth in 2008, Bitcoin, as the first decentralized digital currency, has gradually become a digital asset of global attention due to its decentralized characteristics and scarcity design. Its price fluctuates sharply under the influence of multiple non-linear factors such as technological evolution, supply and demand relations, policy regulation, and market sentiment (for instance, the price dropped by more than 50% during the COVID-19 pandemic in 2020 and soared to $65,000 in 2021 driven by quantitative easing policies), showing highly non-linear and non-stationary characteristics [1]. Therefore, accurately predicting the price of Bitcoin is of great significance for investor risk management and market supervision. Traditional time series models (such as ARIMA) and deep learning models (such as LSTM) each have their own advantages in the field of financial prediction, but their applicability in Bitcoin price prediction still needs systematic verification. This paper will discuss and verify the advantages and disadvantages of the

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autoregressive integrated moving average model (ARIMA) and long short-term memory (LSTM) models through data preprocessing, model design, performance evaluation, and robustness testing. It will develop a multivariable LSTM neural network, integrate historical data of Bitcoin prices and market characteristics, improve prediction accuracy, provide quantitative tools for investors and regulatory authorities, and assist in risk management and policy-making [2].

2 Literature Review

2.1 The application of the ARIMA model

The ARIMA model processes non-stationary sequences through difference processing and is applicable to linear time trend prediction. Duan Gege constructed the ARIMA(4,1,4) model based on Bitcoin data from 2013 to 2019. Its short-term predicted MAPE was 3.657%, verifying the effectiveness of ARIMA in stationary sequences. However, the price of Bitcoin often has sudden changes and heteroscedasticity, and ARIMA has difficulty capturing complex nonlinear patterns [3].

2.2 The advantages of the LSTM model

LSTM solves the long-term dependency problem through the gating mechanism and is good at handling nonlinear sequences. Zhang Ning et al. proposed the CEEMDAN-LSTM hybrid model, which utilized wavelet decomposition to extract multi-scale features and predicted an MAPE as low as 0.04%, significantly superior to a single model. Studies show that LSTM performs better in highly volatile financial time series.

2.3 The potential of the hybrid model

Niu Qing combined wavelet decomposition (WT), ARIMA, LSTM and SVR to construct a hybrid model, which reduced the RMSE by 35% compared with a single model, demonstrating the effectiveness of integrating linear and nonlinear methods. This type of model, through the decomposing-prediction-reconstruction framework, takes into account both trend and fluctuation characteristics and has become a current research hotspot.

3 Time series model

3.1 ARIMA model

The ARIMA model has become one of the most commonly used and relatively efficient methods for solving time series problems. As a relatively mature model in econometrics, the ARIMA model has been widely applied in multiple fields such as energy, agricultural products and stock price prediction. At present, stationary time series models mainly include AR models, MA models, ARMA models and ARIMA models, etc [4].

Among them, the AR model is one with relatively low complexity among the current linear time series analysis models. This model holds that the current value of the time series is only correlated with the values of the previous several periods, and assumes that there is a linear relationship among these values. By utilizing the autocorrelation between the past data and the current data of the variable, the AR model fits the regression equation, thereby achieving the prediction of future values. Its mathematical expression is:

$$X_t = c + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t \qquad (1)$$

Among them, X is the sequence of regression, t is time, c is a constant, φ is the coefficient, ε is the random error value, and σ does not change with t. p indicates that the current period value is correlated with the lagging p period value, and the model is usually denoted as AR(p).

The Moving Average (MA) model focuses on characterizing the correlation between the current value of a variable and a linear combination of white noise terms from previous periods. Specifically, the MA model fits the current value by aggregating weighted white noise sequences of past intervals, which grants it a distinct advantage in capturing stochastic fluctuations within time series data. This approach allows the model to efficiently represent transient disturbances or random shocks in the system. The mathematical formulation of the MA model is expressed as follows:

$$X_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_p \varepsilon_{t-q} \qquad (2)$$

Among them, X is the sequence of regression, t is time, μ is a constant, θ is a coefficient, ε is the random error value, σ does not change with t, and the random errors in different periods are not linearly correlated. q indicates that the current period value is related to the lag q order error term, and the model is usually denoted as MA(q).

The ARMA model is a combination of the AR model and the MA model, which comprehensively considers the influencing factors of each of these two models. The core idea of this model lies in that the current value of a time series can be jointly represented by several orders of its own past values and the linear combination of random error terms. Specifically, the mathematical expression of the ARMA model can be expressed as:

$$X_t = \mu + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_p \varepsilon_{t-q} \quad (3)$$

Among them, X is the sequence of regression, t is time, μ is a constant, φ and θ are coefficients, ε is the random error value, and σ does not change with t. p represents the correlation between the current period value and the lagging p period value, and q represents the correlation between the current period value and the lagging q order error term. The model is usually denoted as $ARMA$(p, q).

In time series analysis, models such as the AR model, MA model, and their combined form, the ARMA model, are effective for modeling stationary data sequences. However, real-world time series data are often non-stationary. To address this, the differencing method is typically applied: non-stationary sequences are transformed into stationary ones through differencing operations, after which AR, MA, or ARMA models are used to analyze the differenced stationary data. This integrated approach, combining differencing and autoregressive-moving-average modeling, is formally termed the Autoregressive Integrated Moving Average (ARIMA) model.

$$\varphi(B)\nabla^d X_t = \theta(B)\varepsilon_t \qquad (4)$$

It can be seen from the above formula that the ARIMA model contains the ARMA, AR and MA models, and they can transform into each other. When the difference order d is zero, it becomes the ARMA model, and when further q=0, it correspondingly becomes the AR model. When p=0, it correspondingly becomes the MA model [5].

3.2 LSTM model

Hochreiter and Schmidhuber innovatively proposed the Long Short-Term Memory Neural Network (LSTM) in 1997. This innovative achievement marked an important improvement direction for recurrent neural networks (RNN). After decades of continuous evolution, the LSTM neural network, with its unique design concept and long-term memory ability, has successfully overcome the problems of "vanishing gradients" and "exploding gradients" that are commonly encountered in the training process of traditional RNN neural networks [6]. Thanks to its unique "gate" structure, the LSTM neural network can achieve accurate prediction of longer time series data.

Specifically, the LSTM network introduces three key components: the input gate, the output gate, and the forgetting gate, which represents a significant expansion compared to the traditional RNN neural network. The addition of these three gates not only enhances the structural complexity of the model, but more importantly, they work together to effectively solve the problems of gradient vanishing and gradient explosion that are inevitable in the prediction of long sequences by RNN. Through this innovative design, the LSTM neural network (see Figure 1) has demonstrated outstanding performance in long-term series prediction [7].

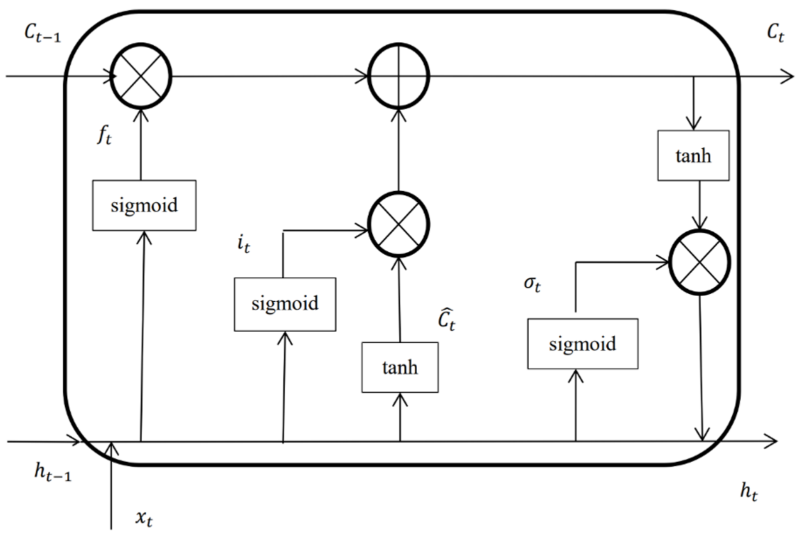

Fig. 1. The principle of LSTM neural network.

A recurrent neural network (RNN) features a chain-like structure where each node receives input from the preceding node, processes it to generate the current state, and propagates this state to the next node. Each memory cell within the network comprises three critical gating mechanisms: the forget gate, input gate, and output gate, which collectively regulate information flow. The forget gate specifically acts as a filter, determining which components of the prior cell state C_{t-1} to retain or discard. This is achieved by calculating a sigmoid function value (ranging from 0 to 1), where 0 signifies complete erasure of information and 1 indicates full retention. The gate's operation is governed by its weight ωf and bf parameters, which are optimized during training to adaptively control the degree of information preservation.

$$f_t = \sigma(wf \cdot [h_{t-1}, x_t] + b_f) \qquad (5)$$

The next stage is the selective memory of the input gate. In this stage, some unimportant information is appropriately abandoned, and important information will account for a large part of the "memory". The gating signal of the input gate is controlled by the tanh function. The calculation formula for this stage is as follows:

$$i_t = \sigma(wf \cdot [h_{t-1}, x_t] + b_i) \qquad (6)$$

$$\hat{C}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \qquad (7)$$

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \qquad (8)$$

The final stage corresponds to the output stage of the model, which takes up the last structure of memory, the ---- output gate, which controls which parts of the information obtained will be the output of the current state, and this process is also controlled by the tanh function. The calculation formula of the entire output gate structure is as follows:

$$\sigma_t = \sigma(W_0 \cdot [h_{t-1}, x_t] + b_0) \qquad (9)$$

$$h_t = \sigma_t * \tanh(C_t) \qquad (10)$$

The above is the basic model structure and calculation process of the LSTM model. In the actual application process of this model, relevant parameters need to be changed according to the actual situation, following the rules of gradient descent and backpropagation.

4 Case Analysis

4.1 ARIMA model

Fig. 2. Closing prices of Bitcoin (2019.12-2022.6)

The figure 2 is the time series graph of the closing prices of Bitcoin from April 1, 2020 to June 30, 2022. It can be initially judged that the closing prices of Bitcoin are non-stationary series. To verify this conjecture, the autocorrelation and partial correlation figures 3-4 are drawn as follows:

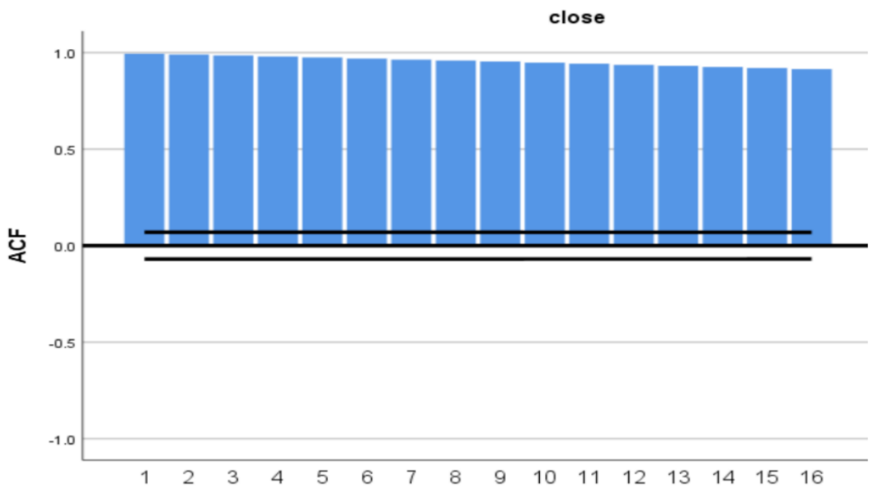

Fig. 3. Autocorrelation graph.

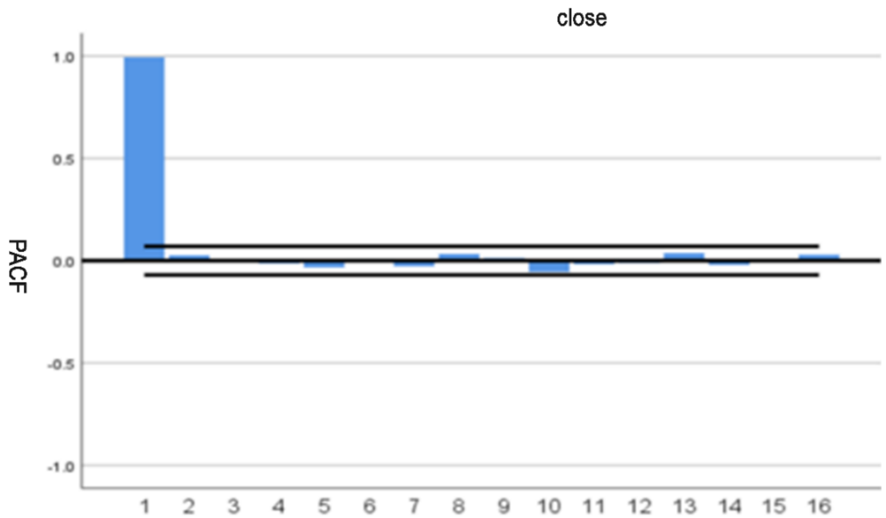

Fig. 4. partial correlation graph.

From the above figure, it can be concluded that this sequence is a non-stationary sequence. For non-stationary sequences, difference operations should be performed to remove their trend factors. The first-order difference results are shown in the following figure 5:

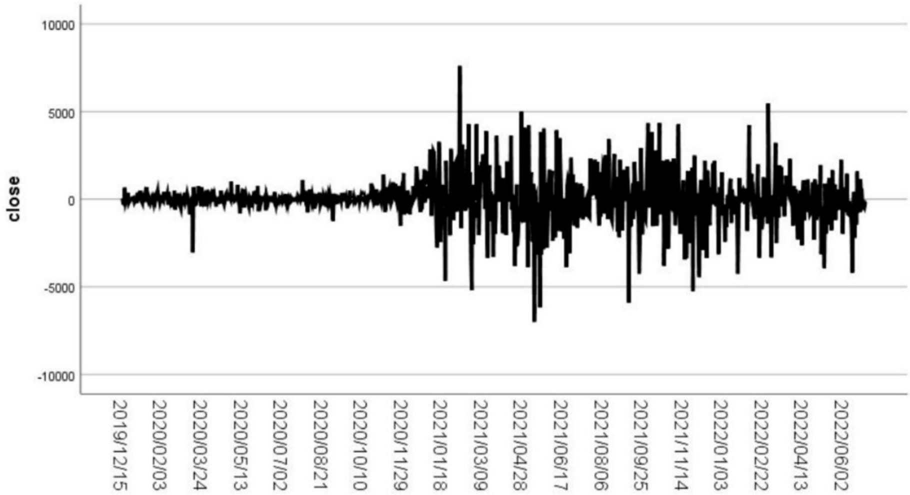

Fig. 5. The first-order difference results.

From the visual analysis, the first-order differenced series can be preliminarily identified as stationary. The auto.arima() function within the R language forecast package was then applied for automated model selection, resulting in an ARIMA(1,1,1) specification. The fitted model underwent a residual white noise test, which confirmed the absence of autocorrelation in the residual series, thereby validating the adequacy. Consequently, the ARIMA(1,1,1) model was deemed appropriate. This model was subsequently employed to forecast Bitcoin's closing prices over a 186-day horizon, with predictions visualized in the accompanying figure. The Root Mean Square Error (RMSE) of the forecasts was calculated as 1435, reflecting the predictive accuracy of the model (see figure 6).

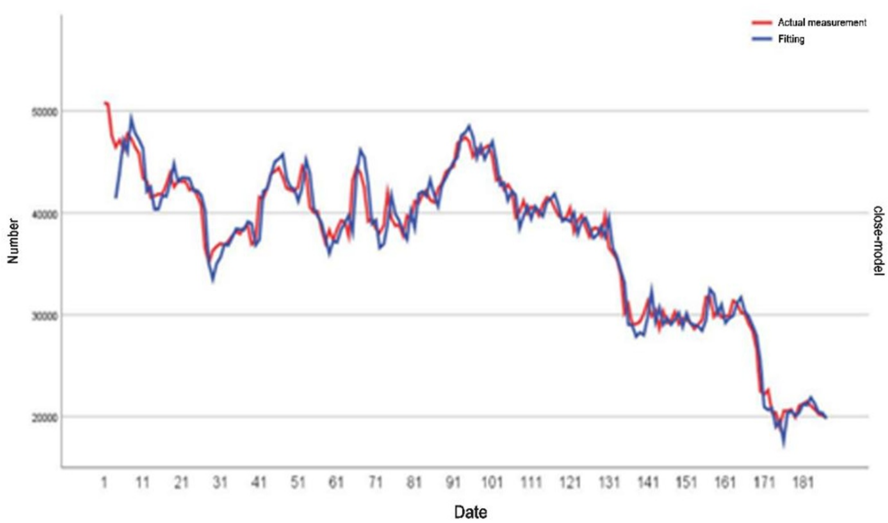

Fig. 6. Bitcoin closing price prediction.

4.2 LSTM model

4.2.1 Data feature processing

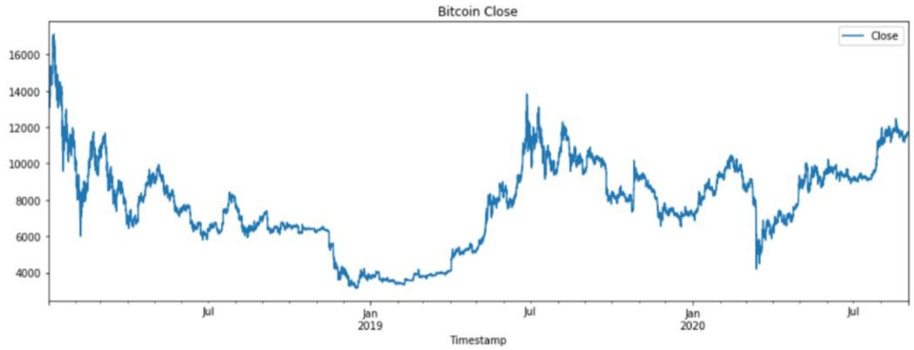

Fig. 7. Closing prices of Bitcoin(2018.1-2020.9).

The dataset (see figure 7) used to verify this LSTM model is the Bitcoin closing price data with the time nodes from January 1, 2018 to September 14, 2020. The closing price data graph is shown as follows. Among them, September 1, 2020 was selected as the division node. The data before this date was the training set, and the data after that date was the test set. There were a total of 23,377 pieces of data in the training set and a total of 320 pieces of data in the test set.

For the LSTM model, the data still needs to be normalized to facilitate the establishment, convergence and input requirements of the model. Due to the significant hourly variation in the closing price data of Bitcoin, the maximum value is approximately 19,665.76, and the minimum value is about 1.5. All the data are unified into a approximately identical numerical interval [8]. Here, the MAX-MIN normalization method is used, along with linear function normalization. The results are mapped to [0,1], and $X_{norm} = \frac{X-X_{min}}{X_{max}-X_{min}}$ is its specific formula. Among them, X_{max} is the maximum value in the sequence and X_{min} is the minimum value in the sequence [9]. The normalized data image is shown as figure 8.

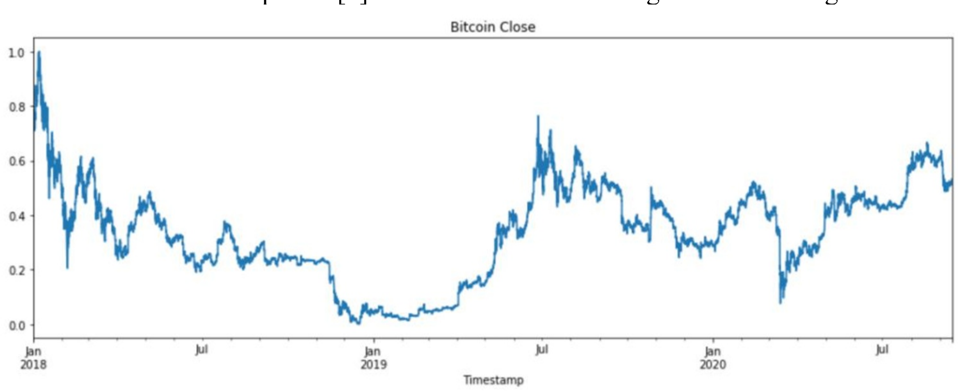

Fig. 8. Normalized Bitcoin closing price data (2018.1-2020.9).

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4.2.2 Prediction results of the LSTM model

After establishing the LSTM model for the relevant data, the predicted values of the training set are obtained. By comparing the two, the image as shown in the following figure can be obtained. It can be seen that the original data and the predicted data are highly consistent, that is, the model has a relatively good effect on the training set (see figure 9).

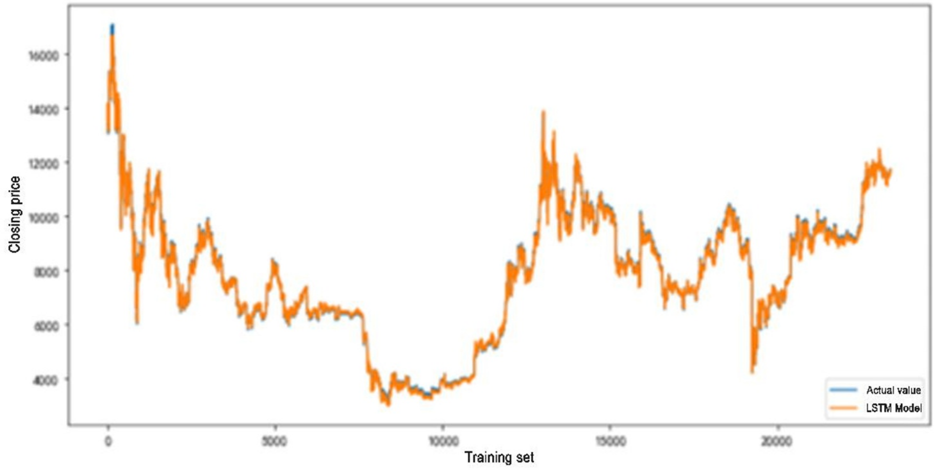

Fig. 9. Normalized Bitcoin closing price data (2018.1-2020.9)

Among them, the relevant evaluation indicators of the calculation model can be obtained. For the original training set, predictions are made. At this time, the rating index values of the LSTM model for the training set are shown in the following table 1.

Table 1. Evaluation index values of the LSTM model training set.

Evaluation index	Index value
MAE	47.33
RMSE	56.43
MAPE	0.46

4.3 Combined model

4.3.1 Sequence reconstruction

Wavelet Transform, developed from the Fourier Transform, decomposes and reconstructs signals through frequency-domain scaling and time-domain shifting. This method splits the original sequence into multiple frequency-based sub-sequences: low-frequency sub-sequences capture the primary linear trends with smooth patterns closely aligned to the original sequence’s trajectory, making them suitable for prediction via traditional time series models like ARIMA. High-frequency sub-sequences display strong nonlinear fluctuations (oscillating near a zero mean), which are challenging for conventional models. Machine learning approaches such as LSTM or SVR are often employed to model these components. Accordingly, this paper proposes a hybrid prediction framework: first, applying WT to split the signal; next, predicting low-frequency trends with ARIMA; modeling high-frequency nonlinear components using LSTM and SVR separately; and finally, integrating the predictions. The WT-ARIMA-LSTM-SVR hybrid model aims to combine the strengths of each method (ARIMA's linear trend accuracy, LSTM's sequence modeling, and SVR's noise robustness) to achieve optimal predictive performance.

4.3.2 Single model combination

Through the model prediction in the above text, the predicted values of the ARIMA model and the LSTM model for the data were obtained. Therefore, the prediction results can be combined based on the addition idea of wavelet decomposition to obtain the overall prediction result for the original sequence. There are two specific merging methods. The first one is to obtain the prediction results of WT-ARIMA-LSTM by merging the results of ARIMA and a single machine learning model. The second one is through the ARIMA module.The prediction results of the type are cross-combined with the results of the two machine learning models to obtain the final result.

By summing the low-frequency data predicted by the ARIMA model and the predicted values of a single machine learning model (LSTM, SVR) for high-frequency sequences, the prediction results of WT-ARMIA-LSTM and WT-ARMIA-SVR are as Table 2 [10]:

Table 2. Comparison of single model combinations.

Model	RMSE	MAPE
WT-ARIMA	0.03389	0.27%
WT-ARIMA+LSTM(d1)	0.02954	0.22%
WT-ARIMA+LSTM(d1,d2)	0.02639	0.19%
WT-ARIMA-LSTM	0.01296	0.09%
WT-ARIMA+SVR(d1)	0.02855	0.21%
WT-ARIMA+SVR(d1,d2)	0.02529	0.18%
WT-ARIMA-SVR	0.01347	0.10%

According to the data analysis in the above table, it can be known that for the two combined models of ARIMA-LSTM and ARIMA-SVR, after gradually incorporating the predicted values of each high-frequency sub-sequence (d1, d2, d3) into the total prediction, the model performance has significantly improved. This fully verifies the effectiveness of the strategy of decomposing the original sequence into low-frequency and high-frequency components for separate prediction through wavelet decomposition and reconstruction; Specifically in the performance comparison of the two combined models, when the prediction of d1 and d2 high-frequency subsequences is added, the prediction effect of the ARIMA-SVR combination is superior to that of the ARIMA-LSTM combination. However, after further adding the prediction of d3 high-frequency subsequences, The performance of the ARIMA-SVR combination is actually lower than that of the ARIMA-LSTM combination. Therefore, it can be concluded that the SVR model performs better in the prediction of the high-frequency subsequences d1 and d2, but its ability is relatively weak in the prediction of the high-frequency subsequence d3.

4.3.3 Model cross-combination

By cross-combining and adding the prediction results of the above three models for the four sequences, that is, a total of 8(2*2*2) combination methods, the specific RMSE and MAPE combinations are as Table 3:

Table 3. Comparison of model cross-combination.

Combination Mode	RMSE	MAPE
ARIMA+SVR(d1)+SVR(d2)+SVR(d3)	0.01347	0.100%
ARIMA+SVR(d1)+SVR(d2)+LSTM(d3)	0.01154	0.081%
ARIMA+SVR(d1)+LSTM(d2)+SVR(d3)	0.01400	0.103%
ARIMA+SVR(d1)+LSTM(d2)+LSTM(d3)	0.01163	0.084%
ARIMA+LSTM(d1)+SVR(d2)+SVR(d3)	0.01372	0.101%
ARIMA+SVR(d1)+SVR(d2)+LSTM(d3)	0.01368	0.103%
ARIMA+LSTM(d1)+LSTM(d2)+SVR(d3)	0.01349	0.100%
ARIMA+LSTM(d1)+LSTM(d2)+LSTM(d3)	0.01296	0.095%

As can be seen from the table above, the hybrid model ARIMA + SVR(d1) + SVR(d2) + LSTM(d3) achieves the lowest values for both RMSE and MAPE. In this combination, d1 and d2 represent predictions generated by the SVR model, while d3 is derived from the LSTM model. This result aligns with the performance comparison between the standalone SVR and LSTM models discussed earlier, demonstrating the complementary strengths of these two approaches in hybrid configurations. To further evaluate the differences between single-model combinations (e.g., pure SVR or LSTM stacking) and cross-model combinations (hybrid SVR + LSTM integration), the following analysis is provided in Table 4:

Table 4. Comparison of combined models.

Combination Mode	RMSE	MAPE
WT-ARIMA-SVR	0.01347	0.10%
WT-ARIMA-LSTM	0.01296	0.09%
WT-ARIMA-LSTM-SVR	0.01154	0.08%

It can be known from the above table that the cross-combination model WT-ARIMA-LSTM-SVR has reduced the RMSE and MAPE indicators by approximately 14% and 20% respectively compared with the WT-ARIMA-SVR model. Compared with the WTARIMA-LSTM model, both the RMSE and MAPE indicators have decreased by approximately 11%. Therefore, the WT-ARIMA-LSTM-SVR model is superior to the results of the single model combination in both RMSE and MAPE. And it can be seen from the following prediction trend chart that WT-ARIMA-LSTM-SVR will not have a large deviation at a single point. Therefore, it can be considered that the WT-ARIMA-LSTM-SVR model has a more effective and stable prediction effect in Figure 10.

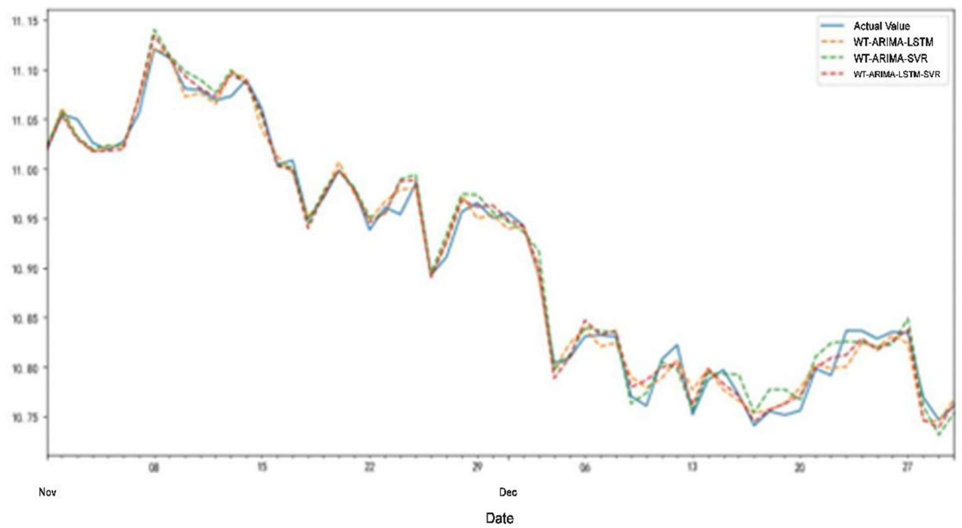

Fig. 10. Comparison of multiple combined models.

5 Conclusion

This study has conducted a comparative study on the applicability of the ARIMA and LSTM models in Bitcoin price prediction. By constructing and verifying the two models based on daily closing price data of Bitcoin from October 2013 to December 2021, it is found that the ARIMA model performs stably in short-term prediction of linear trends, but struggles with capturing nonlinear fluctuations in Bitcoin prices. In contrast, the LSTM model, with its long-term memory capability, demonstrates superior performance in nonlinear feature extraction and long-term dependency processing, achieving significantly higher prediction accuracy than the ARIMA model.

Furthermore, the research explores the potential of hybrid models by combining wavelet decomposition with model fusion. The results show that the hybrid model, specifically the WT-ARIMA-LSTM-SVR model, can further improve prediction accuracy by leveraging the strengths of both linear and nonlinear methods. This model not only considers trend characteristics but also captures fluctuations, making it a promising approach for Bitcoin price prediction.

In summary, this study confirms the advantages of the LSTM model and the hybrid model in Bitcoin price prediction and provides valuable insights for future research. The findings suggest that integrating linear and nonlinear methods through hybrid models can enhance prediction accuracy and stability, offering practical implications for investors and regulatory authorities in managing risks and making informed decisions.

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