Cryptocurrency Price Prediction Based on ARIMA, Random Forest and LSTM Algorithm

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Abstract. Price prediction of cryptocurrencies is bound to get more opportunities for investors engaged in digital currency-related industries in order to earn more revenue. In the traditional forecasting methods, the problem of the high volatility of bitcoin price needs to be effectively solved, making the forecasting accuracy become low and ineffective. Due to the rapid development of artificial intelligence technology, more and more relevant algorithms were used for cryptocurrency price research. This study would compare and analyze the prediction effect of the ARIMA time-series model, the Random Forest algorithm of machine learning, and the LSTM algorithm of deep learning algorithm on cryptocurrencies price prediction to assist investors in making investment decisions. In this paper, five years of time-series data of Bitcoin, Ether, and Dogecoin is obtained from 2018 to 2022. Then, the training set and testing set are separated with 0.8:0.2 to test ARIMA, Random Forest, and LSTM algorithms. To evaluate the model, the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and decidability coefficient (R^2) are chosen as metrics to measure the prediction of each prediction model precision. Comparing the experimental results, the prediction accuracy of LSTM is better than that of Random Forest, and the prediction accuracy of Random Forest is better than ARIMA model. These results shed light on guiding further exploration of significant to cryptocurrency industry practitioners and visitors.

Keywords: Cryptocurrency; machine learning; ARIMA; Random Forest; LSTM.

1. Introduction

In 2008, an article titled "Bitcoin: A Peer-to-Peer Electronic Money System" was published by a person (or group of people) named Satoshi Nakamoto [1], in which he proposed a peer-to-peer cash system and its underlying protocol. This cryptocurrency came to be well-known as Bitcoin and the vehicle for this virtual currency is a globally distributed ledger known as the blockchain. Bitcoin is an Internet-based, P2P, anonymous, cryptographic and the world's first distributed digital currency [2]. The most important feature of BTC is decentralization. With the expanding of blockchain technology, many unorthodox digital currencies based on blockchain technology have emerged (e.g., Ethereum, Dogecoin, and Litecoin), which are called as competing coins. Contemporarily, there are two main methods of acquiring cryptocurrencies: (1) computer algorithm generation, also known as mining (2) trading on the internet exchanges or trading on real exchanges.

Early research on cryptocurrencies focused on legal, security, and computer technology and it has started to become familiar to financial community since 2013. Many scholars around the world have used traditional and novel algorithms to study the prices of cryptocurrencies. Minim et al. introduced a neural network autoregressive (NNAR) model to compare with the ARIMA time series model [3]. Empirical confirmed that ARIMA can obtain more stable results, reflecting the feasibility of time-series models in cryptocurrency price prediction. Zhao et al. pointed out that the model with time-series weighted mean expects the closing price by assigning different weights to the price, which attenuates the lag [4]. Meanwhile, as more and more machine learning methods are applied to stock market forecasting, these methods can also provide new directions and ideas for cryptocurrency forecasting. For the Random Forest algorithm, Xu et al. analyzed that methods such as random forest and Xgboost have the function of feature selection and can be used to process data containing multiple features [5]. Wei et al. used the RF regression as forecasting method to predict the spot market clearing price with the Nordic electricity market and finally fitted a high stability and forecasting accuracy [6]. Liu et al. perform the trend prediction analysis of 15 constituents of A shares in SSE using a feature-selected RF-LSTM model and came up with a standard deviation of 0.02083, yielded high accuracy for all trend predictions of stock prices [7]. For neural networks, Lahmiri and Bekiros compared the righteous regression neural architecture as a benchmark model with the LSTM, which yielded better results despite having a higher computational burden [8]. Ning et al. proposed a hybrid LSTM-Adaboost-based network model with optimal parameters, which indicated that the LSTM-Adaboost model led to a 7%-point improvement in the prediction hit rate [9]. Pan used LSTM to solve long-term memory problems in cryptocurrency price prediction and demonstrated the advantages of LSTM over solving price prediction in cryptocurrency markets characterized by high-frequency decentralized non-stop trading [10]. However, there still have not enough more machine learning algorithms invested in cryptocurrency price prediction yet.

Cryptocurrencies have become one of the most fascinating targets for investors all over the world. One can efficiently and accurately predict the trend of cryptocurrencies and their possible future price movements. In this case, it will largely contribute to better-informed investors, bring lucrative returns, and avoid possible risks. A reasonable approach to cryptocurrency price research is of significant to cryptocurrency industry practitioners and visitors. ARIMA time series model is the most common model among traditional time series forecasting methods, Random Forest is one of the most classical integrated algorithms, and LSTM is a new application algorithm compared to it. This paper will focus on analyzing and comparing the performance of these three forecasting methods in cryptocurrency price forecasting. The remainder of this paper is organized as follow. The Sec. 2 is the data processing and the analysis of model principles, which collates and lists the theory and formulae of the analytical model used in this paper, and organizes the test indicators used in this paper's model and the designed functional model, laying the foundation for the subsequent empirical analysis. Sec.5 is the empirical analysis. This paper obtained 1500 Bitcoin, Ethereum, and Dogecoin data and used three models mentioned above to predict and analyze the output and then measured the prediction values are with performance evaluation index, such as mean square error. Sec. 5 draws conclusions and future outlooks from the models.

2. Data & Methodology

2.1 Data

Bitcoin is the first cryptocurrency proposed by Satoshi Nakamoto, and it is also the most representative virtual currency in terms of trading volume and price. Dogecoin is an emerging virtual currency with a very entertaining nature, which has been gradually sought after by more and more investors since its release. This study imports the price data of these three representative crypto virtual currencies from 2018 to 2022 (2018.10.17-2022.11.22) into Python at investing.com, and for testing the data training of Python. This paper divides the training set and testing set according to the ratio of 0.8:0.2. It means that the first 1200 pieces of data to establish the training set and the remaining 300 pieces of data as a test set for testing.

2.2 ARIMA

ARMA (Autoregressive moving average model) is an organic combination of the AR (autoregressive model) and the MA (moving average model). In ARMA (p, q), p is the order of autoregression, q is the number of moving average terms, and its role is to describe the smooth stochastic process. Φ_i and θ_j are the coefficients to be determined for the model, and ε_t is the error. The ARMA (p, q) model can be described as:

$$y_t = \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots \Phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_p \varepsilon_{t-p} \tag{1}$$

The ARIMA model also combines the features of AR and MA models. However, the difference term d of ARIMA enables the conversion of non-stationary time series into stationary ones. In the model, $\Delta^d y_t$ denotes the non-stationary series y_t formed by the d-difference transformation and turn into a stationary time series. ARIMA (p, d, q) model can be expressed as:

$$\Delta^{d} y_t = \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots \Phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_p \varepsilon_{t-q} \tag{2}$$

2.3 Random Forest

According to the bagging integration method, Random Forest is composed of a series of decision trees to improve the algorithm's accuracy. Let X be the input vector of the random forest, Y be the ideal output vector of the model, and form a combinatorial model from the random rank and file vectors$\{h(\mathrm{X}, \vartheta_{\mathrm{k}}), \mathrm{k} = 1, \mathrm{l}, \mathrm{p}\}$. Then, the decision tree can transform numerical variables into predictor variables and construct a random forest model. The random forest is multivariate and non-linear, with each decision tree$\{h(\mathrm{X}, \vartheta_{\mathrm{k}})\}$. Finally, the mean value of each decision tree is the output result.

2.4 LSTM

LSTM is a time-series recurrent network initially designed to avoid the long-term dependency problem in RNN. It has an additional hidden state variable compared with RNN $\tilde{C}_t$, called cell state, whose role is to record information. In addition to the hidden layer, LSTM contains three gates, in order: forgetting gate, input gate, output gate. The first layer of the forgetting gate can decide to delete non-essential information, a process called "forgetting selectively." The LSTM reads both the current $\mathrm{X_t}$ and the previous moment's $h_{\mathrm{t}-1}$. The LSTM reads both the current and previous moment values, and after processing them in the sigmoid layer, it obtains a result between 0 and 1 and passes it to the cell state. $\mathrm{C_{t-1}}$ The LSTM reads both the current and previous values, and after the sigmoid layer, it gets a result between 0 and 1 and passes it to the cell state, whose role is to decide what information the model should discard. If the output is "1", the information from the previous layer would be wholly retained, and "0" would be discarded entirely. The formula for the forgetting gate is shown in Eq. (3), and the Sigmoid is:

$$f_t = sigmoid\left(W_f\left[h_{t-1}, \; X_t\right] + b_f\right) \tag{3}$$

$$\sigma(\mathrm{z}) = \frac{1}{1+\mathrm{e}^{-\mathrm{z}}} \tag{4}$$

The second layer input gate can select and update the new information in the loop cell by passing the first equation to obtain the information to be updated and pass the data to the tanh layer to obtain a new vector of candidate values:

$$i_t = sigmoid\left(W_i\left[h_{t-1}, \; X_t\right] + b_i\right) \tag{5}$$

Here, i_t is the output of the Sigmoid function. $\tilde{\mathrm{C}}_{\mathrm{t}}$ is the output vector of the tanh function, and the process is shown by following:

$$\tilde{C}_t = tanh\left(W_c\left[h_{t-1}, \; X_t\right] + b_c\right) \tag{6}$$

The next step is to update the cell state with the simple linear interactions that exist:

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{7}$$

The third level “output gate” determines the information output. After the “tanh” function processes the cell and outputs the value between -1 and 1, it multiplies the value with the output of the Sigmoid function to obtain the output of the cell, resulting in the output h_{t}:

$$O_t = sigmoid\left(W_0\left[h_{t-1}, \; X_t\right] + b_0\right) \tag{8}$$

$$h_t = \; O_t \times tanh(C_t) \tag{9}$$

2.5 Metrics

In order to test the prediction effect of the model more intuitively. This paper introduced performance test indicators: MSE (Mean Square Error), RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and R^2 (Resolvability Coefficient) to evaluate the model. The formulas for these four indicators are as follows:

$$\mathrm{MSE} = \frac{1}{m}\sum_{i=1}^{m}(\hat{y} - y_i)^2 \tag{10}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(\hat{y} - y_i)^2} \tag{11}$$

$$\mathrm{MAE} = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{\hat{y} - y_i}{y_i}\right)^2 \tag{12}$$

$$R^2 = \sum_{i=1}^{m}\frac{(\hat{y}_i - \bar{y})^2}{(y_i - \bar{y})^2} \tag{13}$$

All four evaluation metrics provide an appropriate measure of the level of significance levels samples.

3. Empirical Analysis

3.1 ARIMA

To investaigte the stationary of the time seiries, the t-statistics of the output three virtual currency ADF tests are all smaller than the critical values corresponding to the significance levels of 1% (-3.435908), 5% (-2.863994) and 10% (-2.568076), respectively, and the p-values are all greater than 5% (as shown in the Table 1). It concluded that the ADF test results of the original data fall outside the interval of acceptance of the original hypothesis, i.e., the number of closing price time series of the three virtual currencies is non-stationary. Therefore, this study perform first-order differencing on the original data. As a result, the values of the t-statistics of these three cryptocurrencies are all less than the critical values, and the p-values are much less than 5% after the first-order differencing. Therefore, it implies that the time series data is no longer non-stationary after the first-order differencing.

Table 1. T-value and p-value

	t-value	p-value
BTC	-1.207209	0.670486
ETH	-1.562990	0.502152
Doge	-2.255938	0.186572

Cryptocurrency can get the corresponding autocorrelation graph ACF and partial autocorrelation graph PACF by Python and get the p and q values by observing the images of ACF and PACF (seen from Table. 2). However, due to the intense subjectivity of this method, the AIC information criterion is introduced in this paper to make further judgments to ensure the model's optimality. According to the output of Python, the minimum BIC and the optimal p and q values corresponding to the three virtual currencies are shown in the following table.

Table 2. Optimal p, q, and AIC values

Currency	p	q	AIC
BTC	2	2	20221.001603
ETH	2	3	14056.839690
Doge	2	3	-6590.584680

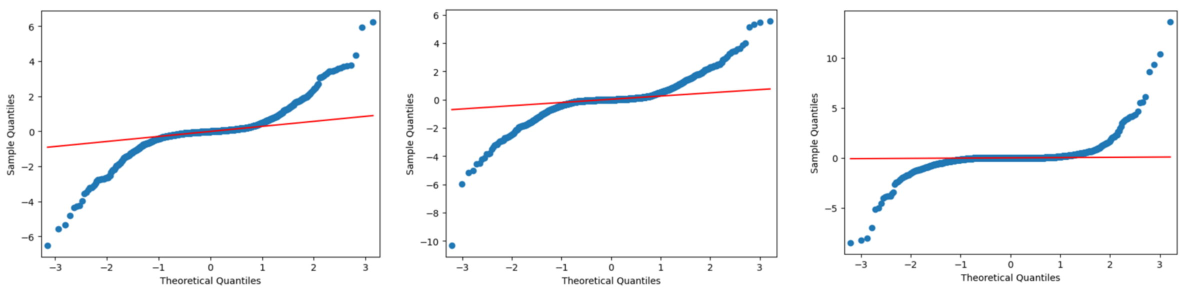

Fig. 1 Q-Q plots of three Cryptos.

This study first tested whether the residual terms of the three models obeyed normal distribution through QQ plots. Then, the P-values corresponding to the residual terms was obtained through LB tests to test whether the residuals were white noise. The model validation results are shown in the Fig. 1. By observing QQ plots, the study found that most of the data points are around the straight line. The residual terms are in line with the characteristics of normal distribution. The p-values of the three virtual currencies are 0.41, 0.97, and 0.23 that all greater than 0.05. It indicates that the residual terms belong to the white noise series. The useful information in the residual terms has been fully extracted, and the model is perfect. This study uses ARIMA to forecast the trading price for the next 300 days and compare the forecast value with the real value, and the Fig. 2 depicts the price forecast results of the test set. The training results analysis shows that the ARIMA prediction effect is similar to the real value with a small error in the short term and gradually converges to the mean value with the cryptocurrency price fluctuation in the long term, showing means reversion and inferior prediction effect.

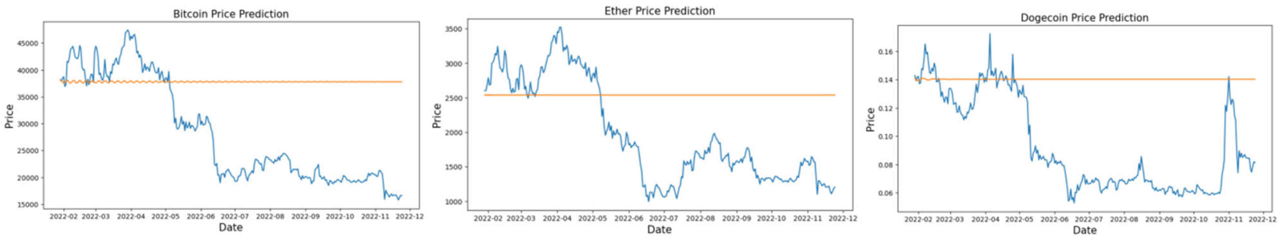

Fig. 2 Doge test set prediction results

3.2 Ranndom Forest

The model extracts the base variables from the primary data of 1500 transactions of bitcoin, Ether, and Dogecoin in the last five years and calculates the simple derived variables and technical analysis derived variables from these primary data, which together constitute the raw data of the model. The raw data contains a total of 17 variables. The data column names include open (open price), date (date), low (the lowest price), high (the highest price), volume BTC (volume), close (close price), etc. This study extracted 17 variables from the raw data and then selected 12 groups of characteristic variables from the raw data. The target variable is the close price, as shown in the Table. 3.

Table 3. Characteristic variables of Random Forest input

Eigenvalue	Number	Indicator Name	Calculation formulae
Base feature variables	X_1	Close	No calculation formula for base data
	X_2	Volume	
Simple feature variables	X_3	CMO	The closing price of the day - The opening price of the day
	X_4	HML	Day's highest price - Day's lowest price
Technical Analysis Characteristics Variables	X_5	MA5	The closing price of the previous five days / 5
	X_6	MA10	The closing price of the previous ten days / 10
	X_7	RSI	N-day average up price / N-day average up price + N-day average down price
	X_8	MOM	C(closing price) - C_n (closing price n days ago)
	X_9	EMA12	$EMA_{today} = \alpha Pricce_{today} + (1-\alpha)EMA$
	X_{10}	MACD	$DEA_n \times \frac{8}{10} + DIF_n \times \frac{2}{10}$
	X_{11}	MACDsignal	
	X_{12}	MACDhist	

After excluding some missing values, this study divided the remaining valid data into training and test sets according to 0.8:0.2. Using the valid training set to form a random forest and the test set to test the model's prediction accuracy. In this paper, the parameters are tuned by setting the detailed parameters of random forest to maximize the prediction accuracy and code execution efficiency.

Experience and tests show that the accuracy and code execution efficiency are highest when the parameters are in the following situation. The tuned parameters can be shown in the Table. 4.

After using the Random Forest algorithm for prediction analysis, this paper tested the accuracy of the three cryptocurrency prediction results through the RF's built-in score function. It came up with a prediction accuracy of 47.96% for Bitcoin, 46.94% for Ether, and 53.24% for Dogecoin. The model prediction accuracy of the three does not reach a particularly desirable level, which reflects the volatile price trading volume of the cryptocurrency market. Meanwhile, the 12 groups of primary and technical indicators selected as feature values in this paper only sometimes all play a positive role in forecasting. In this paper, the importance of the 12 feature variables is calculated by the feature functionality of a random forest. The 12 feature variables are arranged in descending order of importance for visual analysis, which will play a reference role in extracting feature values for future cryptocurrency forecasting studies. The importance of the feature values of each variable of the three virtual currencies is illustrated in the Fig. 3.

Table 4. Random Forest input parameters

Parameters	Assignment			Remarks
	BTC	ETH	Doge	
max_depth	2	3	2	Maximum depth of decision tree
n_estimators	5	10	10	Number of weak learners
min_samples_leaf	20	5	5	Minimum number of samples of leaf nodes
random_state	1	1	1	Keep the results consistent from run to run

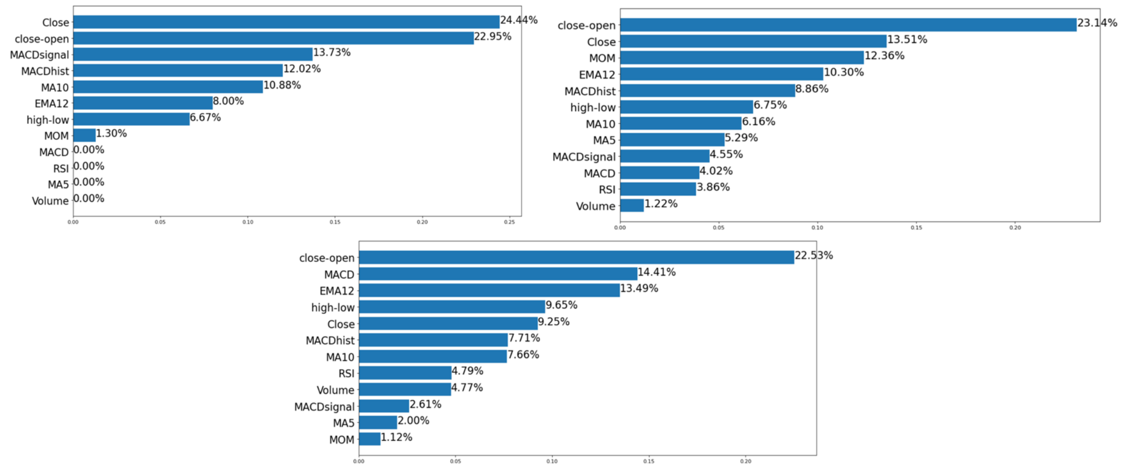

Fig. 3 Eigenvalue Importance of three Cryptos.

Random Forest is also applied to forecast the test set and calculate the return. The trading strategy is to execute buy or sell operations based on the day's trading data to forecast the next day's rise and fall. When the RF forecast is "1" it takes a long operation. When the forecast is "-1" the short operation is executed according to the forecast yield curve of the three currencies. Then the forecast value is compared with the real value to realize the return backtest. The Fig. 4 exhbits the test set prediction results.

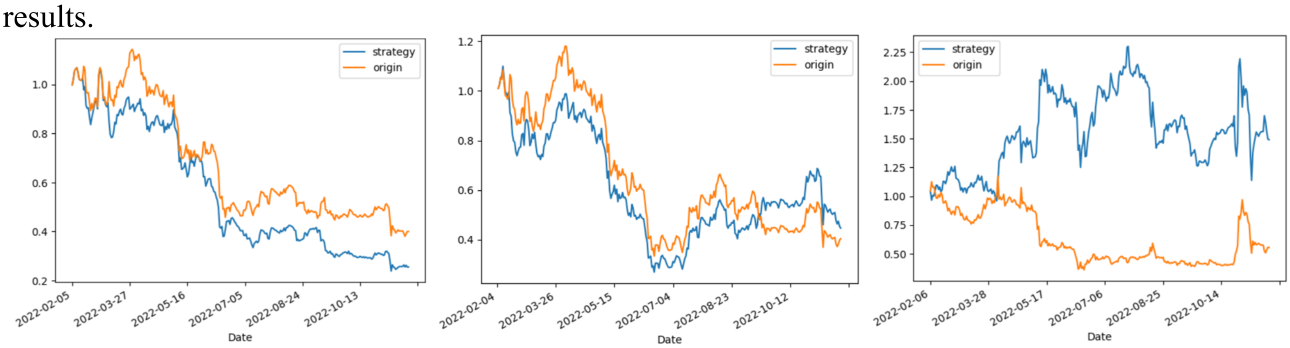

Fig. 4 Test set prediction results for three Cryptos.

According to the results, the random forest performs better in predicting the returns of bitcoin and Ethereum and can predict the return trend more accurately for these two cryptocurrencies. The error between the predicted value and the real value is small. The fitting effect of Dogecoin is worse than the other two, reflecting that investors and market sentiment highly influence cryptocurrencies like Dogecoin and are fully characterized by entertainment.

3.3 LSTM

This model extracts the bitcoin, Ethereum, and dogecoin data for the last five years and divides the training set by 0.8:0.2 and the test set by. Each column contains basic features, including opening price, high price, low price, closing price, trading volume, and price change rate. This study will extract the previous day's closing information from these six variables to predict the next day's closing price. Owing to the extensive cryptocurrency price data, which is difficult to process, and to eliminate the influence of different units of measure and variance on the prediction results, this paper normalizes the data with Python. The calculation formula is

$$X_k = \frac{X_k - X_{min}}{X_{max} - X_{min}} \tag{14}$$

In this paper, Keras deep learning framework of python 3.9 rapidly built the model and established the Sequential model. Furthermore, this paper extracted the parameters with the best prediction accuracy after several experimental tuning experiments. The model uses a single-layer LSTM, sets Dropout to 0.5, adds a Dense layer to aggregate its dimension to 1, and uses 'ReLu' as the activation function and MAE (Mean Absolute Error) as the loss function. After setting the optimal parameters, the output LSTM model in Python can be described as follows. Using the LSTM algorithm analysis, after predicting and testing the three cryptocurrencies. According to the loss calculation (not shown here), it can be inferred that the loss and val_loss is decreasing, indicating no overfitting condition in this experiment. Furthermore, as the number of iterations increases, the training errors of bitcoin, Ether and Dogecoin gradually decrease and remain stable at 0.0015, 0.0009 and 0.0011, and the experimental results are very ideality. Comprehensive training analysis, the LSTM achieved good prediction results, and its prediction results are visualized with the test set fitting effect image as follows. Seen from Fig. 5, the prediction value of LSTM has a small error with the real value, and the prediction accuracy is high. It proved that LSTM can explain the price trend of cryptocurrency accurately.

Fig. 5 Testing set prediction results for three cryptos.

3.4 Performance Evaluation

This paper tested the performance of the above three models for all the results for the three cryptocurrencies using the four model performance metrics what have been mentioned above (MSE, RMSE, MAE, R^2). The outcome can be presented in the Table. 5. The prediction logic of Random Forest is to execute buy and sell strategies for the prediction results of the three cryptocurrencies and this would output the yield prediction, so the MSE, RMSE, and MAE test results could not be that meaningful than other models. However, this paper can still infer the goodness of effect results by comparing the scores of decidable coefficients with the built-in functions of Random Forest. According to the data analysis in the above table, ARIMA has the worst fitting effect, and its MSE, RMSE, and MAE indexes are much larger than those of the LSTM model. By comparing the R^2 of these three, only the R^2 coefficient of ARIMA is negative, which is worse than the other two models. Based on the R^2 coefficients and internal scores of the random forest, there is still a gap between the

LSTM and the LSTM. The R^2 indicators of the LSTM are kept above 0.85, while the highest R^2 coefficient of the random forest is only 0.73, and the fitting effect of the dog coin is poor.

Table 5. Model performance evaluation

		MSE	RMSE	MAE	R^2
ARIMA	BTC	181851294.00	13485.22503	11625.51	-21344.17
	ETH	838949.90	915.94209	818.09	-886554.09
	Doge	0.00327	0.05716	0.04844	-191436.05
Random Forest	BTC	0.01723	0.13126	0.11815	0.73635
	ETH	0.01155	0.10745	0.10179	0.71815
	Doge	1.09511	1.04648	0.93155	-9.28642
LSTM	BTC	4179142.52	2044.30	1480.15	0.94243
	ETH	30467.51	174.55	136.13	0.92087
	Doge	0.00012	0.01115	0.00765	0.85556

4. Conclusion

In summary, this paper compares three mainstream forecasting models through empirical analysis. ARIMA has the worst fitting effect on three cryptocurrencies, which is consistent with the research results output and the initial conjecture of the study. In fact, the cryptocurrency market itself has the characteristics of large trading volume and great price fluctuations, and its non-linear characteristics are very significant. Therefore, the ARIMA model cannot deal with non-linear data very well. In addition, the short-term fitting effect of ARIMA is better than the long-term one, and the predicted price will gradually converge to mean reversion with the increase of time order in the long-term change, and the prediction effect would be extremely poor.

This paper also used the Random Forest model for cryptocurrency yield prediction based on the characteristic price theory and argues the applicability of RF in cryptocurrency prediction. However, there are still some things that could be improved. Most of the feature values in this paper are selected based on technical indicators of stock forecasting and do not perform the detailed meritocracy of eigenvalue combinations. On this basis, it can be observed from the ranking of the importance of the eigenvalues of BTC that four eigenvariables are significantly insignificant if the original variables are re-selected in conjunction with the characteristics of the cryptocurrency market and combined with meritocracy. This paper expects to improve the prediction accuracy by another 5%. For the forecasting method with the neural network LSTM, the neural network belongs to dynamic model forecasting, which has a robust and intelligent learning function, non-linear refraction ability, and self-learning performance. According to the results, LSTM can predict a higher degree of simulation of highly non-linear problems, and its performance is in line with the expectations in this study. The conclusion can be drawn from the empirical analysis that the time series has poor prediction in the short term, and the RF and LSTM have a better prediction in the long term.

Considering that the cryptocurrency market is volatile and dynamic, its future development trend is also influenced by many factors. For example the international economic situation, the political attitude of countries, the development of blockchain and investor sentiment, etc. Therefore, it takes work to earn a stable income by predicting the cryptocurrency's price for the investment. Combined with the characteristics of the current emerging crypto market, this article believes that it is difficult for investors to explore the underlying value of such crypto virtual tokens,(e.g., Dogecoin and Shibacoin), which are more entertaining. These tokens are issued without restrictions, are subject to fluctuations in investor sentiment, and exhibit significant herding effects regarding trading volume and popularity. This paper observe that Dogecoin performs worse in every model through empirical comparison analysis, which indicates that the price prediction of these cryptocurrencies is very different from the traditional stock price prediction. It requires much more factors than initially anticipated in this paper. This paper argues that past cryptocurrency prices can only be used as a reference. There are many significant differences between the cryptocurrency market and the stock market, and there are significant shortcomings in using stock market variables considered in the current study. Many scholars have concluded through case studies that cryptocurrency prices are currently in a bubble, and their trading prices have been deflated already.

This paper expects that after the cryptocurrency market becomes more mature, more factors affecting the trading price of cryptocurrencies and more characteristic variables and evaluation indicators applicable to cryptocurrencies can be identified. The model's output should also be more than one factor for our reference rather than a complete guide for investment. The current modeling approach for cryptocurrency forecasting methods mainly uses multiple linear regression or neural network methods to build forecasting models. These methods have certain shortcomings. This paper expects that more combined models of forecasting methods will be explored in the future to achieve better forecasting in the cryptocurrency market. It is expected to explore more combinatorial models to achieve better forecasting results in the cryptocurrency market. Overall, these results offer a guideline for investors and those engaged in the cryptocurrency industry can not only earn profits for the majority of cryptocurrency investors, but also make the more appropriate ratio of funds in the entire cryptocurrency market, which is of great significance to cryptocurrency development.

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