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Research Article

Application of Traditional Machine Learning Models for Quantitative Trading of Bitcoin

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Abstract: Bitcoin, the most popular cryptocurrency around the world, has had frequent and dramatic price changes in recent years. The price of bitcoin reached a new peak, nearly $65,000 in July 2021. Then, in the second half of 2022, the bitcoin price begins to decrease gradually and drops below $20,000. Such huge changes in the bitcoin price attract millions of people to invest and earn profits. This research focuses on the predictions of bitcoin price changes and provides a reference for trading bitcoin for investors. In this research, we consider a method in which we first apply several traditional machine learning regression models to predict the Changes of Moving Average in the bitcoin price, and then based on the predicted results, we set labels for bitcoin price changes to get the classification results. This research shows that the method of transforming regression results to the classification analysis can achieve higher accuracy than the corresponding machine learning classification models and the best accuracy is 0.81. Besides, according to this method, this research constructs a Machine Learning Trading Strategy to compare with the traditional Double Moving Average Strategy. In a simulation experiment, the Machine Learning Trading Strategy also has a better performance and earns a 68.73% annualized return.

***Keywords*:** bitcoin price prediction, machine learning, quantitative trading, moving average

1. Introduction

Cryptocurrency, as one of the most popular investments in recent years, has attracted a lot of people to pay attention to arbitrage. Bitcoin, which was invented by Nakamoto [1] in 2008, is one of the most famous cryptocurrencies. This cryptocurrency exists on the Internet and can be traded based on a peer-to-peer system anonymously [1]. Meanwhile, compared with traditional financial investments, the price of bitcoin always changes dramatically, and there is not enough effective way to hedge bitcoin that may bring investors more risks [2]. Before December 2020, the price of bitcoin to US dollars never exceeded $20,000. Moreover, the bitcoin price exceeded $60,000 several times in 2021 and even reached a new peak that is nearly $65,000 in July 2021. Then, the price of bitcoin began to decrease gradually and dropped below $20,000 in the second half of 2022. However, such frequent and dramatic volatility in the bitcoin price could create risks for investors and opportunities for speculators.

In this research, we consider a novel way to obtain more benefits and reduce losses in the bitcoin investment from

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investors' perspectives. Different from the traditional way to predict the future prices for the financial market, we first try to apply some popular machine learning regression models to make predictions on the Change of Moving Average of the bitcoin price and then based on the prediction results, we get the predicted bitcoin price of the next day by calculation and set labels for bitcoin price changes of the next day to get the classification results. In this research, we choose five traditional machine learning models-Decision Tree, Support Vector Machine, Random Forest, Bagging, and AdaBoost, to make predictions and get higher accuracies. At last, we provide an experiment of the quantitative trading simulation to test whether machine learning methods can help investors earn more money than the traditional investment strategy or not.

The rest of this research is summarized as follows. Section 2 reviews some related research works on machine learning models applied in financial stocks or bitcoin price predictions. Section 3 describes machine learning models and features of the training data applied in this research in detail. In Section 4, we present the performance of the models' metrics and the performance of the machine learning trading strategy after the experiment. Finally, we conclude this research in Section 5.

2. Related works

For price prediction, people are more familiar with its application in the stock market. In the past, researchers usually consider applying the traditional time series model Autoregressive Integrated Moving Average (ARIMA) to forecast the price changes of stocks [3-5]. With the development of science and technology, the machine learning model becomes a new tool to predict the stock price. Since the advent of cryptocurrencies, the investment value and benefit of bitcoin also attract researchers to predict the bitcoin price. Same to predictions for the price of the traditional financial investment product-stock, people would like to apply machine learning models to predict the bitcoin price instead of traditional time series models only.

In general, researchers consider making predictions on the stock or bitcoin prices through machine learning methods from two perspectives. The first one is to predict its price directly based on regression models. Phaladisailoed and Numnonda [6] use Theil-Sen Regression, Huber Regression, and other machine learning models to predict the bitcoin price directly. Prasad et al. [7] apply XGBoost and other regression models to predict the close price of the stock. The second perspective is to apply classification models to predict the changes in the bitcoin price. Compared with predictions on the price directly, more and more studies focus on predicting stock or bitcoin price changes which seem to improve the experiment performance. Zhang et al. [8] use Support Vector Machine (SVM), Random Forest (RF), and Neural Network to predict the trend of the 30-day stock price changes. Based on some higher dimensional features, Chen et al. [9] apply machine learning classification models including RF, XGBoost, SVM, and others to predict daily and high-frequency trading price changes of bitcoin and compare them with statistical methods. Kamalov [10] uses Random Forest, Long Short-term Memory (LSTM), and other models to forecast significant stock price changes. Similarly, based on the LSTM and Gated Recurrent Unit (GRU) model, predictions of significant bitcoin price changes also have a good performance [11].

Moreover, like the research provided by Chen et al. [9], many researchers would like to collect some meaningful features to build machine learning models. Jang and Lee [12] use blockchain information and macroeconomic variables, such as foreign exchange rates, to predict the volatility and price of bitcoin based on Linear Regression, SVM, and Bayesian Neural Networks. Khaidem et al. [13] consider selecting some financial technical indicators as features to predict the direction of stock prices with the Random Forest. Similarly, some researches choose many popular financial market indicators as independent variables, such as Moving Average Convergence Divergence (MACD), Momentum (MOM), Relative Strength Index (RSI), and so on, to predict stock price changes with machine learning models and get great results [14-15]. In order to reduce the noise from time series data, several researchers apply signal decomposition methods with machine learning regression models on price prediction, and results based on these methods seem to be better than the original one [16-18].

In this research, Decision Tree, SVM, Random Forest, Bagging, and AdaBoost will be used to predict the bitcoin price by regression. Some financial technical indicators will be added as features to help these machine learning models to learn the trend of bitcoin price changes. Since the noise of time series data, this research will propose the Moving Average line as the predicted value and calculate the predicted price via some formulas based on regression models.

Meanwhile, we aim to apply classification labels to construct a machine learning trading strategy that could help investors to earn money.

3. Methodology

3.1 *Framework*

The framework of the whole experience is shown in Figure 1. We treat the original data of the bitcoin price and related technical indicators as independent variables. The Changes of Moving Average are regarded as the predicted value. Based on the five machine learning methods listed in Figure 1, we construct regression models for each model and set classification labels for the predicted results. For the regression part, we train prediction models to get the predicted value and calculate the next day's predicted price of bitcoin by a formula. Meanwhile, we set labels for the next day's predicted Changes of Moving Average and evaluate the results of classification predictions. Based on the predicted results of classification, we provide a Machine Learning Trading Strategy and give experiments comparing with other traditional trading strategies.

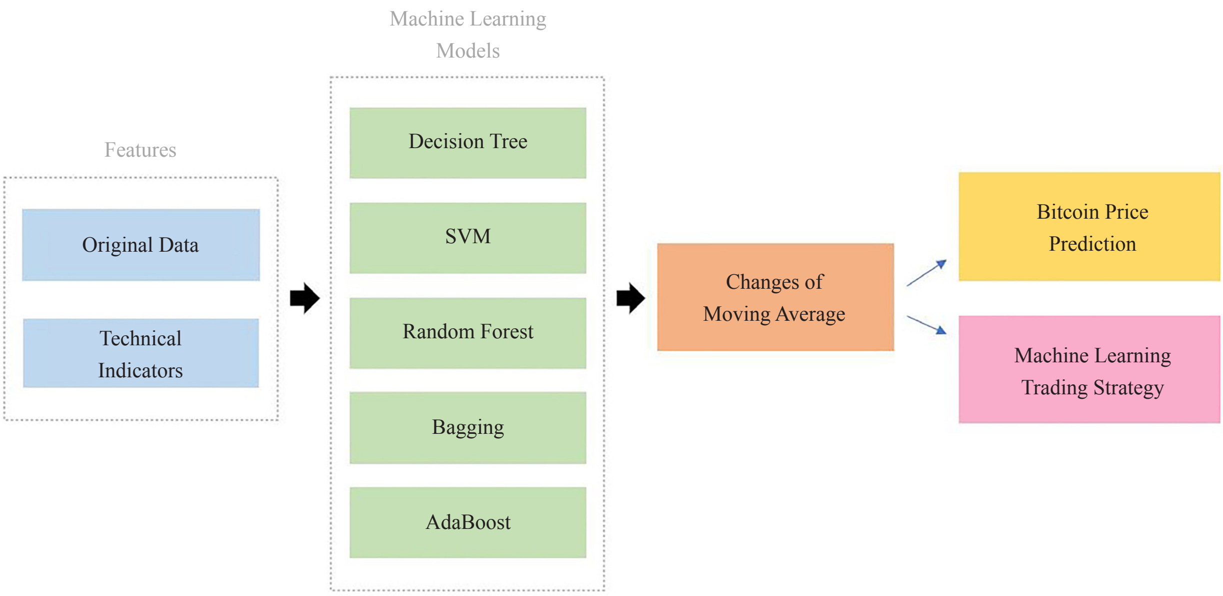

Figure 1. Experimental framework

3.2 *Machine learning models*

In this research, we consider five popular and traditional machine learning models, and these models may get great results in price prediction. The Decision Tree is the one of famous machine learning predictors which could be used in solving both classification and regression problems. In fact, the Decision Tree is an effective prediction model with high prediction results, and the Random Forest as the ensemble model of Decision Trees could have a better performance on the price prediction [19]. Besides, the AdaBoost as another common ensemble learning model could also have a very high result for predicting the price [19]. For this research, we would like to apply another famous ensemble learning model-Bagging to predict the bitcoin price compared with the Random Forest and AdaBoost models since the Random Forest, AdaBoost, and Bagging all are ensemble methods in machine learning models. Meanwhile, the SVM is also a very powerful algorithm to solve linear and non-linear classification and regression problems. According to the research provided by Kurani et al. [20], the SVM can be used effectively in price prediction, and as a single predictor, it could be compared with the Decision Tree model in this research. To complete the experiment, Scikit-Learn from Python is used to construct these prediction models. Besides, the kernel of the SVM model is linear and the number of estimators is set as 50 for three ensemble models.

3.2.1 *Decision tree*

As a single predictor, the Decision Tree model goes from the root node and ends at each leaf node. There are many child nodes between the root node and leaf nodes that recognize input values and move to different child nodes according to features until reached the leaf node. Each input sample goes through this process and gets its target values on the corresponding leaf node. The predicted value is the average of target values related to this leaf node [21]. Scikit-Learn uses the Classification and Regression Tree (CART) Algorithm that non-leaf nodes only have two child nodes [21].

3.2.2 *Support Vector Machine (SVM)*

For the SVM algorithm, both regression and classification models try to find the objective function and build a margin with the boundary of a hyperplane on both sides of the function. The SVM classification model desired to make all instances on the same side outside the margin and the margin can be as large as possible. In contrast to the SVM classification model, the SVM regression model hopes the margin can cover as many instances as possible while limiting instances off the margin [21]. After solving the optimization problem that adjusts the weight vector to optimize the margin, it can get the objective function and find the predicted result.

3.2.3 *Random forest*

Unlike a single predictor, there are many predictors in the ensemble learning models. Since all predictors in the Random Forest are Decision Trees, "a Random Forest is an ensemble of Decision Trees [21]". Different from building a single Decision Tree, the Random Forest finds the optimal feature to divide child nodes by randomly selecting sample features instead of all features in nodes [21]. There is no relationship among different Decision Trees, but the final output of the Random Forest depends on each Decision Tree in the forest. Generally, the predicted result is the average of all Decision Trees in the Random Forest.

3.2.4 *Bootstrap aggregating (Bagging)*

The fundamental of the Bagging model is similar to the Random Forest. However, many different single predictors are used to construct this ensemble learning model. For the Bagging model, it randomly takes samples with the same amount into different sample sets and uses each sample set to train the predictor. Especially, the Bagging model allows training samples can be sampled multiple times by a sample predictor [21].

3.2.5 *AdaBoost*

Same as the Bagging and Random Forest models, the AdaBoost is also a widely used ensemble method. Different from the Random Forest model, predictors in the AdaBoost model have a high correlation. The model is trained to predict at first and the algorithm updates the instance weight according to the sampling error. Then, the AdaBoost is trained repeatedly to optimize its prediction model [21].

3.3 *Data pre-processing*

The steps of pre-processing for the raw bitcoin price data are as follows: first of all, we drop some useless variables and data; then, we construct some variables related to financial indicators and set up the dependent variable; finally, we split the training set and the test set with the ratio of 8:2 and standardize independent variables for each set. In this research, the related data of the bitcoin price can be downloaded at Yahoo Finance [22]. The timeline of the data goes from September 2014 to December 2021 and there are a total of 2,664 samples (the head five samples are shown in Table 1). The original data cover five variables: Open, High, Low, Close, and Volume (i.e., Adj Close is not considered in this research).

Table 1. The original data (head five samples)

Date	Open	High	Low	Close	Adj Close	Volume
17/9/2014	465.864	468.174	452.422	457.334	457.334	21,056,800
18/9/2014	456.86	456.86	413.104	424.44	424.44	34,483,200
19/9/2014	424.103	427.835	384.532	394.796	394.796	37,919,700
20/9/2014	394.673	423.296	389.883	408.904	408.904	36,863,600
21/9/2014	408.085	412.426	393.181	398.821	398.821	26,580,100

The definitions of these original variables are given below.

Close: $Close_t$, $t \geq 1$, close price of bitcoin at day t (sample t)

Volume: $Volume_t$, $t \geq 1$, the volume of bitcoin at day t (sample t)

Open: $Open_t$, $t \geq 1$, open price of bitcoin at day t (sample t)

High: $High_t$, $t \geq 1$, the highest price of bitcoin at day t (sample t)

Low: Low_t, $t \geq 1$, the lowest price of bitcoin at day t (sample t)

In addition, only five independent variables cannot be sufficient enough to describe bitcoin price changes. Then, based on the original variables, we construct some relevant financial technical indicators as independent variables to build prediction models. The financial technical indicators, including the increment of the price and volume, Moving Average, Moving Average Convergence Divergence, Momentum, Rate of Change, Relative Strength Index, Stochastic Oscillator, and On Balance Volume, are always referred on the trade of stock markets and could provide some information for investors about the price changes on stocks. Some researchers consider adding these indicators as independent variables to predict the stock price with machine learning models and have satisfactory performance [13-15]. Different technical indicators could have different effects on the stock price prediction [14] and a greater number of indicators selection could help to get fewer prediction errors [15].

3.3.1 *Close*

Close_1: $Close_{t-1}$, $t \geq 2$, it is the close price of the day before day t.

Close_increasement: $Close_t - Close_{t-1}$, $t \geq 2$, the increasement of the close price from day $t-1$ to day t.

3.3.2 *Moving Average (MA)*

$$MA(d)_t = \frac{Close_t + Close_{t-1} + \ldots + Close_{t-(d-1)}}{d}, \; t \geq d > 0 \tag{1}$$

The Moving Average is the average close price of the past d days at day t and describes the trend of price changes.

MA5: $MA(5)_t$, $t \geq 5$, which represents the short-term Moving Average.

MA5_1: $MA(5)_{t-1}$, $t \geq 6$, which represents the short-term Moving Average of the previous day.

MA5_increasement: $MA(5)_t - MA(5)_{t-1}$, $t \geq 6$, which represents the difference of the short-term Moving Average between the day t and the previous day $t-1$.

MA20: $MA(20)_t$, $t \geq 20$, which represents the long-term Moving Average.

MA20_1: $MA(20)_{t-1}$, $t \geq 21$, which represents the long-term Moving Average of the previous day.

MA20_increasement: $MA(20)_t - MA(20)_{t-1}$, $t \geq 21$, which represents the difference of the long-term Moving

Average lines between the day t and the previous day $t-1$.

MA5_20: $MA(5)_t - MA(20)_t$, $t \geq 20$, which represents the difference between the short-term and long-term Moving Average lines.

3.3.3 *Moving Average Convergence Divergence (MACD)*

$$MACD_t = EMA_{12}(Close_t) - EMA_{26}(Close_t) \tag{2}$$

$$SingalLine_t = EMA_9(MACD_t) \tag{3}$$

where EMA_n is the n-day Exponential Moving Average [13].

The MACD is a momentum indicator that is based on the principle of the Moving Average [14]. It shows a buy signal when $MACD_t > SingalLine_t$ and a sell signal when $MACD_t < SingalLine_t$ [13].

MACD: $MACD_t$.

MACDsignal: $SingalLine_t$.

MACDhist: $MACD_t - SingalLine_t$.

3.3.4 *Momentum (MOM)*

$$MOM(d)_t = Close_t - Close_{t-d} \tag{4}$$

The Momentum describes the speed of price changes and is the difference of the close price between day t and d days ago [23]. Generally, the past d days' changes of close price for day t are plotted around a zero line [23]. If $MOM(d)_t > 0$, the price increases; if $MOM(d)_t < 0$, it decreases [23].

MOM: $MOM(5)_t$.

3.3.5 *Rate of Change (ROC)*

$$ROC_t(d) = \frac{Close_t - Close_{t-d}}{Close_{t-d}}, \; t > d \geq 0 \tag{5}$$

The ROC describes the ratio of the price at day t to the change in the price d days ago [13].

ROC_5: $ROC_t(5)$, which represents the short-term rate.

ROC_20: $ROC_t(20)$, which represents the long-term rate.

3.3.6 *Relative Strength Index (RSI)*

$$RSI_t(d) = 100 - \frac{100}{1 + RS_t(d)} \tag{6}$$

$$RS_t(d) = \frac{Average\ Gain\ Over\ past\ d\ days}{Average\ Loss\ Over\ past\ d\ days} \tag{7}$$

RSI: $RSI_t(12)$ shows the intention of the buyer and the seller to trade, i.e., overbought (above 70) or oversold (below

30), over the past 12 days at day t [13].

3.3.7 *Stochastic oscillator*

$$\%K_t(d) = 100 \times \frac{Close_t - LowestLow_t(d)}{HighestHigh_t(d) - LowestLow_t(d)} \tag{8}$$

$$\%D_t(d) = 100 \times \frac{\sum_{i=0}^{3}\left(Close_{t-i} - LowestLow_{t-i}(d)\right)}{\sum_{i=0}^{3}\left(HighestHigh_{t-i}(d) - LowestLow_{t-i}(d)\right)} \tag{9}$$

where $HighestHigh_t(d)$ is the highest High price in the past d days and $LowestLow_t(d)$ is the lowest Low price in the past d days. It also shows a buy signal when $\%K_t(d)$ is higher than $\%D_t(d)$ and a sell signal when $\%K_t(d)$ is lower than $\%D_t(d)$.

slowk: $\%K_t(9)$.

slowd: $\%D_t(9)$.

3.3.8 *Volume*

Volume_1: $Volume_{t-1}$, $t \geq 2$, it is the volume of the day before day t.

Vol_increasement: $Volume_t - Volume_{t-1}$, $t \geq 2$.

3.3.9 *On Balance Volume (OBV)*

$$OBV_t \begin{cases} OBV_{t-1} + Volume_t, \text{ if } Close_t > Close_{t-1} \\ OBV_{t-1} - Volume_t, \text{ if } Close_t < Close_{t-1} \\ OBV_{t-1}, \text{ if } Close_t = Close_{t-1} \end{cases} \tag{10}$$

OBV: It is an indicator that correlates volume with the close price and describes buying and selling trends at day t [13, 15], $t \geq 2$.

Especially, this research sets up the dependent variable Value that describes the changes of the 5-day Moving Average rather than the direct predicted bitcoin price, to reduce the errors from the time series data and improve the performances of prediction models. Moreover, the changes of the moving average in the bitcoin price can be a good way to present the trend of the bitcoin price changes. Meanwhile, this research uses the classification of trends in the bitcoin price to measure the accuracies of different models.

Value: $MA(5)_{t+1} - MA(5)_t$, $t \geq 5$.

Then, based on the formula (11), it can get the predicted bitcoin price $Close_{t+1}$.

$$Value_t = MA(5)_{t+1} - MA(5)_t = \frac{Close_{t+1} - Close_{t-4}}{5} \tag{11}$$

Thus, there are 27 variables including 1 dependent variable and 26 independent variables in this research. After constructing all variables, it drops non-value sets and divides the remaining samples into the training set and test set. The proportion of the number of samples in the training and test set is about 8 to 2, 2,103 and 526 samples, respectively. Then, we standardize independent variables for each set to prepare predictions of machine learning models.

3.4 *Regression prediction evaluation indicator*

To estimate the results of the regression part, four popular indicators R-Squared, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) were used to evaluate all machine learning models. The R-Squared always describes the comparison of smaller errors between using the predicted value and using the mean only. The value of the R-Squared is normally between 0 and 1. When the value of the R-Squared of certain model approaches 1, the predicted value of this model can get a smaller error that fits more. Similarly, if the value of the R-Squared is close to 0 or even lower than 0, this model gets an extremely bad performance in predictions. The MSE is the average value of the squares of the prediction error, which is expected to be as small as possible. Similarly, since the RMSE is the root of the MSE, the smaller value of the RMSE shows the better performance of the model. Besides, there is another indicator expected to be small enough to measure the degree of fit for regression models-MAE. This is the average of the absolute value of the prediction error.

$$R-Squared = 1 - \frac{\sum_{t=1}^{n}\left(Value_t - \widehat{Value_t}\right)^2}{\sum_{t=1}^{n}\left(Value_t - \overline{Value_t}\right)^2} \tag{12}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(Value_t - \widehat{Value_t}\right)^2 \tag{13}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Value_t - \widehat{Value_t}\right)^2} \tag{14}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Value_t - \widehat{Value_t}\right| \tag{15}$$

where $\widehat{Value_t}$ and $\overline{Value_t}$ are the predicted value and average of $Value_t$, n is the sample size.

3.5 *Classification labels definition & evaluation indicator*

In this research, we classify the predicted value $\widehat{Value_t}$ into two types.

$$Value_t \text{ to } binary = \begin{cases} 1, & \widehat{Value_t} > 0 \\ -1, & \widehat{Value_t} \le 0 \end{cases} \tag{16}$$

Table 2. Confusion Matrix

Confusion Matrix		Predicted Value	
		1	-1
Real Value	1	True Positive (*TP*)	True Negative (*TN*)
	-1	False Positive (*FP*)	False Negative (*FN*)

Since the meaning of the variable $Value_t$ is the changes of the 5-day moving average in the bitcoin price between the day t and the next day $t + 1$, it also represents the bitcoin price changes. We set the label to be 1 when the bitcoin price has an upward trend because $Value_t$ is larger than 0. On the contrary, we set the label to be -1 when the bitcoin price has a downward trend because $Value_t$ is smaller than or equal to 0. For the classification prediction results, there is the confusion matrix listed in Table 2 to explain the evaluation indicators of classification.

Accuracy describes the proportion of the total sample with the predicted and real values equal. Precision is used to measure the proportion of true-positive samples in all samples with the predicted value of 1, while Recall shows the proportion of true-positive samples in all samples with the real value of 1. The F1-score represents the robustness of a certain model. Generally, all values of the evaluation indicators are wished to be high, which means more accurate. The formulas for the four indicators are listed as follows:

$$Accuracy = \frac{TP + FN}{TP + TN + FP + FN} \tag{17}$$

$$Precision = \frac{TP}{TP + FP} \tag{18}$$

$$Recall = \frac{TP}{TP + FN} \tag{19}$$

$$F1 - score = \frac{2TP}{2TP + FP + FN} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{20}$$

4. Experimental results and discussion

As the framework shown in Figure 1, after using machine learning models to predict the trend of the bitcoin price changes, the process of transferring regression results to classification results is provided in this section. Besides, a simulation quantitative trading experiment is also offered to compare the machine learning trading strategy with a traditional trading strategy.

4.1 *Regression results*

The regression results of different machine learning prediction models are shown in Table 3 below.

Table 3. Regression results of 5 ML prediction models

	Decision Tree	SVM	Random Forest	Bagging	AdaBoost
R-Squared	0.378	0.653	0.472	0.463	0.483
MSE	310,416.473	172,860.878	263,210.276	268,071.183	257,873.130
RMSE	557.150	415.765	513.040	517.756	507.812
MAE	436.578	297.519	375.613	380.130	372.680

Because of facing the dramatic bitcoin price changes, in reality, these machine learning models fail to perform well. The best-performing model is the SVM regression prediction model, but its R-Squared is only 0.653, while the other four models have an R-Squared of no larger than 0.5. Since the Changes of Moving Average in the bitcoin price are extremely large, the corresponding MSE, RMSE, and MAE results are high relatively. The performance of three ensemble learning models (i.e., Random Forest, Bagging, and AdaBoost) is very similar. Besides, the Decision Tree model has the worst prediction results since the single predictor might be overfitting for the training set.

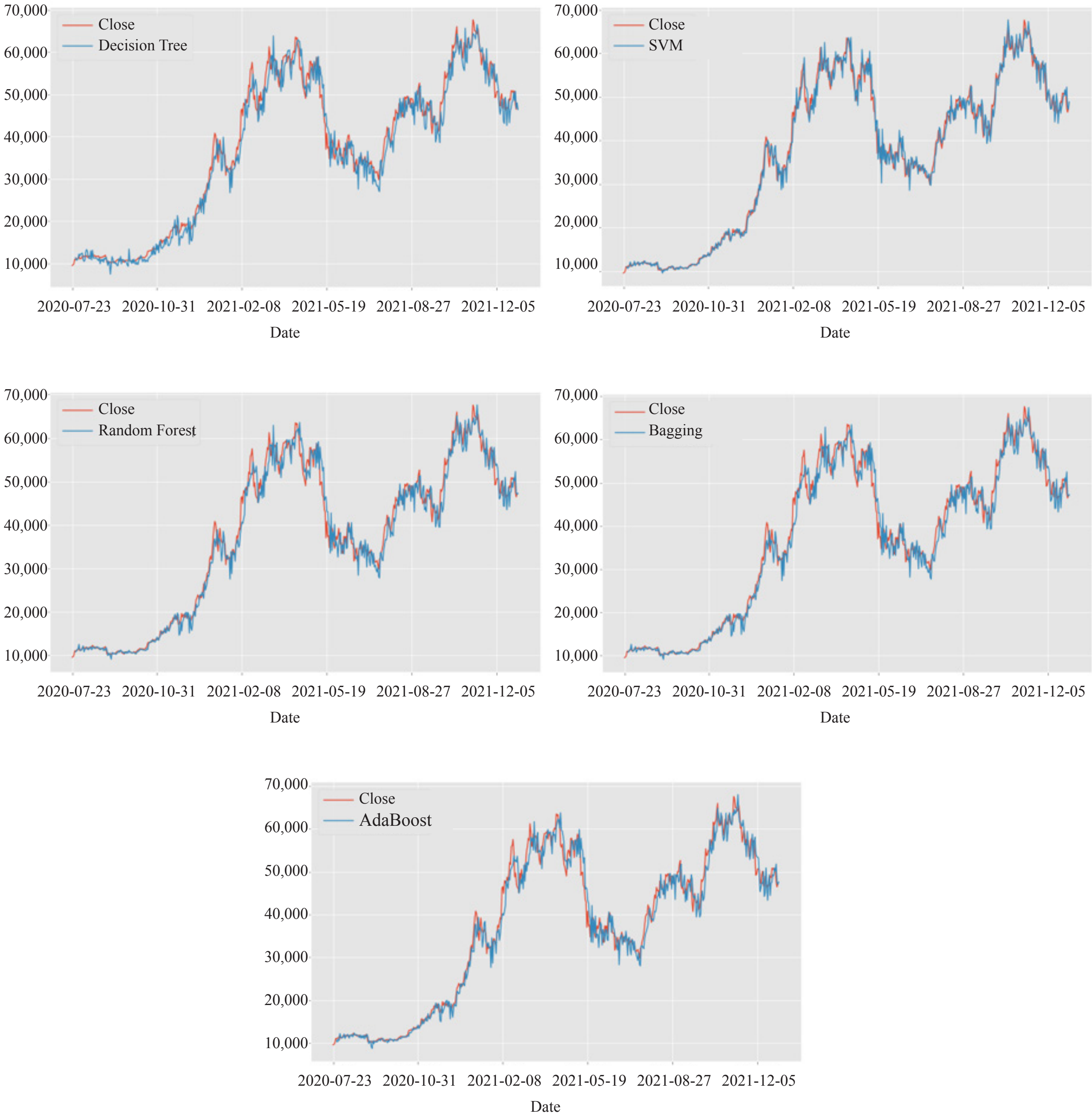

Figure 2. Comparison of the predicted bitcoin price

Since this research uses the trend of changes to make predictions on the bitcoin price and calculates the predicted close price $\widehat{Close_t}$ from the predicted value $\widehat{Value_t}$. The comparisons of the five machine learning models between the predicted close price and the real close price for the test set are shown in Figure 2 above. The predicted close price from these prediction models is more volatile than the real close price. The SVM model as the best-performing prediction model has the closest result to the real close price and has a good performance to catch up with the trend of bitcoin price changes. The remaining four prediction models have significant lags when prices change drastically. According to the regression results in Figure 2, there is a clear gap between the predicted bitcoin price of the Decision Tree model and the real bitcoin close price. Moreover, the Random Forest, Bagging, and AdaBoost regression models have similar results on the bitcoin close price prediction and basically capture the trend of bitcoin price changes very well.

4.2 *Classification results*

Based on the regression results of different prediction models, we set labels to the predicted Changes of Moving Average and use classification evaluation indicators to get the classification results in Table 4 below.

Table 4. Classification results based on labels

	Decision Tree	SVM	Random Forest	Bagging	AdaBoost
Accuracy	0.69	0.81	0.78	0.78	0.79
Precision	0.72	0.80	0.77	0.77	0.78
Recall	0.71	0.80	0.78	0.78	0.79
F1-score	0.69	0.80	0.78	0.77	0.78

We find that these regression prediction models seem to have a good performance on their classification results after setting classification labels. Almost all classification results based on labels given by the regression models have an accuracy of around 0.78, and the result provided by the SVM prediction model has the highest accuracy of 0.81. Although the classification results of the SVM model are not much higher than the other three ensemble learning models, it is easier to construct an SVM prediction model than them. Similar to the regression results shown in Table 3, the Decision Tree has the worst classification results with an accuracy of 0.69 in this situation, but it is also acceptable since the Decision Tree model is a simple single predictor.

Table 5. Classification results based on models

	Decision Tree	SVM	Random Forest	Bagging	AdaBoost
Accuracy	0.43	0.71	0.71	0.62	0.64
Precision	0.43	0.72	0.71	0.62	0.74
Recall	0.43	0.72	0.72	0.62	0.70
F1-score	0.43	0.71	0.71	0.61	0.64

Meanwhile, the results from the direct classification prediction of the same data using the classification model are as follows in Table 5. Compared with the classification results based on the classification prediction models directly, all indicators have increased since the regression results are classified into two labels. Especially, the accuracy of the Decision Tree model increases over 0.26 and reaches 0.69. In the situation of direct classification predictions, the Random Forest model has the best performance with the highest accuracy of 0.71 but still 0.07 lower than its classification result based on labels given by the regression model. Besides, in this situation, the accuracies of the three ensemble learning classification models are different, while the results provided by labels given by their regression models are similar. The SVM model, regarded as a single but very effective predictor, has relatively the best performance in both regression and classification for different situations.

4.3 *Trading simulations*

Since the SVM model is relatively the best machine learning model to predict the bitcoin price and capture the trend of the bitcoin price changes, this research would like to regard it as a Machine Learning Trading Strategy and apply it to a trading simulation.

In this experiment, the investor has an initial balance of \$100,000 and prepares to trade bitcoin in the period of the test set (from 23 July 2020 to 30 December 2021) in this research. There are two strategies for the investor: the traditional Double Moving Average Strategy and the Machine Learning Trading Strategy provided by this research-the SVM model strategy. All the investment results in this part are given by using the back trader package in Python.

The double moving average strategy is very popular in the stock market, which compares the 5-day moving average line with the 10-day moving average line. If the investor does not have a position and MA(5) is higher than MA(10), buy bitcoin as much as possible. Similarly, if the investor has positions and MA(5) is lower than MA(10), sell all positions of bitcoin. The specific operations of this strategy are shown in Figure 3.

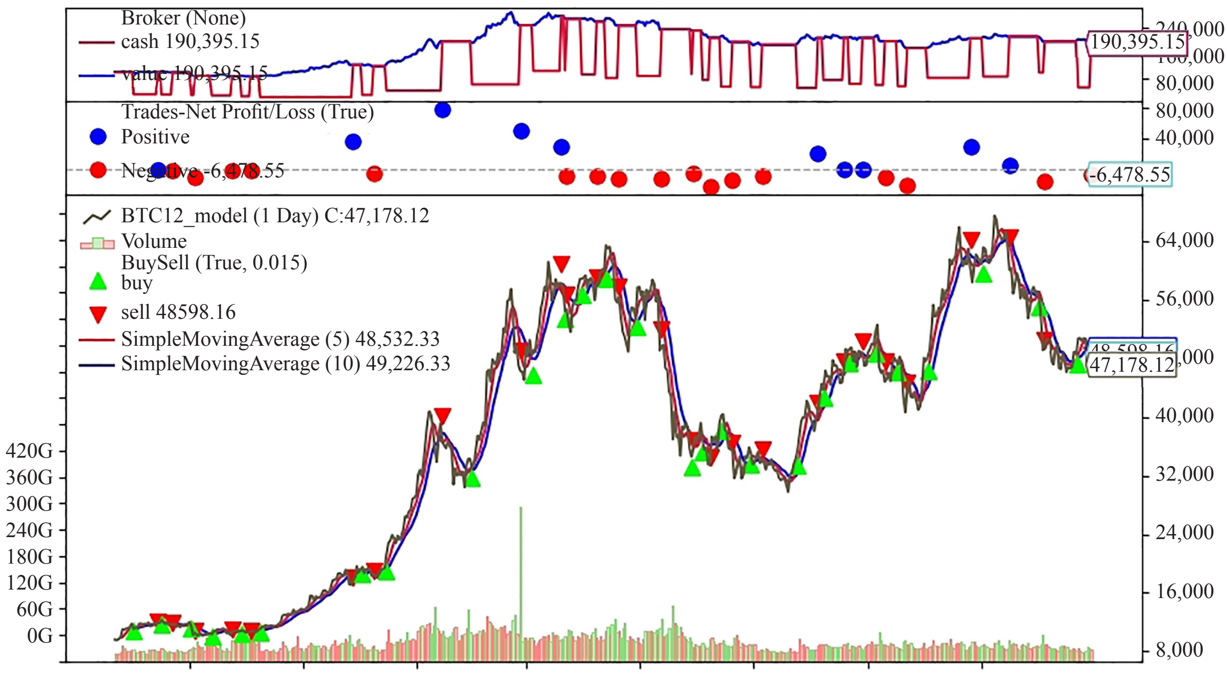

Figure 3. Application of the Double Moving Average Strategy

The SVM model strategy depends on the best prediction model in this research. When the predicted value $\widehat{Value_t}$ is larger than 0 and the investor does not have a position of bitcoin, just long the position of it. When the predicted value

$\widehat{Value_t}$ is smaller than 0, and the investor has positions of bitcoin, sell the positions immediately. In the same way, with the help of the back trader package, the investor's operations are shown in Figure 4.

According to Figure 3 and Figure 4, the final values of the investment by the double moving average and the SVM model strategy are $190,395.15 and $298,015.57, respectively. It concludes that using the SVM model strategy provided by this research can earn more profits in the bitcoin investment than the traditional double moving average strategy during the period of the test set.

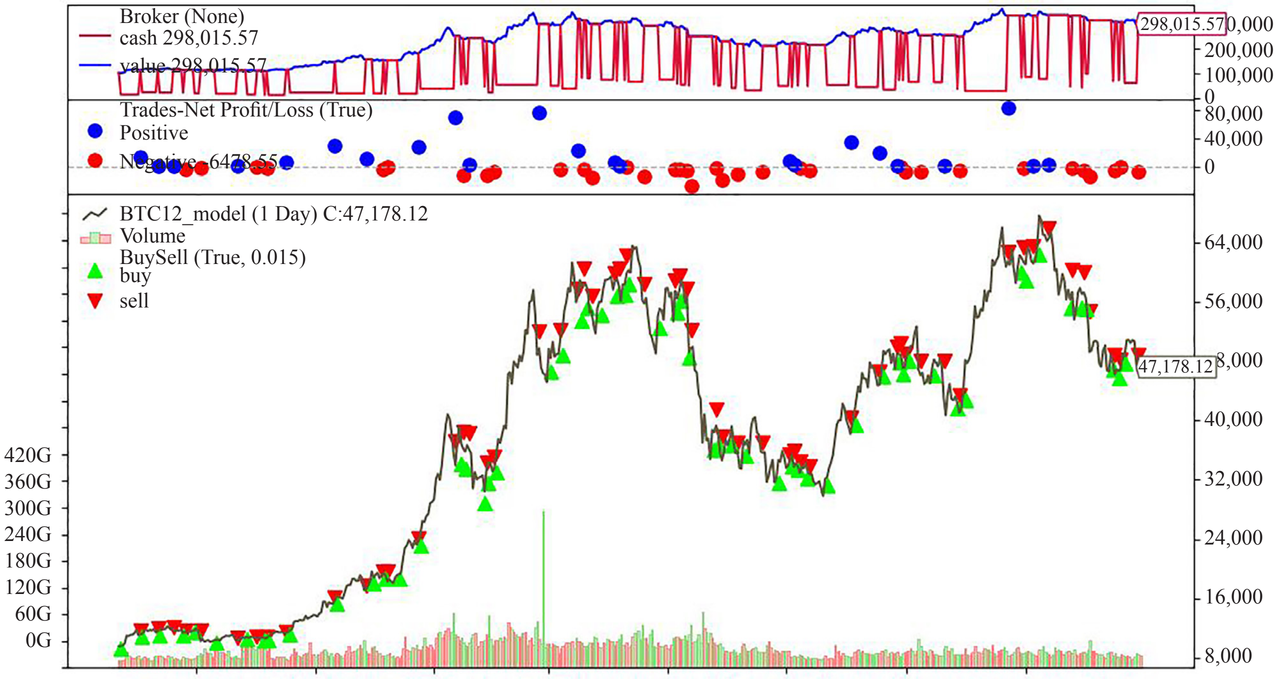

Figure 4. Application of the Machine Learning Trading Strategy-the SVM model strategy

In addition, there are three technical indicators in the stock market to evaluate these two strategies. The annualized rate of return is converted by the daily rate of return, the monthly rate of return, or other current rates of return. Investors hope that every rate of return is higher. Normally, in the stock or fund market, it is pretty good for an annualized rate of return to reach 10%-20%. The Max drawdown is used to describe the maximum loss that every investor may face. Such that, for this technical indicator, investors wish it lower. The Sharp ratio is to measure how much extra return investors gain for each unit of total risk they take. Similarly, the bigger value of the indicator, the higher return.

Table 6. Results of different strategies

	Double Moving Average Strategy	SVM Model Strategy
The Annualized Rate of Return (%)	36.138	68.734
Max Drawdown (%)	39.130	39.448
Sharp Ratio	2.143	2.156

From the results in Table 6, comparing the double moving average strategy with the SVM model strategy, the latter outperforms the former on the annualized rate of return and the Sharp ratio, though the traditional double moving average strategy has a little bit lower max drawdown than the SVM model strategy. It is interesting that the annualized rates of return for both two strategies are higher than ordinary stocks or funds, especially the machine learning trading strategy, which has a very high annualized rate of return of close to 70%. To some extent, the extraordinary changes in the bitcoin price have resulted in such huge gains. This is an important reason why this research focuses on bitcoin.

5. Conclusion

In this research, we apply a special method that uses five machine learning regression models to predict the Changes of Moving Average for bitcoin firstly, and then according to the predicted results, we give labels for bitcoin price changes to get the classification results. For this method, applying the Changes of Moving Average to capture the trend of bitcoin price changes is acceptable, to some extent, it could reduce some noises from the time series data. Besides, based on the regression results, this research gives labels to different trends, and this way helps to get a higher accuracy of each machine learning model than the direct classification predictions. In this research, we get the highest accuracy of 0.81 and consider the SVM model the best-performing machine learning model to predict the bitcoin price changes. Then, in the simulation trading experiment of testing the model, the Machine Learning Trading Strategy-the SVM model strategy helps investors earn more profits than the traditional trading strategy, which proves that the idea of this research is feasible. All in all, the performance of the machine learning regression models to predict the bitcoin price and the classification results based on labels given by the regression models are satisfactory. However, this research also has some problems to continue solving. In future research, we may consider applying deep learning models to predict bitcoin price changes, although the mode of operation of deep learning models is not as clear as traditional machine learning models. In addition, in 2022, the price of bitcoin plunged, and the regular price prediction models for bitcoin become less accurate due to its dramatic price changes. Whether we can find a suitable model that can help investors profit from bitcoin trading in such a scenario will be the direction of our future research.

Conflict of interest

The authors declare no competing financial interest.

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