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Bitcoin Price Prediction using Machine Learning and Technical Indicators

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***Abstract*—With the rise of Blockchain technology, the cryptocurrency market has been gaining significant interest. In particular, the number of cryptocurrency traders and the market capitalization have grown tremendously. However, predicting cryptocurrency price is very challenging and difficult due to the high price volatility. In this paper, we propose a classification machine learning approach in order to predict the direction of the market (i.e., if the market is going up or down). We identify key features such as Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) to feed the machine learning model. We illustrate our approach through the analysis of Bitcoin close price. We evaluate the proposed approach via different simulations. Particularly, we provide a backtesting strategy. The evaluation results show that the proposed machine learning approach provides buy and sell signals with more than 86% accuracy.**

***Index Terms*—Bitcoin price movement; classification models; market predictions; random forest; technical indicators**

I. Introduction

The cryptocurrency market is transforming the world of money and finance [1], and has seen significant growth in the last years [1], [2]. In particular, the number of cryptocurrencies reached more than 7000 in 2021 [3], and the crypto market capitalization hit $3 trillion the same year [3].

The banking and financial industry has taken notice of Blockchain benefits. The underlying technology behind every cryptocurrency is Blockchain technology. Blockchain is a distributed/decentralized database that is organized as a list of blocks, where the committed blocks are immutable. It has many attractive properties including transparency and security [2].

The crypto market has many good characteristics including high market data availability and no closed trading periods. However, it suffers from its high price volatility and relatively smaller capitalization. In crypto financial trading, data can be available to all traders. However, the analysis and the selection of this data makes the difference between executing good trades and bad trades. Therefore, one of the main challenges in financial trading is to develop methods/approaches to extract meaningful knowledge and insights from the data. Furthermore, due to the high price volatility of cryptocurrencies price, forecasting the price becomes more challenging.

Up to now, there are few studies that have attempted to create profitable trading strategies in the cryptocurrency market. In 2018, Saad et al. [4] provided a machine learning model to predict Bitcoin price. In particular, they made use of a regression model and involved many factors that impact the price of Bitcoin. However, they did not provide *Buy* and *Sell* signals, which are the most important in building a trading strategy/approach. Furthermore, they did not consider any kind of technical indicators. The use of technical indicators as features to feed machine learning models for financial trading has been successfully employed by many researchers [5], [6]. McNally et al. [7] proposed a machine learning model that makes a recurrent neural network, called Long Short Term Memory Model (*LSTM*). *LSTM* achieves an accuracy of 52%, for classification. However, this is not acceptable for building a trading strategy. Our approach achieves 86%, which is quite acceptable.

Recently, Jay et all. [8] proposed a stochastic neural network model for cryptocurrency price prediction. Precisely, they made use of random walk theory, and Multi-Layer Perceptron (*MLP*) and *LSTM* machine learning models [8]. The approach achieves good mean absolute percentage error (*MAPE*). However, they did not consider *Buy* and *Sell* signals. They also did not consider any kind of technical indicators to feed their machine learning models.

In a more recent work, Singh et al. [9] proposed three machine learning models to predict the price of cryptocurrency. They reported that Gated Recurrent Unit (*GRU*) provides a good accuracy compared to others with a *MAPE* of 0.2454% for Bitcoin. However, the authors did not provide *Buy* and *Sell* signals, and did not consider technical indicators to feed this machine learning model.

In this paper, we contribute to the development of profitable trading strategies by proposing a new approach that integrates various features including technical indicators and historical data. The key contribution of the proposed approach is providing *buy* and *sell* signals with high accuracy. We evaluate the proposed approach through the analysis of Bitcoin cryptocurrency.

The remaining of the paper is organized as follows. Section II presents the mathematical modelling of the proposed approach. Section III presents four different machine learning models. Section IV compares the machine learning models and evaluates the proposed approach through a backtesting

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strategy and confusion matrices. Finally, Section V concludes the paper.

II. Mathematical Modeling

In this section, we provide a mathematical modelling of the proposed approach.

A. Notations & Definitions

Table I below provides the definitions of parameters and abbreviation.

TABLE I: Notations & Abbreviations

Notation	Description
m	Total number of observations/samples
$n_{training}$	Number of samples in the training set
n_{test}	Number of samples in the test set
n_x	Total number of input features
$\mathcal{C}_p^{(i)}$	Close price at time t_i
$\mathcal{O}_p^{(i)}$	Opening price at time t_i
$\mathcal{H}_p^{(i)}$	High price at time t_i
$\mathcal{L}_p^{(i)}$	Low price at time t_i
$\mathcal{V}^{(i)}$	Volume of the cryptocurrency that is being in trade at time t_i
s	Span ($s \geq 1$)
$RSI_\alpha^{(i)}$	Relative strength index at time t_i within a time period α
$MACD^{(i)}$	Moving average convergence divergence at time t_i
$EMA_\alpha^{(i)}$	Exponential moving average at time t_i within a period of time α
$PROC_\alpha^{(i)}$	Price rate of change at time t_i within a period of time α
$\%K_\alpha^{(i)}$	Stochastic oscillator at time t_i within a period of time α
$MOM_\alpha^{(i)}$	Momentum at time t_i within a period of time α
$\mathbb{R}$	Set of real numbers
$\mathcal{T}$	Set of targets, $\mathcal{T} = \{1, -1\}$

Definition 1 (Backtesting)**.** Backtesting is a technique that allows the evaluation and the assessment of a trading strategy through data-driven simulations using historical data.

B. Mathematical Model

In this section, we present a mathematical modeling of our approach.

Let $(x^{(i)}, y^{(i)})$ denotes a single sample/observation. The set of samples is represented by:

$$\mathcal{S} = \left\{ \left(x^{(1)}, y^{(1)}\right), \left(x^{(2)}, y^{(2)}\right), \ldots, \left(x^{(m)}, y^{(m)}\right) \right\} \quad (1)$$

where $x^{(i)} \in \mathbb{R}^{n_x}$ and $y^{(i)} \in \mathcal{T}$.

Since we consider both technical indicators and Blockchain historical data to predict the price, we need to combine/merge different data sets. Specifically, technical indicators and historical data are input to our model. Our feature vector in a given time t can be expressed as follows:

$$x^{(i)} = \begin{pmatrix} \mathcal{C}_p^{(i)} \\ \mathcal{V}^{(i)} \\ RSI_{14}^{(i)} \\ RSI_{30}^{(i)} \\ RSI_{200}^{(i)} \\ MOM_{10}^{(i)} \\ MOM_{30}^{(i)} \\ MACD^{(i)} \\ PROC_9^{(i)} \\ EMA_{10}^{(i)} \\ EMA_{30}^{(i)} \\ EMA_{200}^{(i)} \\ \%K_{10}^{(i)} \\ \%K_{30}^{(i)} \\ \%K_{200}^{(i)} \end{pmatrix}, \quad x^{(i)} \in \mathbb{R}^{n_x} \quad (2)$$

Let us generalize our model by stacking all features vectors in one matrix X. This matrix can be expressed as follows:

$$X = \begin{array}{c c} & \begin{array}{ccc} x^{(1)} & \cdots\cdots\cdots & x^{(m)} \end{array} \\ \begin{array}{c} \mathcal{C}_p \\ \mathcal{V} \\ RSI_{14} \\ \vdots \\ \%K_{30} \\ \%K_{200} \end{array} & \begin{pmatrix} \mathcal{C}_p^{(1)} & \mathcal{C}_p^{(2)} & \cdots & \mathcal{C}_p^{(m)} \\ \mathcal{V}^{(1)} & \mathcal{V}^{(2)} & \cdots & \mathcal{V}^{(m)} \\ RSI_{14}^{(1)} & RSI_{14}^{(2)} & \cdots & RSI_{14}^{(m)} \\ \vdots & \vdots & \ddots & \vdots \\ \%K_{30}^{(1)} & \%K_{30}^{(2)} & \cdots & \%K_{30}^{(m)} \\ \%K_{200}^{(1)} & \%K_{200}^{(2)} & \cdots & \%K_{200}^{(m)} \end{pmatrix} \end{array} \quad (3)$$

where

$$X \in \mathbb{R}^{n_x \times m}$$
$$\mathcal{C}_p = \left(\mathcal{C}_p^{(1)}, \mathcal{C}_p^{(2)}, \ldots, \mathcal{C}_p^{(m)}\right)$$
$$\mathcal{V} = \left(\mathcal{V}^{(1)}, \mathcal{V}^{(2)}, \ldots, \mathcal{V}^{(m)}\right)$$
$$RSI_{14} = \left(RSI_{14}^{(1)}, RSI_{14}^{(2)}, \ldots, RSI_{14}^{(m)}\right)$$
$$\cdots\cdots\cdots$$
$$\%K_{200} = \left(\%K_{200}^{(1)}, \%K_{200}^{(2)}, \ldots, \%K_{200}^{(m)}\right)$$

The output matrix can be expressed as follows:

$$Y = \left(y^{(1)}, y^{(2)}, \ldots, y^{(m)}\right) \quad (4)$$

where $y^{(i)} \in \mathcal{T}$ and $i \in \{1, 2, \ldots, m\}$.

C. Features

In this section, we present different features. In particular, we make use of historical market data and technical analysis indicators. All these features are evaluated in Section IV by using the random forest model; most of these features show good importance to contribute to the accuracy of our approach (see Figure 4).

1) Historical Data: Regarding the historical data, we consider close price and volume.

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a) Close Price: Close price refers to the price at which a cryptocurrency closes at a given time period.

b) Volume: Volume is the number of units (e.g., number of Bitcoins) traded in the market during a given time period.

2) Technical Analysis Indicators: Technical analysis is a trading discipline employed to evaluate investments and identify trading opportunities by analyzing statistical trends gathered from trading activity, such as price movement and volume [10]. In this work, we consider the exponential moving average, moving average convergence divergence, relative strength index, momentum, price rate of change, and stochastic oscillator.

a) Exponential Moving Average: The exponential moving average (EMA) was first introduced by Roberts (1959) [11]. It is a type of moving average (MA) that places a greater weight and significance on the most recent data points. EMA is also referred to as the exponentially weighted moving average.

$C_p^{(1)}$ represents the closing price at time t_1, $C_p^{(2)}$ represents the close price at time t_2, and gradually $C_p^{(m)}$ represents the close price at time t_m. Knowing that $t_1 < t_2 < \dots t_{m-1} < t_m$ $\gamma = t_k - t_{k-1}$ measures the step time (e.g., 1 minute, 15 minutes, 1 day). EMA can be expressed recursively as follows:

$$\begin{aligned} EMA_1 &= C_p^{(1)} \\ EMA_t &= (1-\alpha)EMA_{t-1} + \alpha C_p^{(t)}, \end{aligned} \tag{5}$$

where α is smoothing factor ($\alpha \in [0,1]$) and is expressed as $\alpha = 2/(s+1)$.

b) Moving Average Convergence Divergence: Moving Average Convergence Divergence ($MACD$) is a technical indicator created by Gerald Appel in 1970 [12]. $MACD$ helps investors understand the movement of the price (i.e., the market will be in bullish or bearish movement) [12]. Usually, *MACD* is calculated by subtracting the 26-period *EMA* from the 12-period *EMA*. Formally, it is expressed as follows:

$$MACD = EMA_n - EMA_{n+j} \tag{6}$$

where EMA_i is the i-period *EMA* and j equals 14 ($j = 26 - 12$).

c) The relative strength index: The relative strength index (*RSI*) is a technical indicator used to chart the current and historical strength or weakness of a stock/market based on the closing price of a recent trading period. It was originally developed by J. Welles Wilder [13]. *RSI* is classified as a momentum oscillator, which is an indicator that varies over time within a band. Technically, *RSI* is typically used on a 14-days period and is measured on a scale from 0 to 100. *RSI* takes the values 70 and 30 with high and low levels of the market [13]. *RSI* within a band α (α usually equals 14) can be mathematically expressed as follows:

$$\begin{aligned} RSI_\alpha &= 100 - \frac{100}{1+RS} \\ RS &= \frac{A_\alpha^g}{A_\alpha^l} \end{aligned} \tag{7}$$

where A_α^g and A_α^l represent average gain over α-days and average loss over α-days, respectively.

d) Momentum: Momentum (MOM) measures the velocity of a stock price over a period of time, which means the speed at which the price is moving; typically we use the close price [14]. MOM helps investors identify the strength of a trend [14]. Formally, the momentum can be expressed as follows:

$$MOM_\zeta = \mathcal{C}_p^{(i-(\zeta-1))} - \mathcal{C}_p^{(i)} \tag{8}$$

where ζ is the number of days.

e) Price Rate of Change: The Price Rate Of Change (PROC) measures the most recent change in price. It can be expressed as follows:

$$PROC_t = \frac{C_p^t - C_p^{t-n}}{C_p^{t-n}} \tag{9}$$

where $PROC_t$ is the price rate of change at time t and n is the number of periods to look back.

f) Stochastic Oscillator: A stochastic oscillator is a popular technical indicator for generating overbought and oversold signals. Usually the current value of the stochastic indicator is denoted by $\%K$ and it is computed as follows:

$$\%\mathcal{K} = \frac{\mathcal{C} - \mathcal{L}_d}{\mathcal{H}_d - \mathcal{L}_d} * 100 \tag{10}$$

where $\mathcal{C}$ represents the most recent closing price, $\mathcal{L}_d$ represents the lowest price traded during the d previous periods, and $\mathcal{H}_d$ represents the highest price traded during the d previous periods.

g) Signal: Let $\mathcal{Y}$ be a random variable that takes the values of 1 or -1 (*Buy* and *Sell*, respectively).

To generate *Buy* and *Sell* signals, we employ a technical indicator called Moving Average (MA). MA identifies the trend of the market. The MA rule that generates *Buy* and *Sell* signals at time t consists of comparing two moving averages. Formally, the rule is expressed as follows:

$$\mathcal{Y}(t) = \begin{cases} 1 & \text{if } \mathrm{MA}_{s,t} \geq \mathrm{MA}_{l,t}, \\ -1 & \text{if } \mathrm{MA}_{s,t} < \mathrm{MA}_{l,t} \end{cases} \tag{11}$$

where

$$\mathrm{MA}_{j,t} = (1/j)\sum_{i=0}^{j-1} \mathcal{C}_p^{(t-i)}, \quad \text{for } j = s \text{ or } l; \tag{12}$$

s (*l*) is the length of the short (long) MA ($s < l$). We denote the MA indicator with MA lengths *s* and *l* by MA(*s*, *l*). In this paper, we consider the MA(10, 60) because of it high accuracy.

III. Machine Learning Models

In this section, we propose the most common and popular machine learning models for classification: logistic regression, support vector machine, random forest, and voting classifier.

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A. Logistic Regression

In Logistic Regression (*LR*) we use a linear function, $wX + b$, followed by the sigmoid function σ to get an output y, denoted by $\hat{y}$, such that $0 < \hat{y} < 1$ and $b \in \mathcal{R}$.

B. Support Vector Machine

Support Vector Machine (*SVM*) is a robust and versatile machine learning model [15]. It is based on Vapnik–Chervonenkis theory (VC theory), which provides the classification and learning process from a statistical point of view. Particularly, *SVM* is well suited for classification of complex but small or medium data sets [15].

C. Random Forest

Random Forest (*RF*) classifier is a combination of decision tree [16]. *RF* uses averaging over all the tree predictors to improve the accuracy and control over-fitting [17]. Furthermore, one of the main qualities of *RF* is that it helps us to measure the importance of each feature.

D. Voting Classifier

Voting Classifier (*VC*) consists of aggregating the predictions of each classifier and determining the class that gets most votes. This *VC* is called Hard voting classifier. Technically, this classifier determines the class that has been predicted most frequently by other participating models. In this study, the *VC* model can be modelled as follows:

$$\hat{y_j}^{(0)} = mode\{\hat{y_j}^{(1)}, \hat{y_j}^{(2)}, \hat{y_j}^{(3)}\} \tag{13}$$

where $\hat{y_j}^{(0)}$ is the predicted outcome (target) by the VC model corresponding to the j^{th} vector x_j^T, $n_{training} \leq j \leq m$. And $\hat{y_j}^{(1)}$, $\hat{y_j}^{(1)}$, and $\hat{y_j}^{(3)}$ are the predicted targets, corresponding to the j^{th} vector x_j^T, by the *RF*, *SVM*, and *LR* models. The term "mode" represents the statistical mode.

IV. Results & Evaluation

In this section, we compare the proposed machine learning models and present a simulation-based evaluation of our approach.

A. Simulation Setup

We make use of *sklearn* Python package to simulate the proposed approach. In particular, we take advantage of *sklearn.preprocessing* module to scale the data, and *sklearn.metrics* module to calculate the accuracy, classification report, and confusion matrix. We make use of *sklearn.ensemble* module to import random forest classifier and voting classifier, *sklearn.linear_model* to import logistic regression classifier, and *sklearn.svm* to import support vector machine classifier.

For the data, we stream real-time historical market data directly from Binance via Binance API [18]. The data is from 01 February, 2021 to 01 February, 2022 and with a time step of 15 minutes (i.e., $\gamma = 15$ minutes). We choose 15 minutes because it gives us good accuracy. We split the data into 80% for training set and 20% for testing set.

B. Evaluation Parameters

To evaluate and measure the robustness and the goodness of the proposed approach, we present different evaluation parameters:

- Accuracy: It is the fraction of predictions our model got right. Formally, accuracy can be expressed as follows:

$$Accuracy = \frac{TP + TN}{n_{test}} \tag{14}$$

  where TP is the number of true positives and TN is the number of true negatives.
- Precision: It is expressed as follows:

$$Precision = \frac{TP}{TP + FP} \tag{15}$$

  where FP is the number of false positives.
- Recall: It is expressed as follows:

$$Recall = \frac{TP}{TP + FN} \tag{16}$$

  where FN is the number of false positives.

C. Results & Analysis

TABLE II: K-fold Comparison

Model	LR	SVM	RF	VC
Score	0.863	0.854	0.867	0.864

Table II provides a K-fold cross-validation comparison among the different proposed machine learning models. This comparison is based on the score (accuracy) presented in Table II. This score is calculated as the average of the accuracy of 10 folds. Table II shows that the four models provide approximately the same score. We choose RF (an ensemble model) to forecast crypto market since it has the ability to deal with very larger sizes of data, a large number of features, and an expected non-linear relationship between the predicted variable and the features [19].

TABLE III: Classification Report

			Precision		Recall	
	Model	**Accuracy**	**1**	**-1**	**1**	**-1**
Bitcoin	RF	0.884	0.885	0.884	0.891	0.876

Table III shows the classification report of the proposed approach. It shows the accuracy, precision, and the recall.

Figure 1 shows the distribution of the predicted variable for Bitcoin. Particularly, Figure 1 shows that the predicted variable's class 1 is slightly more bigger than 50% of the time, meaning there are more *buy* signals than *sell* signals. The predicted variable is relatively balanced.

Figures 2, 3, and 4 show an evaluation of the proposed approach (which makes use of the RF classifier), starting by a simple backtesting strategy, then the calculation of the confusion matrix, and eventually the evaluation of the feature's importance. The proposed backtesting strategy consists of

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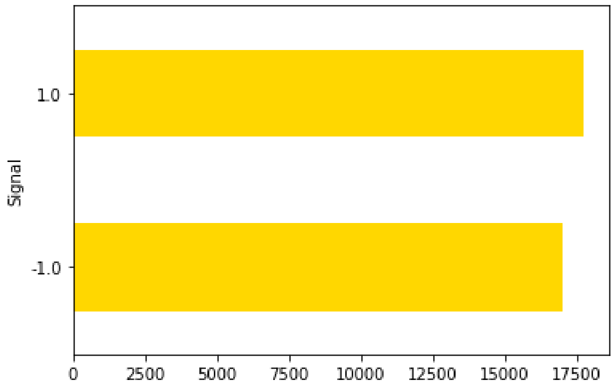

Fig. 1: The predicted variable of Bitcoin.

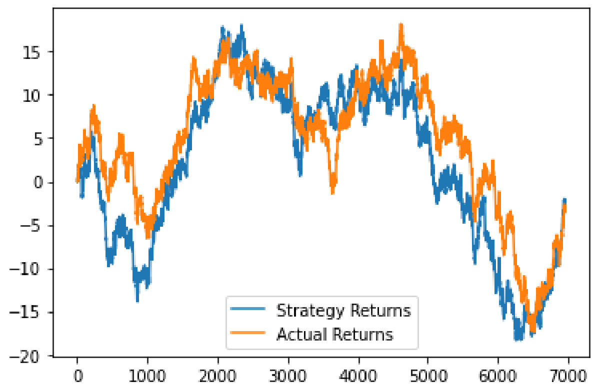

Fig. 2: Bitcoin backtesting.

calculating the predicted returns (aka, strategy returns) and comparing it with the actual returns.

Figure 2 shows that the predicted returns are very close to the actual returns. This means that the proposed approach performs well for predicting Bitcoin.

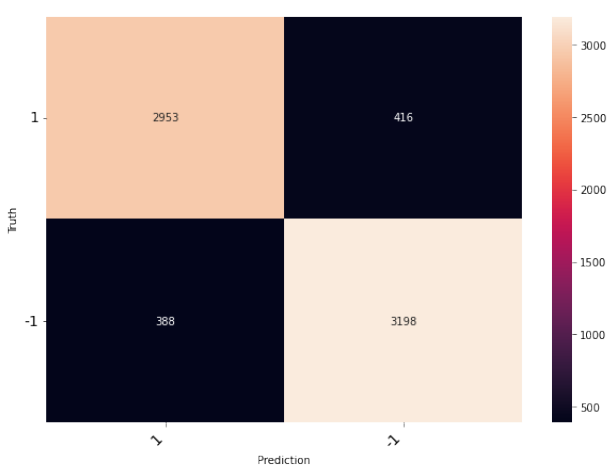

Fig. 3: Bitcoin confusion matrix.

Figure 3 shows the confusion matrices corresponding to Bitcoin. In particular, Figure 3 shows that (in the first column of the matrix) the model predicts that we should execute $2953 + 388$ *Buy* operations. However, the truth is that we should only execute 2953 Buy operations and the rest (388) should be executed as a *Sell* operations. Moreover, in the second column of the matrix, the model predicts that we should execute $416+3198$ *Sell* operations. However, the reality is that we should only execute 3198 *Sell* operations and the rest (416) should be executed as *Buy* operations.

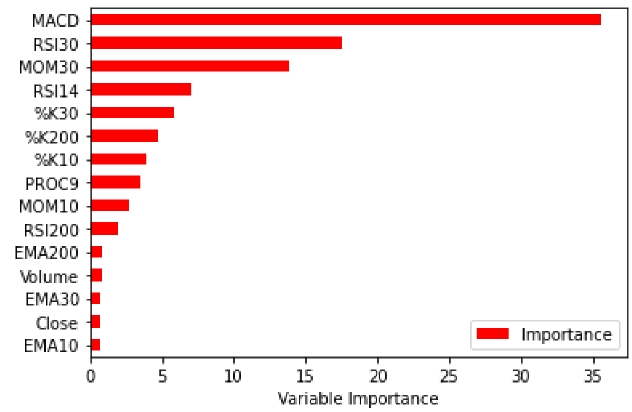

Fig. 4: Bitcoin feature importance.

Figure 4 shows that $MACD$, RSI_{30}, and MOM_{30} are the features that contribute highly in improving the performance of the proposed approach. $\mathcal{C}_p$ (Close price), EMA_{10}, EMA_{30}, EMA_{200}, and the $\mathcal{V}$ (Volume), are the features that contribute less in improving the performance of our approach.

To conclude, we collect crypto market data and employ the most significant features that influence the price including volume and technical indicators. Technical indicator features appear to be most influential (Figure 4) compared to close price and volume. Our approach achieves a good accuracy, precision, and recall. However, this approach still needs improvement (for making actual/real returns as close as possible to the returns of our approach/strategy returns).

It is worth noting that predicting cryptocurrency price is very challenging since unconventional factors such as social media, investor psychology have great influence on the crypto market. Future research directions could focus on building upon a forecasting approach that involves more features (e.g., cash flow, mining rate, number of transactions) as well as employing more machine learning models.

V. Conclusion

In this paper, we analyze cryptocurrency market price by using the most common technical indicators and compare four well-known classification machine learning models. We get historical market data from Binance to compute the technical indicators. We also add the volume and the close price as features. We predict the direction of market by providing *buy* and *sell* signals. Compared to the existing models that predict the future price based on the past price or even models that use other features, our approach is highly accurate. In the future,

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we aim to identify more key features by adding more technical indicators and compare more classification models, including *XGBoost*, for the purpose of enhancing the speed and accuracy of the proposed approach.

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