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Predicting the Top and Bottom Prices of Bitcoin Using Ensemble Machine Learning

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ABSTRACT

The purpose of the present study is to use the ensemble learning model to combine the predictions of Random Forest (RF), Long-Short Term Memory (LSTM), and Recurrent Neural Network (RNN) models for the Top and Bottom Prices of Bitcoin. To this aim, in the first stage, Bitcoin's top and bottom prices are predicted using three machine learning models. In the second stage, the outputs of the models are presented as feature variables to the Extreme Gradient Boosting (Xgboost) and Light Gradient Boosting Machine (LightGBM) models to predict the price tops and bottoms. Then, in the third stage, the outputs of the second stage are combined through the voting ensemble classifier pattern to predict the next top and bottom prices. The data of top and bottom Bitcoin prices in the 1-hour time frame from 1/1/2018 to the end of 6/30/2022 are used as target variables, and 31 technical analysis indicators as feature variables for the three models in the first stage. 70% of the data is regarded as learning data, and the remaining 30% is considered for the second and third stages. In the second phase, 50% of the data is considered for learning the output of the previous stage and 50% for the test data. Finally, the prediction values are evaluated with real data for the three models and the proposed ensemble learning model. The results reveal the improvement in the performance, precision, and accuracy of the ensemble model compared to weak learning models.

1 Introduction

Predicting prices in financial markets is one of the key factors of success for traders and investors. Increasing the accuracy of price prediction can help financial market actors in the following cases [8]:

1. The efficiency of trading strategies is enhanced;
2. Investors can seek to cover their risk based on prediction results;
3. Speculators and arbitrageurs can increase their outcomes and reduce risk based on their prediction results;
4. They can generally comment on financial markets by predicting important indicators.

Therefore, price prediction is of great importance for financial market actors. Among the financial markets, the cryptocurrency market has attracted the attention of investors and activists due to its stunning growth in the years 2015 to 2017 and 2019 to 2021. As the most prominent cryptocurrency, Bitcoin is

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a digital currency introduced by Nakamoto in 2008. This cryptocurrency uses blockchain and cryptography technology to securely enable people to perform peer-to-peer financial transactions [13]. The main reasons for the growth of Bitcoin in 2019-2021 were the halving effect (the halving of the Bitcoin network reward) in 2020, the Covid-19 pandemic, the expansionary policies of the Federal Reserve, and the support of large organizations around the world. Predicting the price of Bitcoin as the biggest cryptocurrency in this market can be representative of other cryptocurrencies because the correlation of other currencies (altcoins) with Bitcoin is high. Hence, predicting Bitcoin price for the actors of international financial markets with the aim of inflation shield can be considered as the contribution and significance of present study.

This study aims to predict the price of Bitcoin as a representative of the cryptocurrency market using machine learning models. In a study, Gupta and Nain indicated that time series models, specifically the weighted moving average model and ARIMA, outperform machine learning or deep machine learning models in predicting the price of Bitcoin for one day. They were also provided 86% accuracy in the best case [7]. Of course, other studies have shown that machine learning models have enhanced prediction accuracy due to overcoming the linear limitations of classical models [6]. Instead of the time series approach and predicting one subsequent data, the present study looks for the next top and bottom prices for Bitcoin in a 1-hour time frame. The accuracy of machine learning models in prediction can be improved through a discrete approach and top or bottom classification.

Due to the random behavior and nature of prices in financial markets, a single prediction model cannot have a reliable performance at different times. Therefore, a model that can make decisions about the prediction of models according to the market conditions can enhance the accuracy of the prediction. In this regard, this study aims to predict Bitcoin price tops and bottoms using supervised machine learning models. The proposed model has three main stages. In the first stage, Bitcoin price tops and bottoms are predicted using Random Forest (RF), Long-Short Term Memory (LSTM), and Recurrent Neural Network (RNN) models. The resulting outcome is fed as input to XGBoost and LightGBM models, and the results of these two models are combined using the voting ensemble classifier. The final prediction result is comparable to real data. These steps are explained in detail in the following sections of the article.

2 Theoretical background and literature review

Predicting the price of financial assets is essential for activists, investors, traders, and arbitrageurs in financial markets. Generally, price prediction methods in financial markets can be classified into two main categories: classical and intelligent. In classical methods, it is assumed that the future values are predicted with explanatory variables that can be the factors affecting the price or the price itself with a time interval. In these models, it is necessary to determine the relationship between explanatory and dependent variables. The data should be matched with the models' assumptions through pre-tests to achieve the desired results. In contrast, intelligent methods use machine learning. In these methods, the relationship is not known in advance, and the algorithms seek to discover a mathematical relationship.

A review of the literature reveals that machine learning algorithms significantly help classify and predict prices in financial markets [23]. While machine learning models have attracted the attention of many activists in predicting financial markets, in recent studies, various ensemble learning models have been shown to increase prediction accuracy [see 18, 19]. Faghihi Nezhad and Minaei [6] classified the studies that have been conducted on price prediction using machine learning (intelligent models) into three groups: the first group is studies that use only one model or algorithm for prediction; the second group

uses several models in combination, and the third group uses ensemble learning models to aggregate the outputs. In the following, the studies using ensemble learning models for price prediction are reviewed. Nti et al. also conducted an extensive comparative analytical study of ensemble learning models, including Bagging, Boosting, Blending, and Stacking. The decision tree, support vector machine, and neural network models with 25 different modes were combined with ensemble learning. They predicted the stock market indices of Ghana, Johannesburg, Mumbai, and New York from 2012 to 2018 using models and compared their performance. This study indicated that Blending and Stacking had higher accuracy than Bagging and Boosting. These models were also found to have fewer errors [15].
Consistent with these studies, Zi et al.'s also showed that the ensemble method had an acceptable performance in predicting Bitcoin’s next 30-minute prices. In this study, a novel ensemble deep learning model was proposed to predict Bitcoin’s next 30 min prices by using price data, technical indicators, and sentiment indexes, integrating two kinds of neural networks, long short-term memory (LSTM) and recurrent gate unit (GRU), with stacking ensemble technique to improve the accuracy of the decision. They found that the ensemble method had a better performance, with a mean absolute error (MAE) 88.74% better than the daily prediction. The purpose of this work is to explain our solution and show that [25]. The findings of Zhang et al. are somehow inconsistent with those of Ampomah et al. They proposed a model using RF, disequilibrium learning, feature selection, and pruning to predict stock price trends and their growth (or decline) rate intervals. Using more than 70 technical analysis indices as input, this model classified prediction targets into four classes: high, low, flat, and unknown. This model was evaluated with more than 400 stocks in the Shenzhen market. The results indicated that the proposed model outperformed the artificial neural network, support vector machines (SVMs), and K-nearest neighbors’ algorithm regarding accuracy and efficiency in each transaction [11].
Another study referring to the superiority of hybrid models was conducted by Yun et al. They proposed a hybrid model of XGBoost and a genetic algorithm with an extensive feature engineering process on over 60 technical analysis indicators for stock market predictions. Their hybrid model performed better than LSTM models in terms of performance and interpretability [9]. In contrast, Koosha et al.’s findings revealed that the RF model was more accurate than the LSTM and RNN models in predicting the Bitcoin price. In this study, they used machine learning models to predict the price of Bitcoin. They measured and compared the accuracy and precision of RF, LSTM, and RNN models in predicting the top and bottom of Bitcoin prices. Their result also indicated over 80% accuracy in predicting the top and bottom Bitcoin price [29]. Sun et al. predicted the cryptocurrency market trend using GBDT and LightGBM. For this prediction, 42 types of cryptocurrencies with key economic indices were used. The results pointed to the stable and better performance of LightGBM compared to other models [17]. However, Yang et al. used XGBoost and LightGBM models to predict stock prices. The results of their study revealed the better performance of the ensemble method compared to each of the models separately [16]. In another comparative study, Ampomah et al. compared the effectiveness of different tree-based ensemble models, including RF, XGBoost, Bagging, AdaBoost, Extra Trees Classifier, and Voting Classifier, in predicting the direction of stock price movement. They used eight different stock data from three stock exchanges, NYSE, NASDAQ, and NSE. They used principal component analysis to select the features of 45 inputs, including 40 technical analysis indicators. Their experimental results showed that the Extra Trees classifier performed better than other models in all rankings [1].
Li and Pan proposed a novel deep-learning model to predict stock price movements. This model used an ensemble learning model to combine two recurrent neural networks. In this study, the S&P 500 index data was used. Their study showed a 57.7% reduction in the mean squared error and an increase in the

indicators of accuracy by 40%, recall by 50%, and F1 by 44.78% [10]. Aggarwal et al. used machine learning models to discover the nature of Bitcoin price and predict it. The ensemble learning model (CEEMD) was used in this study. The daily price of Bitcoin from 2012 to 2018 was divided into three sections; short, medium, and long-term. This study used the SVM model, which can predict Bitcoin for five short-term steps [5]. In the first step of their study, Dennys et al. also implemented feature engineering and different algorithms of feature variable selection for predicting the price of Bitcoin. Then they used artificial neural network models, support vector machines, and ensemble learning models based on recurrent neural networks and K-means clustering to predict the price of Bitcoin. Their study resulted in a 10% increase in the prediction accuracy of the results of previous studies [4].

In an attempt to predict the bitcoin price, Lahmiri and Bekiros [24] used three different ML models, including LSTM, GRNN, and Nearest Neighbors, to investigate the nonlinear structure of Bitcoin. Consistent with Yun et al., LSTMs were found to significantly surpass the GRNN in terms of the RMSE. They also found that the generalized regression neural networks were not as successful as LSTM in finding patterns in addition to being time-consuming. Similarly, Jaquart et al. analyzed the predictability of the bitcoin market across prediction horizons ranging from 1 to 60 min. Testing various machine learning models, they found that, while all models outperformed a random classifier, recurrent neural networks and gradient-boosting classifiers were especially well-suited for the prediction tasks. They also used comprehensive feature variables such as technical, blockchain-based, sentiment-/interest-based, and asset-based features. Their study revealed that the technical features were the most relevant for most methods, followed by selected blockchain-based and sentiment-/interest-based features. They also observed that predictability increased for longer prediction horizons [26].

Nti, Adekoya, and Weyori [14] proposed a homogeneous ensemble classifier based on the genetic algorithm for feature selection and optimization of SVM parameters to predict 10-day price movement in the Ghana Stock Exchange. They used the simple voting ensemble method to combine the results of 15 different support vector machine models using 14 technical analysis indices as inputs. Their empirical findings indicated that their ensemble model had higher accuracy in predicting stock price trends compared to the decision tree, random forests, and neural network. Ta et al. developed a portfolio using LSTM neural network and three portfolio optimization methods, i.e., equal weights method, Monte Carlo simulation, and MV model. They also used linear regression and SVM as a comparison in the stock selection process. The experimental results revealed that the LSTM neural network had a higher prediction accuracy than linear regression and SVM, and its constructed portfolios outperformed others. These models apply different methods for stock selection, then develop portfolio optimization models with selected stocks for business investment. These methods show a promising direction for developing portfolio models in practice. However, classical models of securities optimization are often unsuitable for practical short-term investments. Hence, it is essential to discover a more efficient approach to combine return prediction results with portfolio optimization models [18].

Nagula and Alexakis, too, proposed a hybrid model of classification and regression models for predicting bitcoin prices. To this aim, they used many technical indicators. They found that in terms of risk and profitability, the hybrid model's bitcoin futures strategy performed better than the deep cross-network regression and buy-and-hold benchmark strategies [28]. Kim developed a new adaptive trading system using machine learning and back-testing for the bond market. This system proposed a prediction model that predicted the spread between 10-year and 3-year treasury bonds. Subsequently, back-testing was employed to verify the performance of the prediction model, where AdaBoost performed better than other prediction models. In addition, when back-testing was applied based on the results of the

predicting models, up to 54.2% was achieved in return on investment over six months [22]. Faqihi Nezhad and Minaei presented a model for predicting the stock market using intelligent and machine learning models. They used a model based on the ensemble learning algorithm with basic neural network models to improve accuracy. It was concluded that, firstly, it was possible to predict the behavior of the stock market despite its fluctuating and unstable nature. Secondly, the proposed model could overcome market fluctuations more accurately than other methods [6]. Livieris et al. developed a combination of three of the most widely-employed ensemble learning strategies: ensemble-averaging, bagging, and stacking with advanced deep learning models for forecasting major cryptocurrency hourly prices. Their detailed experimental analysis indicates that ensemble learning and deep learning can efficiently benefit each other, developing strong, stable, and reliable forecasting models [19].
Chowdhury et al. predict the closing price of the cryptocurrency index 30 and nine constituents of cryptocurrencies using machine learning algorithms and models. They also compared their approach with similar state-of-the-art works in the literature, where machine-learning approaches are considered for predicting the prices of these currencies [20]. Manchanda and Aggarwal, arguing that the econometric models such as ARIMA and ARMA fail to capture the non-linearity of data putting forth the need to adopt other models for forecasting in cryptocurrency data, used ensemble learning technique of AdaBoost to boost the weak learners, namely MLP, ELM, SVR, and LSTM, all of which individually suffering from the problem of overfitting for Bitcoin, Ethereum, Litecoin, XRP, and Stellar. It was concluded that boosting gives significantly better performance accuracy than individual learning methods [21].

Table 1: Categorization of Articles reviewed

Raw	Category name	Reference No.	Abstract	Markets	Offer
1	Prediction based on the combination of machine learning models (using Ensemble learning)	[1],[6],[19],[25],[14],[16],[10],[5],[4],[15].	Machine learning models are combined using Ensemble learning. The results of these articles show the better performance of Ensemble learning than each of the machine learning models separately.	• Stock market • Cryptocurrency • Forex • Bond, etc.	Looking at price bottom and top predictions can increase Ensemble learning performance over price or return forecasting.
2	Comparison of machine learning models in price prediction	[17],[11],[9],[20],[21],[24],[26],[27],[28],[18],[22],[29].	In these articles, machine learning models have been compared in price prediction. The authors concluded which model performed better		Looking at price bottom and top predictions can increase Ensemble learning performance over price or return forecasting.

Ji et al. studied and compared various state-of-the-art deep learning methods, such as a deep neural

network (DNN), a long short-term memory (LSTM) model, a convolutional neural network, a deep residual network, and their combinations for Bitcoin price prediction. Experimental results showed that although LSTM-based prediction models slightly outperformed the other prediction models for Bitcoin price prediction (regression), DNN-based models performed the best for price ups and downs prediction (classification) [22]. Borges and Neves proposed a machine-learning-based system to develop an investment strategy capable of trading on the cryptocurrency exchange markets. They used Logistic Regression, RF, Support Vector Classifier, and Gradient Tree Boosting models to predict with the help of technical indicators as feature variables. They indicated that regardless of the resampling method used, all learning algorithms performed better than the Buy and Hold (B&H) strategy in the overwhelming majority of the 100 markets tested [27]. To summarize, according to Kervancı and Akay's review article, many studies have sought to compare statistical models and machine learning. Machine learning models have generally shown better performance than statistical models [23]. Now, considering the activists' interest in cryptocurrency price prediction (especially Bitcoin), many other studies have compared the performance of machine learning models or their combination in forecasting accuracy (according to Table 1). In articles that have used ensemble learning, this approach has enhanced the performance and accuracy of price prediction. It should be noted that the above articles have examined different financial markets, such as the stock market, bonds, stock market indices, cryptocurrencies, and commodities, which leads to strengthening the conclusion of the superiority of ensemble learning.
However, the research gap addressed in this research is the price data modeling approach. Many studies seek to predict the price value or the return value due to reasons like stationary, while this approach can reduce the prediction accuracy. Although the price is a time series data, it can be viewed discretely. That is, instead of predicting the price or return, one should try to predict the state of the top or bottom. If knowing that we are on the way to building a price top or bottom increases the accuracy and efficiency of prediction models, more reliable algorithmic trading can be designed and implemented accordingly. Therefore, this study seeks to predict the state of the price top or bottom on machine learning models. In the following, the research method and the way to predict the condition of the top and bottom used in this research are explained.

3 Research Methodology

Since the present study intends to predict the top and bottom prices of Bitcoin using machine learning models, the following research questions are formulated:

1. What are., the accuracy and precision of ensemble machine learning in predicting the top and bottom prices of Bitcoin?
2. Are the accuracy and precision of predicting top and bottom prices of Bitcoin using ensemble machine learning higher than weak algorithms?

Since the target financial market of this study is the cryptocurrency market (Bitcoin), using a reliable database is of great importance. In this study, the candle price data (OHLCV) of Bitcoin as the most prominent cryptocurrency representing this market in the 1-hour time frame was selected. The Historic-Crypto Python module was utilized to extract this data, which extracts data from the CoinBase Pro exchange API. The cryptocurrency market has a 4-year cyclical behavior due to halving the mining reward. Hence, the 2018- 2022 period is selected from the entire Bitcoin data available since 2010. In 2018, Bitcoin experienced a stagnant and then declining market. In 2019-2021, it experienced an upward trend due to the Covid-19 pandemic and the halving of the reward in 2020. In 2022, there is also

a recession and downward trend that can be said to be a return to 2018, which shows that our sample is representative of all cyclical phases. The first 70% of the data were given to the model as training data. 20% of the data were considered validation data, and the last 10% were fed to the model as test data.
The present study is conducted using Python programming language and its valid modules. It is undertaken in the Google Colab platform, considering GPU sharing. Numpy, Pandas, Ta, Tensorflow, Sklearn, and Scipy libraries are specifically used for implementation.
The research variables are divided into two main categories; the target and feature variables. The target variable is the variable that is sought to be predicted. Our target variable in this study is the top or bottom variable (1 or 0), adopted from the closing price of candles using the Awesome Oscillator (AO) indicator. Other variables are technical analysis indicators as feature variables for predicting price tops or bottoms. To select these variables from the available libraries, the correlation of over 150 indicators and oscillators with our target variable was examined, and (numerical) indicators with a Pearson correlation above 70 and a p_value of 0.05 were selected as feature variables. The list of these indicators is presented below. The learning data seek to discover the relationship between the list of indicators and the target variable, i.e., tops and bottoms, using RF, RNN, and LSTM models. The values related to the indicator and oscillator are normalized by dividing by the closing price value to be on the same scale. As mentioned, 70% of the data is considered learning data, and the remaining 30% is used to implement the next stages. The list of indicators and oscillators used in this study is as follows:

Table 2: The list of feature variables used in the first stage

Name in the model	Name of the variable	Name in the model	Name of the variable
volume_mfi	Volume (Money flow index)	'volume_sma_em'	Average volume
'volatility_bbp'	BBP fluctuation	'volatility_kcp'	KCP fluctuation
'volatility_dcp	DCP fluctuation	'trend_macd'	MACD trend
'trend_macd_diff'	MACD trend difference	'trend_adx_pos'	ADX trend
'trend_vortex_ind_pos'	VORTEX trend	'trend_vortex_ind_diff'	VOREXT trend difference
'trend_cci'	CCI trend	'trend_aroon_up'	AROON trend
'trend_stc'	STC trend	'momentum_rsi'	RSI momentum
'momentum_ tsi'	TSI momentum	'momentum_uo'	UO momentum
'momentum_ stoch'	STOCHASTIC momentum	'momentum_stoch_signal'	STOCH SIGNAL momentum
'momentum_wr'	WR momentum	'momentum_ao'	AO momentum
'momentum_roc'	ROC momentum	'ao'	AO
'RSI'	Relative strength index	'aboveEMA10'	Above moving average, 10
'aboveEMA15'	Above moving average, 15	'aboveEMA20'	Above moving average, 20
'aboveEMA30'	Above moving average, 30	'aboveEMA40'	Above moving average, 40
'aboveEMA50'	Above moving average, 50	'aboveEMA60'	Above moving average, 60

The above list introduces technical analysis indices concerning the volume of transactions, price volatility, trends, price momentum, and binary indicators. These indicators have significant relationships with the target variable (top or bottom price). It should be mentioned that binary indicators are added from the feature engineering section of the study to this list as they play a significant role in improving the models' accuracy.

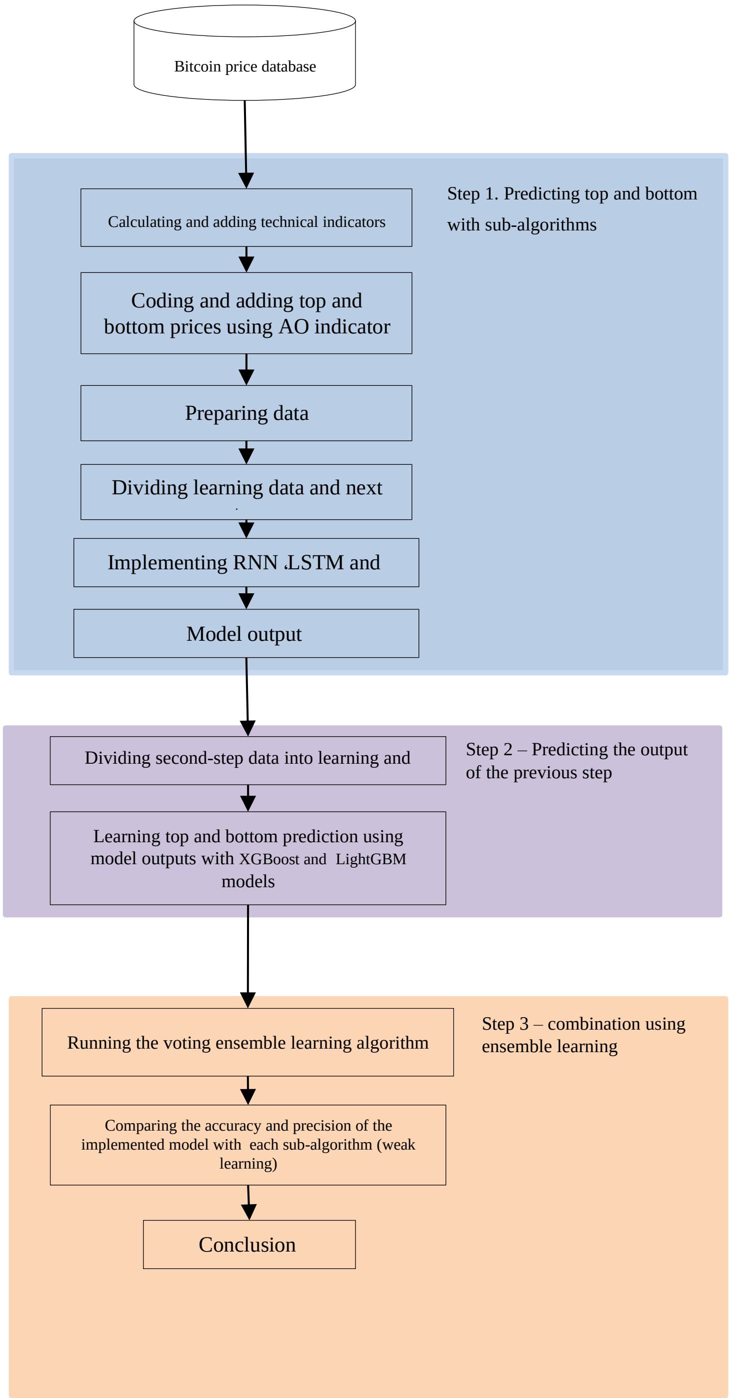


Fig. 1: Research stages

To better explain binary indicators, consider the indicator “aboveEMA(10),” a binary, 0 and 1, indicator. If the price is above the moving average (10), it will be 1; if it is below it, it is assigned 0. The steps for implementing the model are as follows:

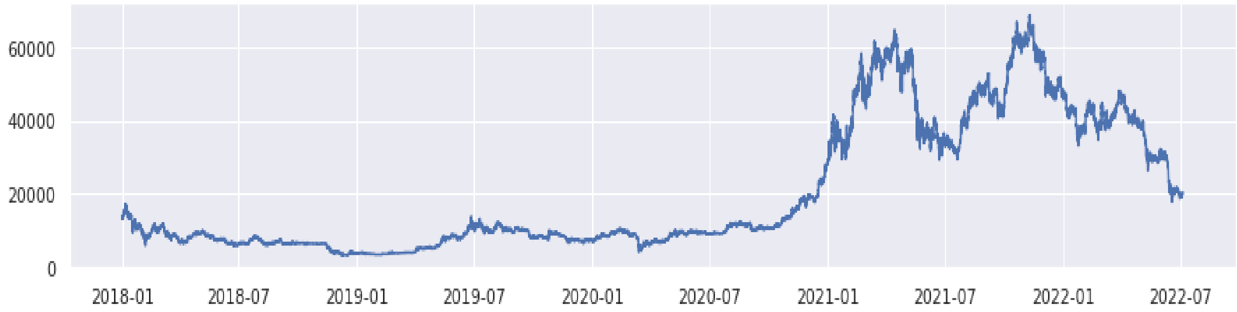
Step 1 - Bitcoin top and bottom data are predicted as the target variable using RF, LSTM, and RNN models with the feature variables of Table 2. The outputs of this step are the top and bottom predictions of each model, along with their scores.

Step 2- The outputs of the first step (predictions of tops and bottoms and their scores) as feature variables and tops and bottoms as target variables are provided to XGBoost and LightGBM models for learning.
Step 3- The outputs of the second step are predicted using the ensemble voting learning algorithm so that the final prediction results are obtained and compared with the real data.

4 Implementing the models

4.1 A review of the data

As mentioned in the previous section, the cryptocurrency market has a 4-year cyclical behavior due to halving the mining reward. Hence, the 2018- 2022 period was selected from the entire Bitcoin data available since 2010. In 2018, Bitcoin experienced a stagnant and then declining market. In 2019-2021, it experienced an upward trend due to the Covid-19 pandemic and the halving of the reward in 2020. In 2022, there is also a recession and downward trend that can be said to be a return to 2018, which shows that our sample is representative of all cyclical phases. Thus the Bitcoin price data in the period from 2018 to 2022 was used in the 1-hour time frame for all steps after the cleaning process. Graph 1 shows the price of Bitcoin linearly from 2018 to the end of the first half of 2022 as follows:



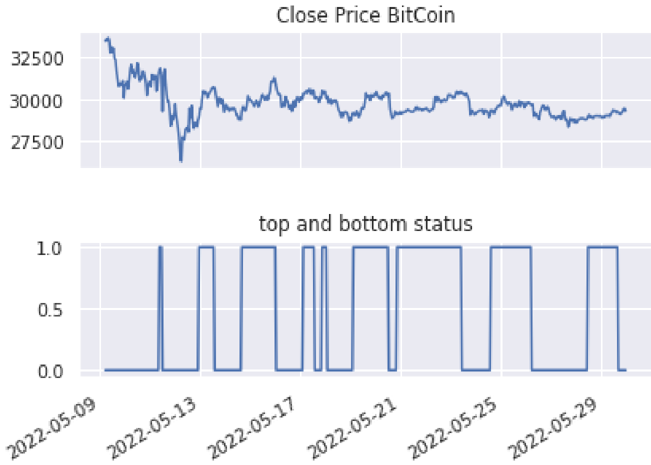
Graph 1: Line graph of Bitcoin price in dollars

The descriptive statistics of Bitcoin price data in the mentioned time interval are as follows:

Table 3: Descriptive statistics of the closing price of 1-hour Bitcoin candles from 2018 to the end of the first half of 2022

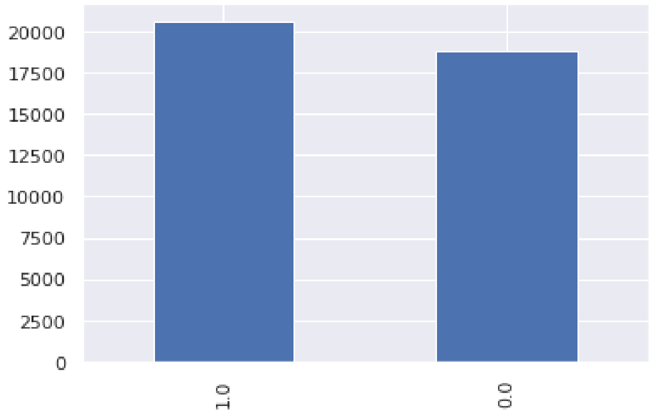
row	Indicator name	Indicator value
1	Price data number	39484
2	The largest data	68639
3	The smallest data	3139
4	Median	10142
5	Mean	20384
6	Mode	6399
7	SD	17876
8	Skewness	0.97
9	Kurtosis	-0.56

In Graph 2, for the last 500 data of the Bitcoin graph, the bottom and top prices are specified, which are provided as the target data (label) for the machine learning models:



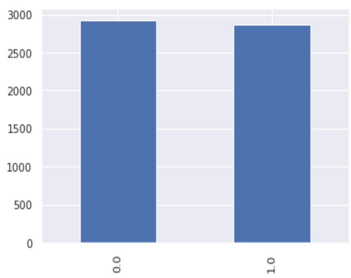
Graph 2: Bitcoin prices, together with the bottom and top status for the last 500 data

The number of data is 39484. Of all these data, 20663 (52%) show the top, and 18,821 (47%) show the bottom status, which refers to the relative balance between the number of top and bottom data.

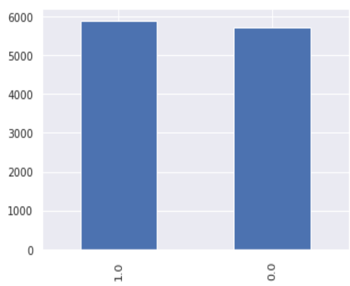


Graph 3: The number of the top (1) and bottom (0) situations in Bitcoin price data for all stages

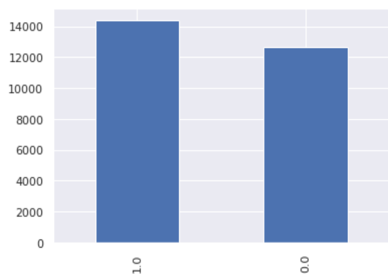
The balance of top and bottom data for all stages should be checked independently. In graphs 4 to 6, the number of tops (1) and bottoms (0) are specified according to research stages. This number shows the balance in the target variable in all stages.



Graph 6: The number of tops and bottoms in step 3
Total number of data: 5791
Top data percentage: 50.52%
Bottom data percentage: 49.47%



Graph 5: The number of tops and bottoms in step 2
Total number of data: 11583
Top data percentage: 50.8%
Bottom data percentage: 49.19%



Graph 4: The number of tops and bottoms in step 1
Total number of data: 27028
Top data percentage: 53%
Bottom data percentage: 46%

4.2 The structure and parameters of models' inputs

Step 1 models with input structure and parameters

Table 4: The structure of RNN and LSTM models in the first step

ROW	Model	Layer information	Number of units	Input zeroing ratio	Activity function
1	RNN	The first layer (input layer)	64	-	hyperbolic tangent (tanh)
		The second layer	64	-	hyperbolic tangent (tanh)
		Output layer	2 (binary)	-	sigmoid
2	LSTM	The first layer	64	-	hyperbolic tangent (tanh)
		Dropout	-	0.2	-
		The second layer	64	-	hyperbolic tangent (tanh)
		Dropout	-	0.2	-
		The third layer (output)	2	-	softmax

It should be noted that the input parameters are obtained using a window search.

Table 5: The learning and stop learning indices of the RNN and LSTM models in the first step

Model name	Learning indices			Stop learning indices		
	metrics	loss	optimizer	verbose	patience	Monitor
RNN	['accuracy']	binary_ cross-entropy	adam	1	3	'loss'
LSTM	['accuracy']	sparse_ categorical_ cross-entropy	adam	1	3	'loss'

Table 6: The structure of the RF model in the first step

	Model name	Criterion	Number of trees	Maximum depth	Number of simultaneous tasks	Minimum number of samples required to be at a leaf node
1	Random Forest	Gini	20	20	using all processors	2

Table 7: The structure of the XGBoost and LightGBM models

	Model name	Number of enhanced trees	Learning rate	Maximum depth of trees	Subsample proportion	The minimum total sample weight required in one child (leaf)	The proportion of subsample to test sample	Gamma
1	XGBOOST	21	0.3	5	0.25	4	0.21	0.22
2	LightGBM	15	0.19	1	0.4	3	0.58	

The remaining parameters are considered default values. The above values are obtained based on tune hyperparameters. For example, the learning rate passed values between 0.01 and 0.5 with 0.01 steps to reach the optimal number of 0.19 for LightGBM and 0.3 for XGBoost. The rest of the parameters are also tuned. In this section, the output of each model is presented and analyzed independently with the indicators of accuracy, precision, recall, and F1. By accuracy, it is meant the result of dividing the correctly-predicted cases into all cases. The precision index is the result of dividing the positive cases recognized as true by the positive cases recognized as true or false. Finally, the recall index is the positive cases recognized as true divided by the sum of the positive data recognized as true and the negative cases recognized as false. The F1 score, which is calculated as follows, is an average of precision and recall indices:

Table 8: Confusion matrix

		Prediction by algorithm	
Real label		Yes	No
	Yes	True Positive (TP)	False Negative (FN)
	No	False Positive (FP)	True Negative (TN)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$f1\ score = \frac{2 \times (precision \times Recall)}{precision + Recall} \quad (4)$$

5 Models' outputs

The outputs of LSTM, RNN, RF, and ensemble learning models in the third test interval (step) are presented in the following tables. The time period of all the outputs is similar so that the performance of the models can be compared with each other. Thus, according to the ensemble learning model's final output (test data), the outputs of the RNN, FR, and LSTM models are arranged to compare the results. The RNN model with the input parameters specified in Tables 3 and 4, the target variable of the status of the top and bottom prices, and the introduced feature variables yields the following results:

Table 9: Evaluation indices of the RNN model

RNN model – accuracy 79%				
Target	**Support**	**F1**	**Recall**	**Precision**
0	1012	0.79	0.76	0.83
1	919	0.79	0.82	0.76
Accuracy	1931	0.79	–	–
Macro average	1931	0.79	0.79	0.79
Average weight	1931	0.79	0.79	0.79

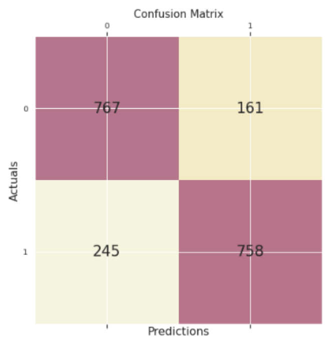


Fig. 2: RNN confusion matrix on test data

As shown in Table 9, the accuracy of the RNN model in predicting the top and bottom is 79%. The precision of the model is 83% in recognizing bottoms and 76% for tops, which refers to the better performance of this model in detecting bottoms compared to tops. Of course, the declining market of cryptocurrencies during the testing period may be another justification for this difference. The recall index for bottom conditions is 76%, and for top states is 82%. The model's F1 index, which is a moderate index, is 79%. In general, it can be said that 79% of the top and bottom prices are predicted correctly. In Fig. 2, the confusion matrix of this model is shown for the test data. The next model is LSTM, whose evaluation indices are presented in Table 10. This model is also implemented based on the structure and hyperparameters specified in Tables 3 and 4.

Table 10: Evaluation indices of the LTSM model

LSTM model – accuracy 80%				
Target	**Support**	**F1**	**Recall**	**Precision**
0	1012	0.81	0.77	0.84
1	919	0.80	0.84	0.77
Accuracy	1931	0.80	–	–
Macro average	1931	0.80	0.81	0.81
Average weight	1931	0.80	0.80	0.81

As shown in Table 10, the accuracy of the LSTM model is 80% and one percent higher than the RNN model. The precision of the model in predicting the condition of the bottoms is 84%, and 77% in predicting the situation of the tops. Similar to RNN, this model performs better in recognizing bottoms than tops. The recall index for the bottoms is 77% and for the tops is 84%. The F1 index also shows 81% precision for this model. Figure 3 presents the confusion matrix for this model on the test data.

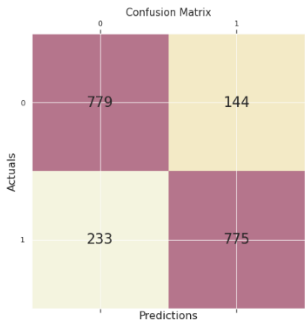


Fig. 3: LSTM confusion matrix on test data

The RF model is the third model implemented based on the model structure and parameters of Table 6 on the data. Table 11 presents the evaluation indices of the RF model.

Table 11: Evaluation indices of the RF model

RF model – accuracy 80.83%				
Target	**Support**	**F1**	**Recall**	**Precision**
0	1012	0.81	0.80	0.83
1	919	0.80	0.82	0.79
Accuracy	1931	0.81	–	–
Macro average	1931	0.81	0.81	0.81
Average weight	1931	0.81	0.81	0.81

As shown in Table 11, the accuracy of the RF model is 80.83%. This model is more accurate than

LSTM and RNN models. The precision of the model in predicting the condition of the bottoms is 83%, and that of the tops is 79%. The recall index for the bottom is 80% and for the top is 82%. The F1 index for the bottom and top is 81 and 80%, respectively. Figure 4 shows the confusion matrix for RF.

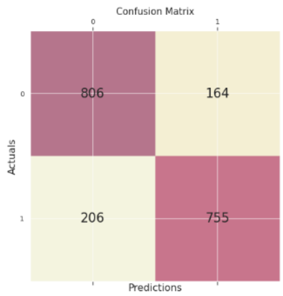


Fig. 4: RF confusion matrix on test data

The ensemble learning model is run on XGBoost and LightGBM models, and the results of the evaluation indices of this structure are presented in Table 12.

Table 12: Evaluation indices of the ensemble learning model

Ensemble learning model on the outputs of the XGBoost and LightGBM models– accuracy 81.30%le				
Target	**Support**	**F1**	**Recall**	**Precision**
0	1012	0.82	0.79	0.85
1	919	0.81	0.84	0.78
Accuracy	1931	0.81	–	–
Macro average	1931	0.81	0.81	0.81
Average weight	1931	0.81	0.81	0.82

As indicated in Table 12, the model's accuracy is 81.30%, which is relatively higher than all models (RF, LSTM, RNN). The precision of the model in predicting bottoms is 85%, and 78% in the prediction of tops. The recall index is 79% for bottoms and 84% for tops. The F1 index is 82% for the bottoms and 81% for the condition of the tops. These values show the superiority of the model developed in this study. The confusion matrix for the ensemble learning model is provided in Figure 5.

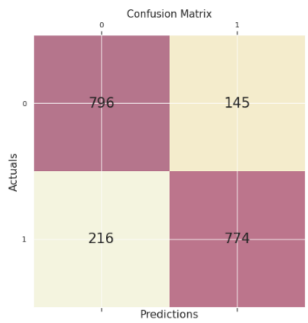
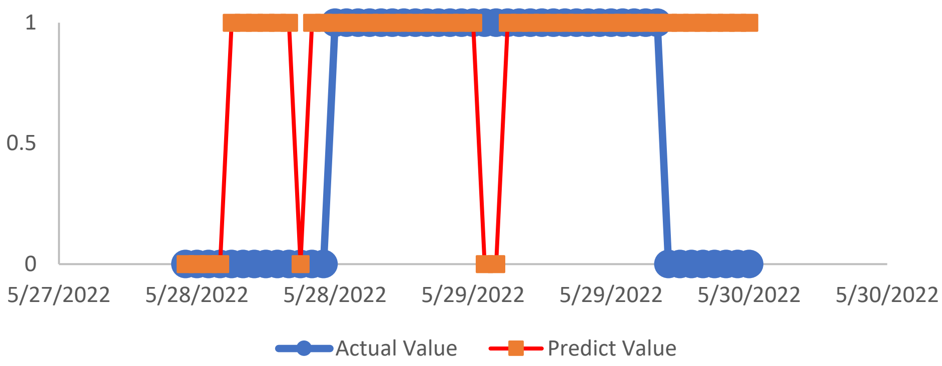


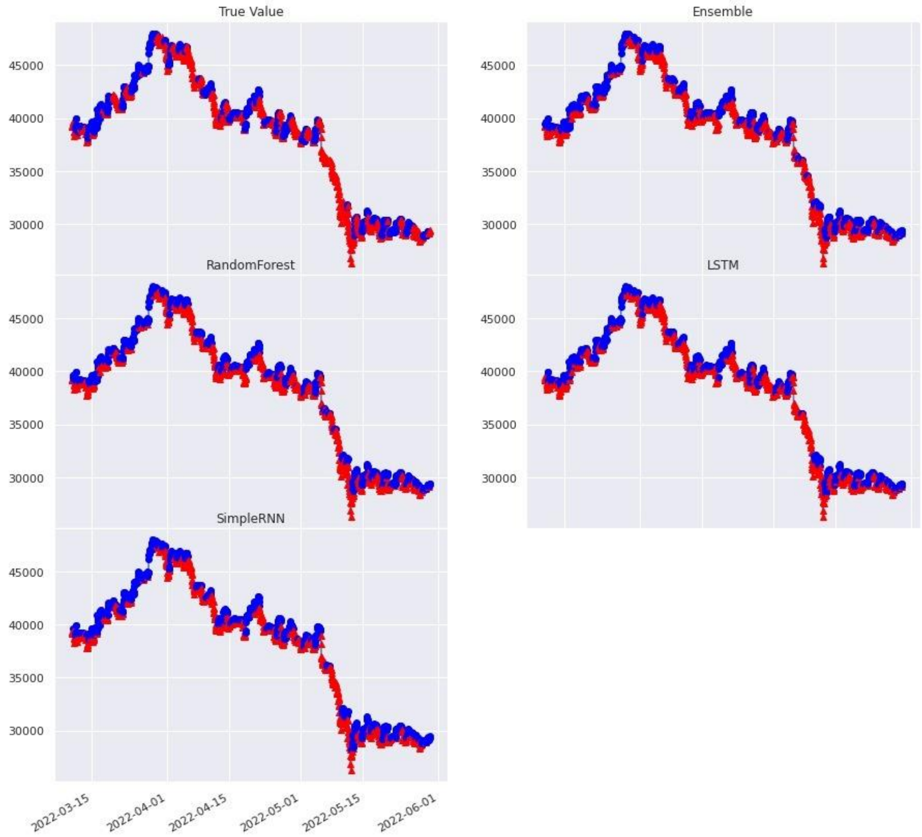
Fig. 5: The ensemble confusion matrix on test data

In graph 7, the actual values of the top and bottom prices of Bitcoin for the last 100 data are presented along with the predicted values of the ensemble learning model. The red line shows the predicted values, and the blue line represents the actual values. It is evident that many states (top or bottom) are correctly predicted.



Graph 7: The actual top and bottom values compared to the values predicted by the ensemble learning model for the last 100 data

Graph 8 visually compares the prediction power of each algorithm can against the real top and bottom conditions.



Graph 8: Comparison of the prediction performance of the ensemble learning models, RF, LSTM, and RNN, in predicting the real top and bottom prices

In Graph 8, the graph True Value presents the Bitcoin price by marking the actual top and bottom. The state of the top is marked with blue, and that of the bottom is marked with red. Prediction models try to predict these situations (tops and bottoms). All models, i.e., Ensemble, RF, LSTM, and SimpleRNN, are indicated in graph 8 with the predicted states (blue top and red bottom). This graph shows the proper performance of all models in predicting the top and bottom prices. Table 13 presents the evaluation indices of all models together.

Table 13: Comparison of evaluation indices of models collectively

	Model	Top/bottom	Accuracy	Precision	Recall	F1-Score
1	RNN	0	79%	0.83	0.76	0.79
		1		0.76	0.82	0.79
2	LSTM	0	80%	0.84	0.77	0.81
		1		0.77	0.84	0.80
3	RF	0	80.83%	0.83	0.80	0.81
		1		0.79	0.82	0.80
4	Ensemble	0	81.30%	0.85	0.79	0.82
		1		0.78	0.84	0.81

Table 13 shows the enhancement of models in the model presented in this study. The ensemble model is able to provide better performance than all other models, with an F1 index of 82% for the bottom condition and 81% for the top condition. Therefore, it can be argued that the Ensemble model of this study outperforms (accuracy, precision, recall, and F1) RF, RNN, and LSTM models in predicting the condition of the top and bottom prices of Bitcoin.

6 Conclusion and discussion

In the previous section, the output and evaluation indicators were presented and reviewed independently. This section seeks to answer the research questions clearly. Considering the strengths of each machine learning model in prediction, which can also be improved, it can be argued that if a model aggregates the outputs of the models and makes decisions as an ensemble model, it can have a better prediction performance. In this study, the results of RNN, LSTM, and RF models were provided as input to an ensemble learning module. Using XGBoost and LightGBM machine learning models, the ensemble learning module combines the mentioned models' outputs with the voting ensemble learning algorithm. The hypothesis of the present study is to strengthen the prediction accuracy of the presented model compared to each sub-algorithm (weak algorithms). This hypothesis was substantiated based on the outputs presented in the model implementation section. According to Table 13, the ensemble learning module performs better than any of the sub-algorithms in the same period based on accuracy, precision, recall, and F1 indices. Therefore, the research questions can be answered as follows:

1. The accuracy and precision of the ensemble learning model in predicting the condition of the top and bottom prices of Bitcoin are 81.30% and 82%, respectively.
2. The accuracy and precision of the ensemble learning model are higher than all the sub-algorithms based on the indices of accuracy, precision, recall, and F1 (Table 13).

In the current study, the prediction accuracy increased to 81.31% by this model, while in other studies, the accuracy of this model was 56% (Bashiri & Paryab, [2]) and 69% (Moshari et al., [12]). Furthermore, the results of this study are consistent with the findings of Basak et al.' [3] study. In their study, the RF model was also compared with XGBoost, ANN, SVM, and logistic regression models, showing that the RF model is more accurate. The findings of this study are also in line with the results of the studies showing that ensemble learning performs better in predicting prices in financial markets. Yang et al. [16], Li and Pan [10], Sun et al. [17], Aggarwal et al. [5], and Faghi Nezhad and Minaei [6] proved the better performance of ensemble learning compared to weal algorithms which are consistent with the results of the current study. However, the distinguishing feature of this study is taking the top and bottom prices into account for prediction and the developed model. The following can be presented as suggestions for further research:

- Providing a trading strategy based on the prediction of the ensemble learning model, that is, the prediction of this model is used and back-tested with the profit and loss limit of a trading strategy.
- Using the data of multiple assets simultaneously and integration, that is, instead of the model being trained and predicted only on Bitcoin data, it can simultaneously learn multiple assets in the same market (Ethereum, Litecoin, etc.) or even several markets (gold, currency, US stock index, etc.) and then predict them.
- Using other indicators to detect the top and bottom, such as ZigZag, and comparing them with the result of the current model that used the AO indicator.
- Adding fundamental and sentimental market variables as feature variables to increase prediction accuracy can be greatly helpful. Also, comparing the models and the impact of adding these data can contribute to other research results.
- Using model outputs to distribute capital among sub-algorithms. In other words, in this study, the ensemble learning model predicts the state of the next top or bottom based on the outputs of the sub-algorithms. However, it can assign weight to each one so that all models work but have different capitals.

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