Chapter 6
An Ensemble Machine Learning-Based Approach Toward Accuracy in Bitcoin Price Prediction

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1 Introduction

Bitcoin, introduced in 2009 by the enigmatic Nakamoto [1], has transformed into a revolutionary digital currency, disrupting old financial principles and challenging mainstream economic assumptions. Its decentralized nature, made possible by blockchain technology, distinguishes it from government-issued fiat currencies, providing users with a greater degree of control and independence over their financial transactions.

Bitcoin's scarce supply of 21 million coins, together with its use of a decentralized blockchain system, has endowed it with characteristics similar to digital gold, making it an interesting investment option and inflation buffer in an increasingly uncertain economic environment.

Despite the inherent hurdles given by Bitcoin's price volatility, researchers have attempted to construct prediction models and analytical frameworks for forecasting future price changes [2]. To understand the complex dynamics of the Bitcoin market, a range of methodologies have been explored, including technical analysis tools such as charts and graphs and advanced machine learning algorithms.

In this paper, we seek to give a complete examination of Bitcoin price movements using a range of methodologies, from machine learning approaches to an ensemble of their varieties. Furthermore, we propose using an ensemble technique, which leverages the capabilities of many predictive models [3–5] to enhance the precision and strength of Bitcoin price prediction [6, 7].

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We hope to contribute to the ongoing discussion about Bitcoin price prediction by reviewing existing research, examining various methodological approaches, and doing empirical analysis of historical price data. By shedding light on the underlying variables driving Bitcoin's price movements and analyzing the efficacy of different prediction models, we hope to give vital insights for investors, traders, and researchers navigating the complicated and fast-changing world of cryptocurrencies.

The structure of the paper is designed as follows: Sect. 2 provides a comprehensive literature survey on Bitcoin price prediction. Section 3 introduces our methodology, detailing the various approaches and techniques utilized in our analysis. In Sect. 4, we delve into the ensemble models employed, discussing their strengths and limitations. Finally, Sect. 5 presents the results of our analysis and discusses their implications for Bitcoin price prediction.

2 Literature Survey

Cryptocurrencies have gathered massive popularity as financial resources, inciting broad investigation into predicting their costs [8, 9]. This survey compiles discoveries from numerous papers, investigating different strategies, approaches, explorations, and forecasts of various digital currencies, including Bitcoin.

The volatility of Bitcoin's price has drawn the attention of investors, traders, and academics alike, demanding extensive research and analysis [10, 11]. A number of variables influence Bitcoin's price, notably macroeconomic conditions, trends, innovations in technology, changes in regulations, and market sentiment. These variables contribute to a turbulent and dynamic market environment.

The study by Sittivangkul et al. 2022 [12] uses clustering procedures to distinguish people having interests in investing in this sector from the other. The outcome showed increased interest among individuals to invest in the cryptocurrency market. Nonetheless, it also has limitations, including dependence on a small amount of data and user-generated content, which confines the model's scope.

The target of the work by Bangroo et al. 2022 [13] was to predict digital currency's cost, utilizing machine learning calculations like Random Forest, Direct Relapse, and so forth [14, 15]. The Random Forest regressor stands apart for its strength with enormous datasets and great accuracy. Limitations include the absence of interpretability for the prediction.

Concerning the research by Parab and Nitnaware, 2022 [16], aimed to forecast cryptocurrency prices utilizing long short-term memory (LSTM) and Autoregressive Integrated Moving Average (ARIMA) [17, 18]; these models exhibit strengths in handling time series data and capturing complex patterns. However, their computational intensity and reliance on large training datasets pose limitations.

The work by Sihananto et al. 2022 [19] explores the use of reinforcement learning for automated cryptocurrency trading [20]. The adaptability and ability to learn from experience stand out, but challenges like limited interpretability and handling high volatility exist.

Qing et al. 2022 [21] integrate deep learning with autoencoder algorithms for effective dimensionality reduction [22]. However, the challenge lies in finding algorithms that preserve fluctuating features while improving signal-to-noise ratio.

The study by Lyu 2022 [23] focuses on short-term trading and compares 10 algorithms for time series forecasting, with Gradient Boosting showing promising results. Limitations include the need for larger datasets and attributes to enhance model performance.

The effort by Encean and Zinca, 2022[24], toward Cryptocurrency Price Prediction uses a Gated Recurrent Unit (GRU) and long short-term memory (LSTM) networks that exhibit effectiveness in predicting cryptocurrency evolution [25, 26]. Yet, the study's reliance solely on historical price and social media sentiment data limits its predictive scope. Long short-term memory (LSTM) networks achieve higher prediction accuracy by considering external factors influencing cryptocurrency fluctuations. However, the model's efficiency is limited due to using data from a specific time frame.

3 Methodology

After careful and rigorous research, we determined that random forest and gradient boosting are ideal choices for forecasting Bitcoin prices in the volatile cryptocurrency market due to their excellent ability to handle large datasets and their predictive accuracy. Therefore, we began developing separate prediction algorithms. The dataset we utilized consisted of 7 columns and 1449 rows. It encompassed data from January 11, 2019, to January 11, 2023, with each row representing the highest value, lowest value, open price, close price, volume, date, and adjacent close price for the respective day. The input features for training included date, open, high, low, adjacent close, and volume along with the newly engineered features are discussed later in the paper.

3.1 Overview of Random Forest and Gradient Boosting Regressor

Random Forest and Gradient Boosting are strong ensemble learning strategies broadly utilized in machine learning to improve predictive performance. Random Forest is a collection of various decision trees that are developed during training, and predictions are made by averaging or voting over the individual tree forecasts. Every tree is based on an arbitrary subset of the preparation data and utilizes an arbitrary subset of elements at each split. This randomness decreases overfitting and floods the model's strength. Random Forest is known for its adaptability, dealing with both classification and regression tasks effectively.

Then again, Gradient Boosting is a boosting method that forms trees consecutively, with each tree rectifying the blunders of the past one. In this technique, the model is prepared stage by stage, and each new tree centers around limiting the blunders of the consolidated ensemble. Gradient Boosting is especially successful in taking care of perplexing connections within the data and succeeds in predictive tasks where high accuracy is essential. Common implementations include “Adaptive Boosting (AdaBoost)”, as well as the more refined Extreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM).

While both Random Forest and Gradient Boosting aim to improve the predictive accuracy through ensembling, they vary in their methodologies. Random Forest forms autonomous trees equally, while Gradient Boosting assembles trees in a steady progression to address mistakes. The decision between them frequently depends on the distinct attributes of the dataset and the suitable balance between interpretability and predictive power.

3.2 Pre-Processing and Feature Engineering

Pre-processing followed by feature engineering was performed on the dataset of Bitcoin prices. The pre-processing steps included removing outliers, checking data types, and normalizing the data using the MinMaxScaler function. Removing outliers is important because they can skew the analysis and lead to inaccurate predictions.

After removing the outliers, the subsequent step included checking the data types of the columns. This step is significant because machine learning models require data, and a few sections might be changed from categorical to numeric. For this paper, all segments were numerical except for the date section, which was switched over completely to a datetime format. The following stage included normalizing the information utilizing the MinMaxScaler function.

Daily Price Range, change, and range change ratio are the new features designed. These feature engineering steps provide additional insights into the price dynamics and relationships between different price attributes, which can be valuable for further analysis and modeling.

3.3 Graphical Interpretation

To understand the relationship between Bitcoin price and the engineered features, various visualizations were used. These visualizations included line plots showing the daily price range, change, and range change ratio over time. They are useful for understanding historical price movements and identifying patterns such as trends, seasonality, and volatility. Figure 1 shows the volatile surges that make the market very unstable.

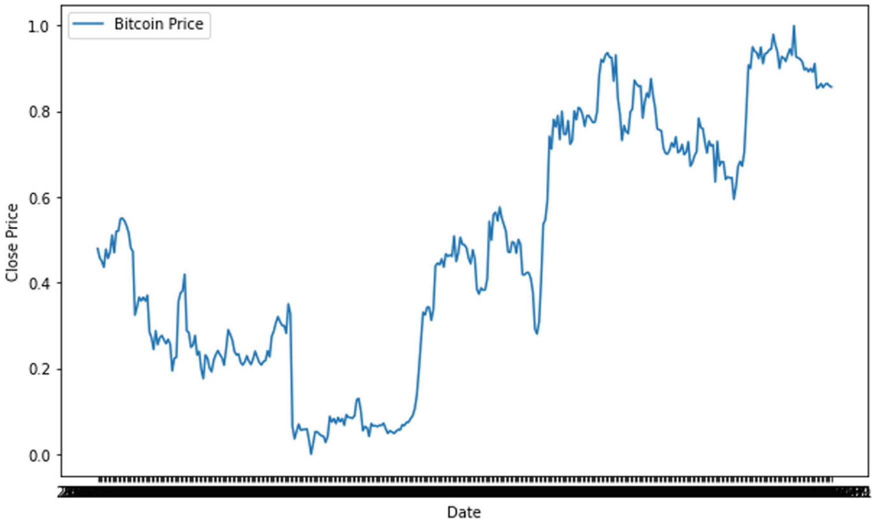


Fig. 1 Bitcoin close price trend

Candlestick charts are frequently employed in the financial market for technical analysis. It offers a graphic depiction of price changes over a certain time frame. As Fig. 2 illustrates, these charts help spot pricing patterns and trends as well as forecast future price changes. This was primarily used to assess the varied surges and depreciations that occurred during the year.

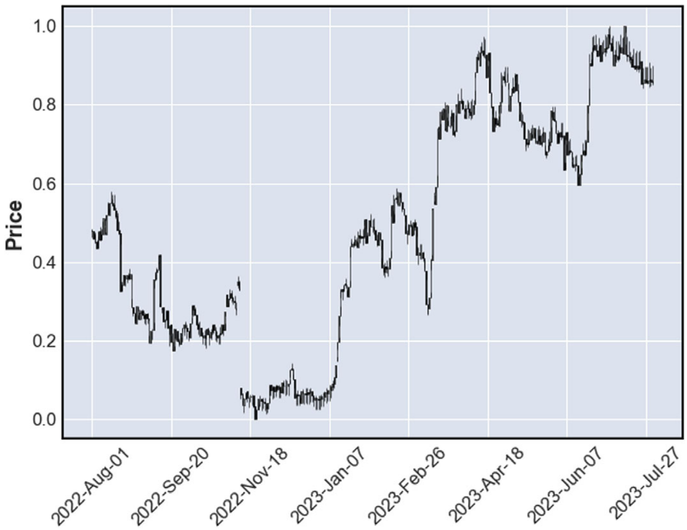


Fig. 2 Bitcoin candlestick chart

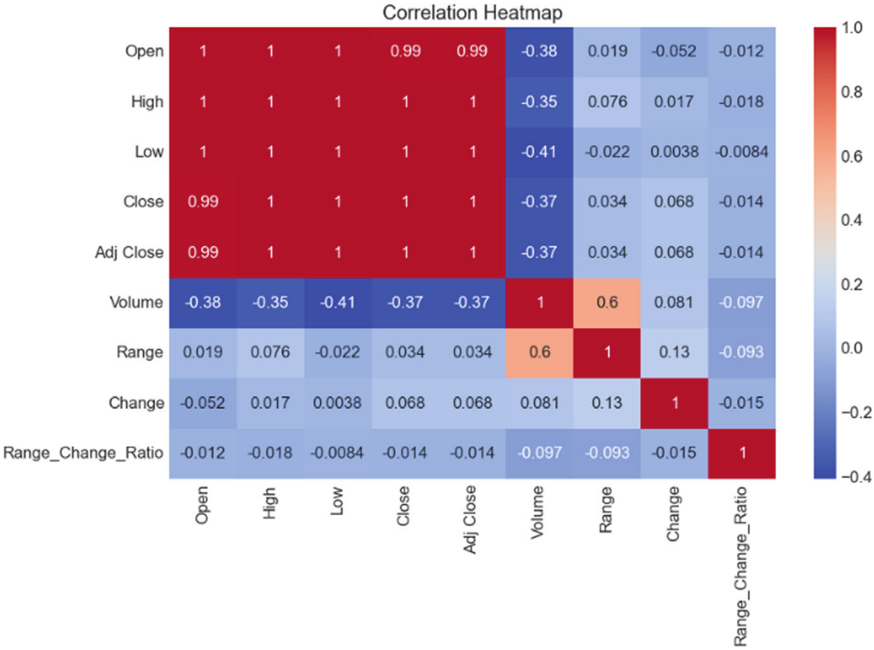


Fig. 3 Correlation heatmap

The correlation heatmap as shown in Fig. 3 was created to analyze the relationships between Bitcoin price and the engineered features. The heatmap visualizes the correlation between different attributes in the dataset. This can be very significant for feature selection in modeling and evaluating the impact of different attributes on the target variable. Open, high, low, and close were the attributes with the highest correlation among themselves.

The relationship between the price and trading volume of Bitcoin is visualized in Fig. 4 by plotting the price and volume trend of Bitcoin. It helps figure out possible trends and patterns as well as comprehend how price changes and trade activity are related.

Figure 5's box plot illustrates how the price of Bitcoin varies by the day in a week. It helps comprehend how prices fluctuate on different days and spot any trends or unusual price movements on a particular day of the week. The 50-day moving average price of Bitcoin superimposed upon the actual price is visualized in Fig. 6. It highlights and helps to smooth out short-term pricing data swings and identify long-term trends.

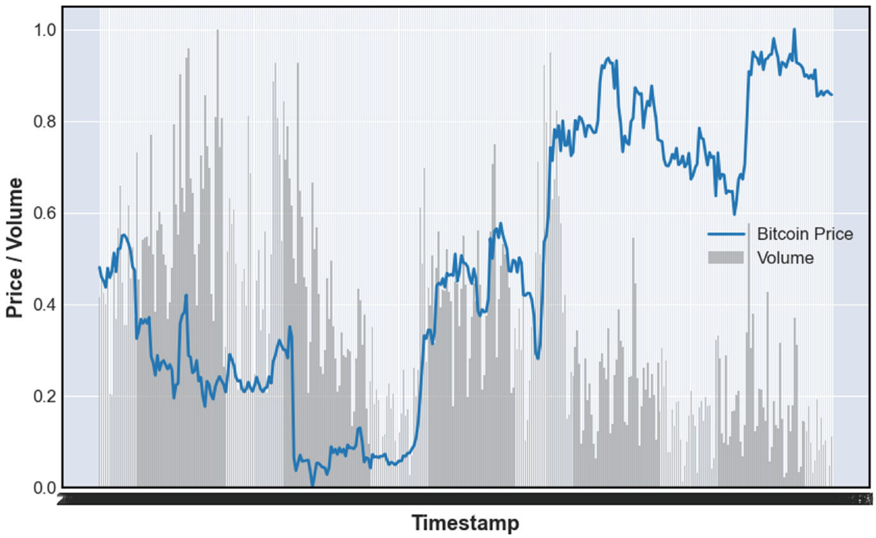


Fig. 4 Bitcoin price value trend

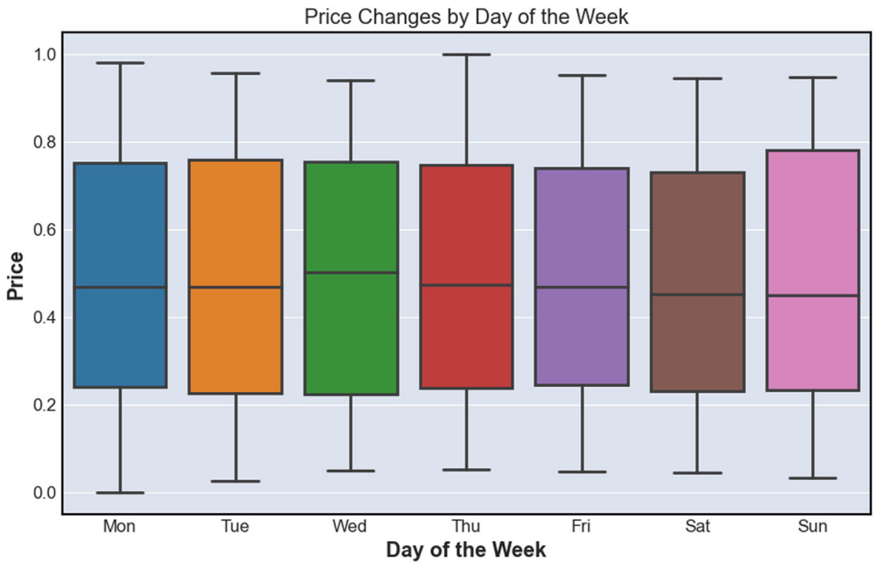


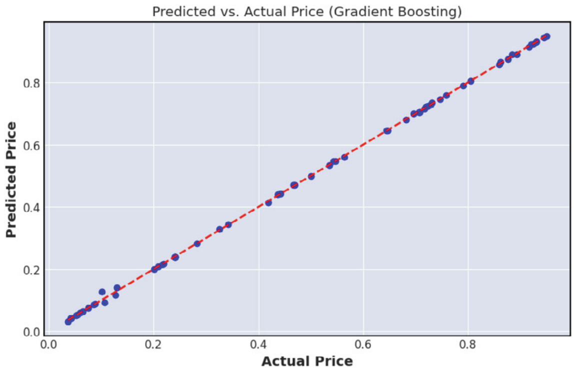
Fig. 5 Boxplot of price change by day of the week

Fig. 6 50-day moving average

3.4 *Implementation of the Models*

Using Random Forest for Bitcoin price prediction. Random Forest combines several decision trees to provide predictions of Bitcoin price. The Random Forest algorithm was used in the current work for regression analysis to predict the next day's "Close" price of Bitcoin as seen in Fig. 7. Upon deploying the model, it was found that the mean squared error obtained was approximately 6.38. This metric measures the average of the squares of the errors or deviations, which provides a measure of the quality of the model's predictions. In general, the Random Forest Regressor showed solid predictive performance, as shown by the low mean squared error and low R-squared score of 0.87. These outcomes propose that the model performed satisfactorily in anticipating the following day's "Close" cost of Bitcoin given the chosen features.

Fig. 7 Actual versus predicted bitcoin close prices (Next Day)



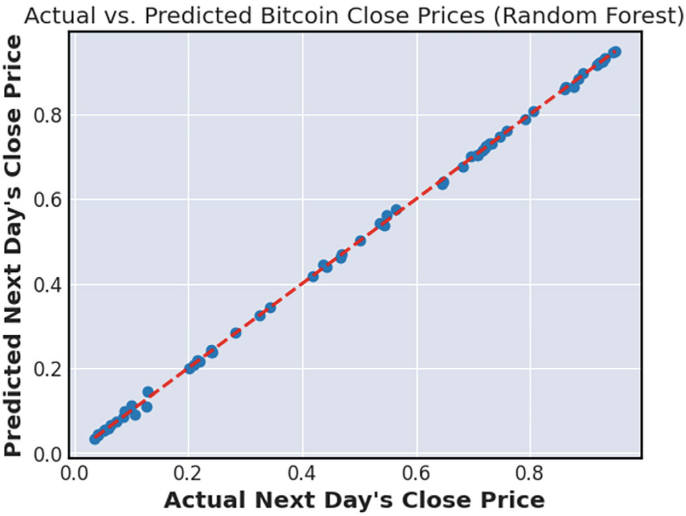


Fig. 8 Actual versus predicted bitcoin close prices (Gradient Boosting)

Using Gradient Boosting for Bitcoin price prediction. One more way to deal with foreseeing the cost of Bitcoin is to utilize Gradient Boosting, which is also an ensemble machine learning algorithm. Gradient Boosting is known for its capacity to deliver profoundly precise prediction which is accomplished by utilizing the qualities of weak models and iteratively refining them. Gradient Boosting can frequently outflank other machine learning algorithms in terms of precision in prediction.

It is powerful at detecting non-linear connections and complex examples in the data. This makes it reasonable to demonstrate the unpredictable elements of monetary business sectors, for example, the value developments of Bitcoin, which frequently show non-direct and complex ways.

After considering the feature-engineered variables, the mean square error (MSE) was observed as 2.43. This demonstrates that the Gradient Boosting model displayed in Fig. 8 achieved a value extremely close to the actual "Close" cost of Bitcoin for the following day, further indicating the viability of the model.

4 Ensemble of Models

While analyzing the results of both models, a disparity was seen between them. Approximately 45% of the close price values anticipated by Random Forest were lower than the actual close price, while 56% of the values predicted by Gradient Boosting were higher than the actual closing price. If a lower value was predicted by Random Forest, a higher value was predicted by Gradient Boosting, and vice versa. We realized that the best approach was to combine the predictions from both the

Random Forest and Gradient Boosting models to obtain a more precise forecast of the cost of Bitcoin, which represents our novelty. Moving forward with the ensemble, we employed four different types of ensemble: a stacking model, a bagging model, a blending model, and a voting model.

4.1 Stacking Model

The stacking model is an ensemble learning strategy that consolidates various base models to work on predictive performance. The stacking model involves training multiple distinct base models on the dataset, such as Gradient Boosting Regressor and Random Forest Regressor, for Bitcoin price prediction. Rather than directly utilizing their forecasts, the stacking model finds a way to join these predictions by utilizing a meta-learner (e.g., Extreme Gradient Boosting (XGBoost) Regressor) to make the final prediction.

We used stacking because it aims to capture various aspects of the underlying data and takes advantage of the variety of predictions made by various base models. By joining the qualities of numerous models, stacking might overcome the limits of individual models and accomplish better prediction accuracy. Also, stacking provides greater adaptability in identifying complex connections within the Bitcoin cost data, prompting more accurate predictions. Here are the explanations for the parameters used.

Base Models: The variety of predictions and their performance are determined by the selection of base models. We have used Gradient Boosting Regressor and Random Forest Regressor as base models.

Meta-Learner: The meta-learner, such as the Extreme Gradient Boosting (XGBoost) Regressor, oversees learning how to effectively combine base model predictions. Extreme Gradient Boosting (XGBoost) was used as a meta-learner for the project.

Stacking Architecture: The stacking architecture determines how predictions from base models are integrated to train the meta-learner. This involves deciding whether to use the already defined probabilities or other modified representations as input features for the meta-learner. We independently trained the two base models on the training data. After training the base models, predictions were obtained on a holdout validation set using both base models. Subsequently, the predictions from both base models were stacked horizontally to create a new feature matrix. Each row of the matrix contains the predictions made by both base models for a specific sample in the validation set. The meta-learner, an Extreme Gradient Boosting (XGBoost) Regressor, was then trained on the stacked predictions along with the corresponding actual values. The meta-learner learns to effectively combine the predictions from the base models to determine the final prediction. Finally, the meta-learner predicts the target variable (Bitcoin price) using the stacked predictions obtained from the

```
+----------------------+  +----------------------+
| Base Model 1         |  | Base Model 2         |
| (Gradient Boosting)  |  | (Random Forest)      |
+----------------------+  +----------------------+
            |                        |
            v                        v
     Training Data              Training Data
   (X_train_base, y_train_base)  (X_train_base, y_train_base)
            |                        |
            +------------+-----------+
                         |
                         v
                 Blended Predictions
               (X_val_blend, y_val)
                         |
                         v
               Meta-Learner (XGBoost)
                     (Trained)
                         |
                         v
              Blended Test Predictions
                   (X_test_blend)
                         |
                         v
                  Final Prediction
```

Fig. 9 Used stacking architecture

test set. The predictions made by the meta-learner represent the final prediction of the stacking model, as depicted in Fig. 9.

Strategy for Cross-Validation: Stacking generally includes a cross-validation methodology to prevent overfitting.

To provide a more detailed understanding Fig. 10 and to depict the differences between the actual price and the predicted price, Fig. 11 are used.

4.2 Bagging Model

An ensemble learning technique called "bagging," also known as "Bootstrap Aggregating," tries to increase the precision and stability of machine learning algorithms. Making the final prediction involves averaging the predictions of numerous instances of the same base model that have been trained on diverse subsets of the training data (usually sampled with replacement). The bagging regressor is made involving the Random Forest Regressor and Gradient Boosting Regressor as the base assessors.

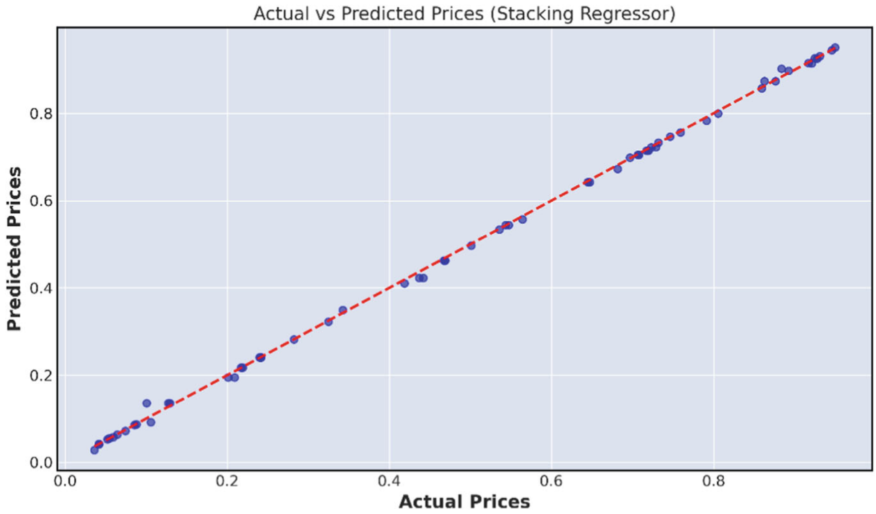


Fig. 10 Stacking results

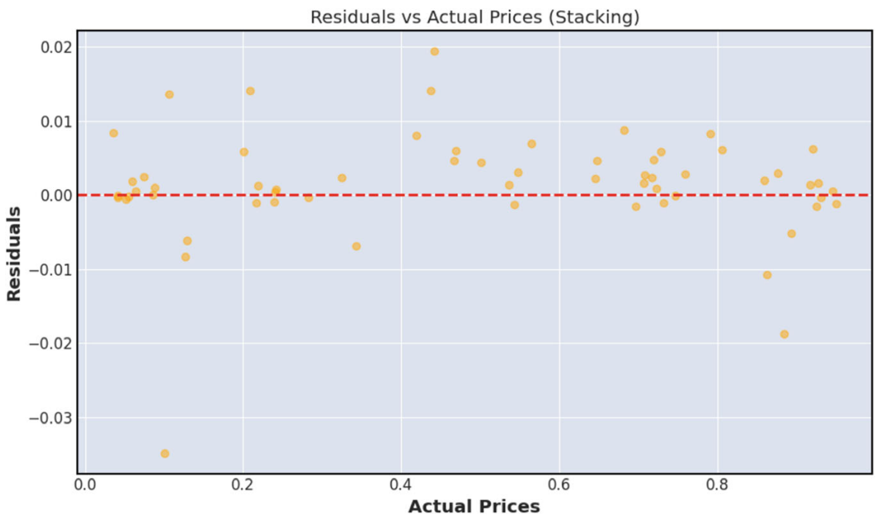


Fig. 11 Stacking the difference between the actual and predicted prices

Bagging is utilized since it reduces overfitting and variance in the model by presenting diversity in the preparation cycle. Both the models are trained using different subsets of training data and later averaged to get the final prediction. Bagging can boost a model's stability and generalizability by training multiple models on various data subsets and averaging their predictions. With regards to the Random Forest Regressor, bagging further upgrades the power of the model by lessening the effect of individual trees' overfitting, and bagging reduces the variance of individual Gradient Boosting Regressor models, therefore increasing their robustness. Figure 12 depicts the basic workings of a bagging model.

To provide a more detailed understanding Fig. 13 and to depict the differences between the actual price and the predicted price, Fig. 14 are used.

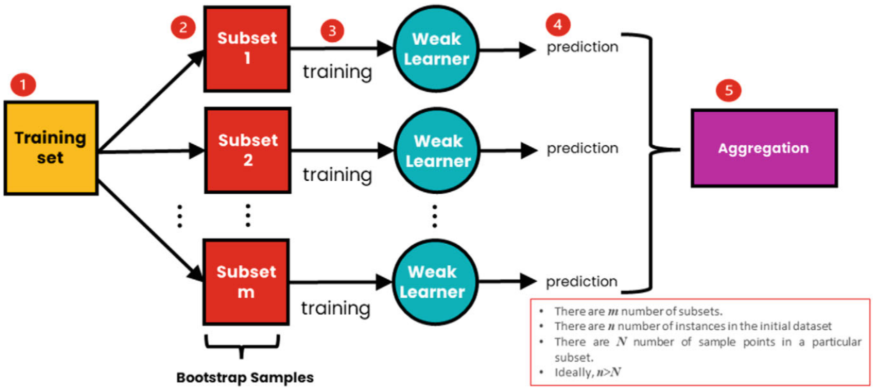


Fig. 12 Bagging

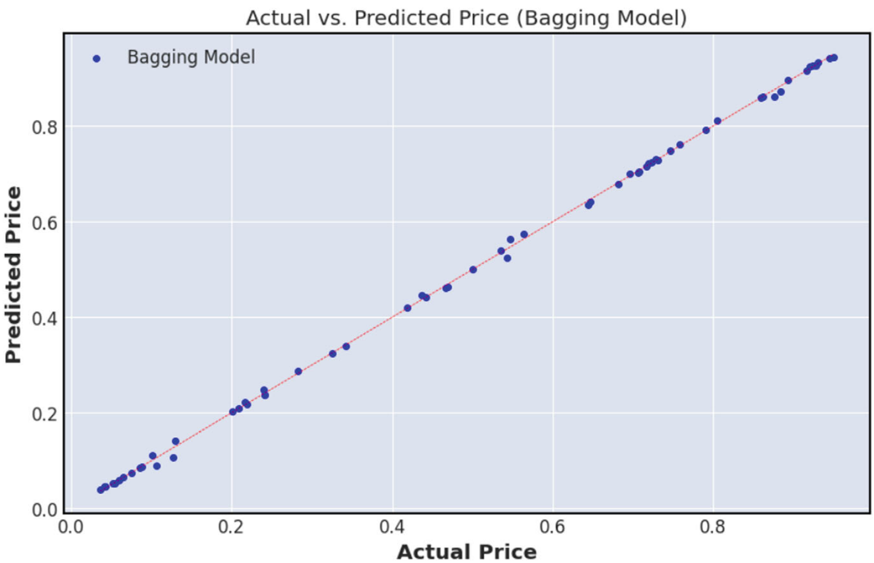


Fig. 13 Bagging results

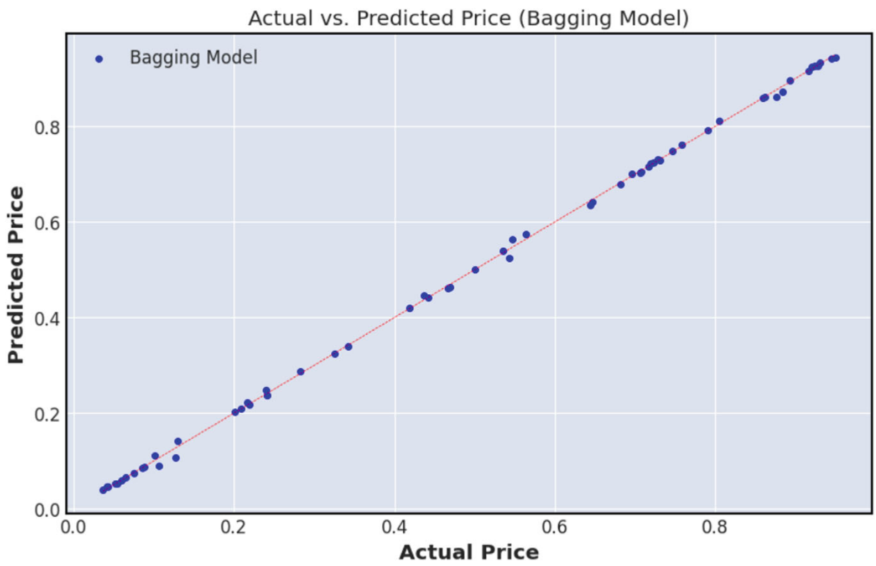


Fig. 14 Bagging with difference between the actual and predicted prices

4.3 Blending Model

Blending is an ensemble learning technique where predictions from many base models are blended using a meta-model. It is sometimes referred to as meta-learning or model stacking. We independently trained two basic models: a Random Forest Regressor and a Gradient Boosting Regressor. A meta-model, in this case a Linear Regression model, is trained with the predictions from these underlying models as features. To get at the ultimate prediction, the meta-model acquires the ability to efficiently integrate the predictions from the basis models.

We used blending because it enables the blending of predictions from various base models. Blending attempts to make use of the strengths and weaknesses that each base model possesses and may increase overall accuracy. Blending can outperform individual models in terms of generalization and performance by teaching a meta-model how to weigh the predictions from various base models. To provide a more detailed understanding Fig. 15 and to depict the differences between the actual price and the predicted price, Fig. 16 are used.

4.4 Voting Model

Voting in the context of ensemble learning is calculating the arithmetic mean of the predictions given by several different individual models. To get the final prediction,

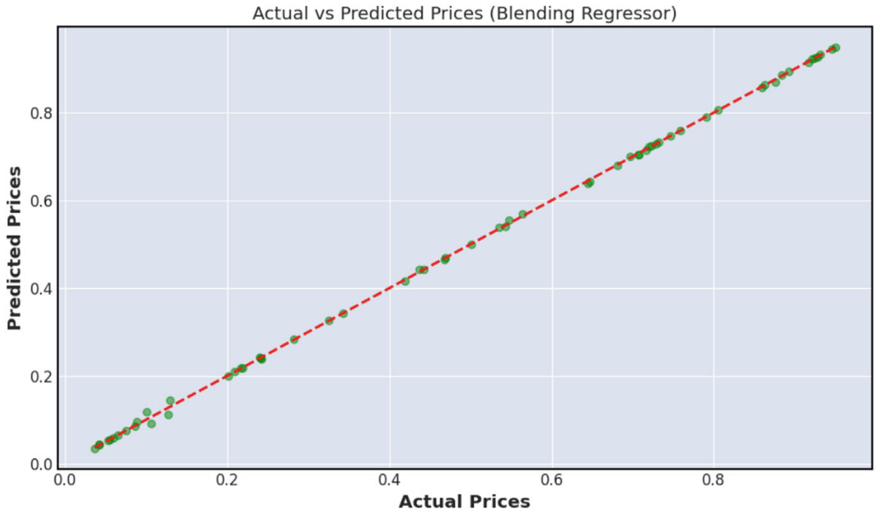


Fig. 15 Blending results

this straightforward ensemble technique averages the predictions of each base model. Furthermore, we tried altering the weights given to each of these model's predictions and found out 0.6 and 0.4 for Gradient Boosting and Random Forest respectively was the best combination. To provide a more detailed understanding Fig. 17 and to depict the differences between the results of the actual price and the predicted price, Fig. 18 are used.

5 Result Analysis

We designed six different models, two individual models—Random Forest and Gradient Boosting and four ensemble methods (Stacking, Bagging, Blending, and Voting) as shown in Table 1 given below. Training, testing, and validation ratio was 70:15:15.

The market can be influenced by several factors that may lead to the downfall or spike in the Bitcoin price. Keeping this in mind, we investigated the spreadsheet with predicted and actual prices, realizing that the prediction was approximately \$50 higher or lower than the actual price only on the days when celebrities publicized crypto growth or made comments against the crypto market. Hence, the model admissibly could not capture the change. Which is why the maximum error remained constant.

Table 1 shows that the ensemble of the models stands out significantly from the base models. The ensemble approaches lower the mean squared error by approximately 99% for both the base models and improve the R-square value by 26%

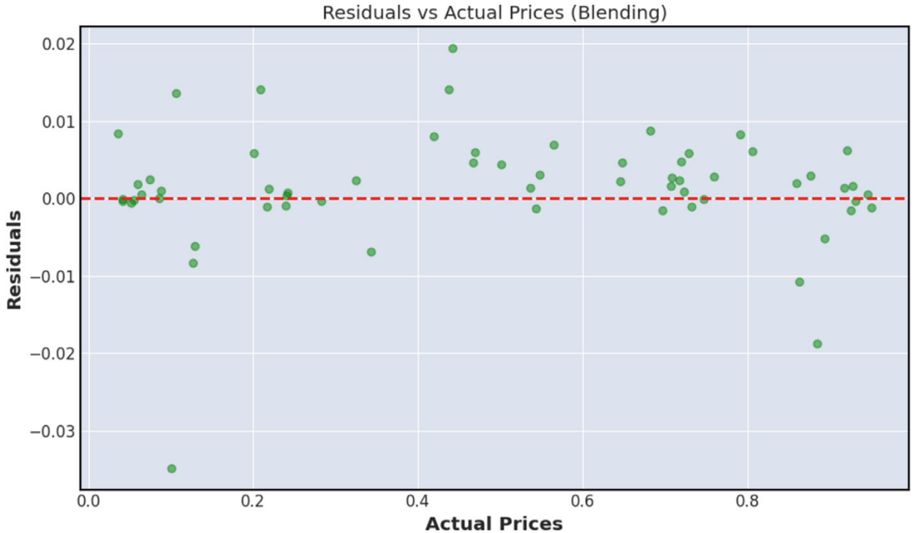


Fig. 16 Blending the difference between the actual and predicted prices

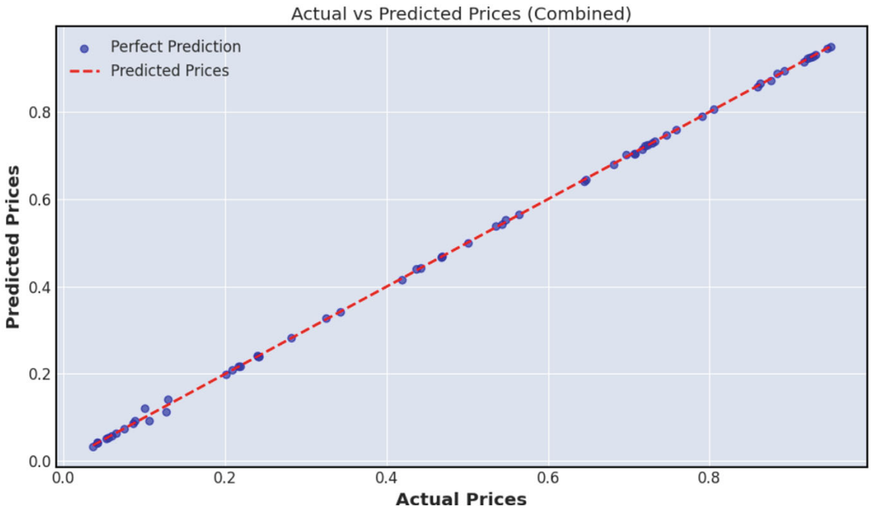


Fig. 17 Voting results

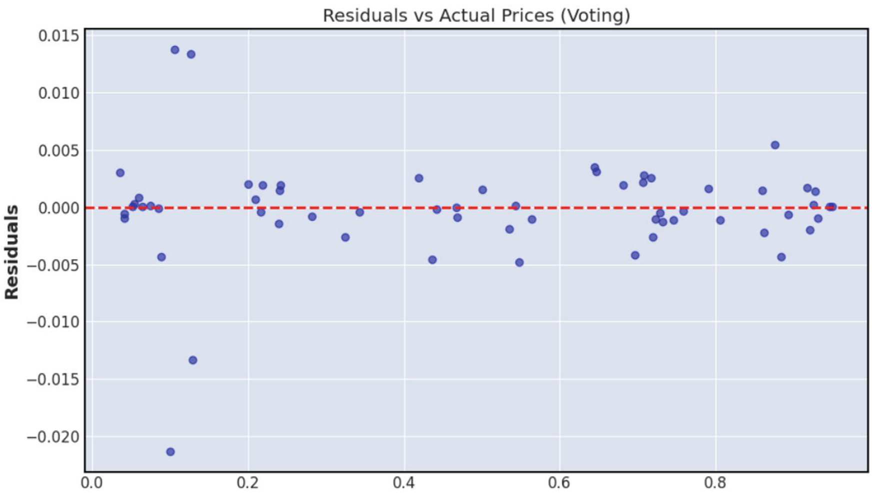


Fig. 18 Voting with difference between the actual and predicted prices

compared to the Random Forest model and by 16% compared to Gradient Boosting on average. These computations further show that Voting (0.6,0.4) performs better than the other ensemble methods with the least maximum error, mean squared error, and highest R-square value. Hence, an ensemble approach by voting to predict the subsequent day's Bitcoin price is the best approach.

Table 1 Results obtained

Models	Mean square error	R-Square	Maximum error
Random forest	6.38	0.78465	52.32
Gradient boosting	2.43	0.85134	52.43
Stacking	0.0000238	0.99975	52.01
Bagging	0.0000432	0.99952	52.20
Blending	0.0006765	0.99301	52.08
Voting (0.6,0.4)	0.0000207	0.99983	51.40

6 Conclusion

In this review, we directed a thorough examination of Bitcoin price data, utilizing different data pre-processing procedures and visualization methods to gain insights into its patterns and trends. Our investigation included the execution of machine learning models, including Random Forest Regressor and Gradient Boosting Regressor, to anticipate the following day's Bitcoin close price. While these underlying models showed a few limitations in R-square scores and mean square error, we realized the valuable chance to upgrade their performance through ensemble learning.

To address this, we utilized a range of ensemble techniques, including Stacking, Bagging, Blending, and Voting. Our trial and error uncovered that a carefully weighted voting ensemble of Random Forest and Gradient Boosting outperformed all remaining methodologies. By allocating weights of 0.4 and 0.6 to Random Forest and Gradient Boosting, individually, we accomplished unrivaled predictive accuracy at Bitcoin costs.

Consequently, we reason that the ensemble of Random Forest and Gradient Boosting models offers a compelling strategy for predicting Bitcoin prices. This approach uses the strengths of the two models while overcoming their shortcomings, improving accuracy, and delivering reliable predictions. Moving forward, the paper does not include sentiment analysis which would be the solution for the undetected price peaks and high maximum due to semantic reasons, i.e., an influential person promoting or discouraging a coin, providing room for further study.

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