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Comparing Machine Learning Algorithms for Predicting Cryptocurrency Prices: An Analytical Study

Pappula Ashok[1]*, D. Mallikarjuna Reddy[2], B. Vittal[3], V. Sree Ramani[4] Ameen Saheb Shaik[5], T. Satish Reddy[6]

[1,5,6]Department of Mathematics, Anurag University, Hyderabad-500088, Telangana, India.

[2]Department of Mathematics, GITAM University, Hyderabad- 502329, Telangana, India.

[3]Department of Statistics, CVR College of Engineering, Hyderabad- 501510, Telangana, India.

[4]Department of Mathematics, Chaitanya Bharathi Institution of Technology, Hyderabad- 500075, Telangana, India.

ashokhs@anurag.edu.in*

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Abstract:

Introduction: Due to advances in financial technology, cryptocurrency is a new asset with outstanding academic potential. Price volatility and dynamism make Cryptocurrency prediction difficult.

Objectives: This paper presents three Recurrent Neural Network (RNN) methods for predicting Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB) prices to predict the price of Cryptocurrency.

Methods: This study uses two Machine learning algorithms, Random Forest (RF) and Gradient Boosting (GB), to predict the prices of Bitcoin (BTC), Binance Coin (BNB), and Ethereum. (ETH)

Results: Two machine learning algorithms predict BTC, ETH, and BNB prices. The model's accuracy was assessed using performance metrics. We followed this by comparing the actual and expected prices of the models. The GB algorithm surpassed its competitor, attaining MAPE values of 2.884169154 for BNB3.612352523 for ETH and 4.593971246 for BTC.

Conclusion: The prices of cryptocurrency swing regularly. Since the cryptocurrency market is nonlinear, time series data is challenging to evaluate when making price predictions. Machine learning algorithms are used in many financial and economic activities. Investors, researchers, and professionals need cryptocurrency value forecasts. In this study, GB and RF algorithms are used to predict the prices of BTC, ETH, and BNB.

Keywords: Cryptocurrency; GB, RF, BTC, ETH, BNB.

1. Introduction

Digital cryptocurrencies use blockchain-based cryptography. Using blockchain technology, users can transfer and receive cash on a peer-to-peer network, Nakamoto [1]. Bitcoin was invented by Satoshi Nakamoto in 2008. Numerous coins followed this development. The Coin Market Cap research estimates 22,932 cryptocurrencies worth $1.1 trillion. BTC has the most significant market capitalization of 1,196,246,313,443 USD, followed by Ethereum at 319,441,241,336 USD. Cryptocurrencies are used for everyday payments, speculation, and non-monetary activities. The digital payment method cryptocurrency is unregulated by the government. According to Farell [2], bitcoin was utilized to make payments. Globally recognized cryptocurrencies are now employed as speculative investments. First cryptocurrency transaction: Hal Finney and Nakamoto used Bitcoin on January 2, 2009. There are cryptocurrency exchanges in Singapore, Switzerland, Australia, and other countries, with over 425 million users. According to Lahmiri and Bekiros [3], cryptocurrencies are of interest to the public since they may quickly accumulate money. Its decentralized peer-to-peer architecture, excellent liquidity, high returns, anonymity, and lower transaction costs make cryptocurrencies stronger than traditional currencies. Despite expected rewards, cryptocurrencies are riskier due to their heightened volatility, price swings, and shocks. For example, Bitcoin declined 68.23% to $20331.28 by September 2, 2022, from $64,000 in the first half of 2021. Currently, this problem exists. As of February 23, 2024, Bitcoin is worth $51319.50, which is low compared to the first half of 2021. Investors are still accumulating losses on other cryptocurrencies; thus, the future of this market remains guesswork. GB, RF, and Bagging regression are attractive alternatives to standard regression algorithms for forecasting financial series prices due to their resistance to overfitting. The algorithms tested by Derbentsev et al. [4] showed that RF performed better than other ensemble approaches. Similarly, RF regression outperformed other algorithms in forecasting Bitcoin prices, according to Farouk et al. [5]. RF regression outperformed ensemble approaches. Farouk et al. employed open, high, close, and low prices as characteristics. However, this analysis included prior closing price delays. The lack of pre-release open, high, close, and low prices makes them unsuitable for forecasting. However, historical lag values of closing prices help. This study is vital for investors, intended investors, and crypto market practitioners since it helps anticipate future cryptocurrency values, aiding decision-making. Bitcoin investing is dangerous; thus, a trustworthy price prediction will help you decide when to purchase or sell, limiting the enormous loss from a bad investment choice. This study uses ML algorithms to estimate the daily closing price of three cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Binance (BNB).

2. Literature Review

Numerous research studies have shown the efficacy of machine learning algorithms in anticipating Bitcoin trends. Alshehri [6] used both regression and machine learning models to predict the future returns of Bitcoin. The analysis included logistic regression, linear discriminant analysis (LDA), k-nearest neighbors (KNN), decision trees (DT), naive Bayes (NB), support vector machines (SVM), random forests (RF), light gradient boosting machine (LGBM), and extreme gradient boosting (XGBoost) as methodologies. Research showed that the XGBoost regressor outperformed other machine learning approaches. Shilpa et al. [7] investigated how LSTM, MLP, and RNN may help predict cryptocurrency prices. In several machine learning models, Jaquart et al. [8] predicted the daily movements of the 100 most significant coins. According to the data, these models accurately predicted these coins. Coin market performance is poor, according to these data. Limits on arbitrage may affect it. Pan [9] tried ARIMA, RF, and LSTM deep learning systems to estimate three cryptocurrency values between 2018 and 2022. There was Bitcoin, Ether, and Dogecoin. We tested these approaches using MSE, RMSE, MAE, and R^2. Combining RF and Bagging, Basher and Sadorsky [10] predicted Bitcoin prices using interest rates, inflation, and market movements. RFs outperform logit models in forecasting Bitcoin and gold values. Bagging and RFs made 75%–80% successful five-day forecasts. Bagging and RFs each forecast 10- to 20-day events with around 85% accuracy. With regression, PSO, and XGBoost, Srivastava et al. [11] forecasted Bitcoin, Dogecoin, and Ethereum prices. The new method has the least RMSE, MAE, and MSE than the old one. Yan [12] used LR, GB, and RF to forecast Bitcoin's high-frequency time series. Yan found that LR outperforms RF and GB. SAAD et al. [13] tested LR, RF, and GB to predict Bitcoin and Ethereum values. In their study, LR functioned best with $1/10^{th}$ of the data and GB and RF with $1/20^{th}$. Deep learning system LSTM outperformed XGBoost in predicting Bitcoin value, according to Turukmane et al. [14]. Sakran [15] tested these ML algorithms: LR, DT, RF, and others. Sakran also used other deep learning algorithms to predict Bitcoin values, including ANN and CNN. The survey [16] revealed that CNN predicted Bitcoin values best. The main gap in this research is that most evaluated studies focus on cryptocurrencies, whereas this analysis considered another cryptocurrency trading with Bitcoin. Bitcoin exhibits the most significant standard deviation, which signifies greater risk. Furthermore, the data from Gupta and Vaishali [17] supports that Bitcoin exhibits the most volatility compared to other cryptocurrencies, as seen by its most significant standard deviation. This work further demonstrates that cryptocurrencies have heavy-tailed distributions, a conclusion supported by Osterriedder [18] and Palstand and Ryden [19], who observed that Bitcoin has significant non-normal properties. All cryptocurrencies exhibit a positive skewness, which is consistent with the results reported by Karagiorgis et al. [20], Yang [21], and Liu and Tsyvinski [22]. The study demonstrates RF regression's superiority over other machine-learning techniques, as supported by Alarcon [23]. The seminal work by Box and Jenkins [24], Time Series Analysis: Forecasting and Control (1970), introduced the Box-Jenkins approach, which remains a fundamental framework for ARIMA model development. Their methodical approach to developing, evaluating, and using ARIMA models established a robust foundation for time series analysis, significantly impacting forecasting methodologies in economics and other fields. Aanandhi et al. [25] used the Autoregressive Integrated Moving Average (ARIMA) model to predict the prices of many cryptocurrencies via machine learning. Benzekri et al. [26] Studies on Bitcoin's price predictability underscore the conflict between risk and return for investors. Researchers employing the ARIMA model, specifically ARIMA (1,1,0), successfully predicted short-term Bitcoin prices, especially during market disturbances such as COVID-19. These findings illustrate ARIMA's effectiveness in forecasting Bitcoin's quarterly price fluctuations while highlighting the necessity for models capable of adjusting to abrupt market changes. Bitcoin volatility makes forecasting challenging. According to the 2013-2018 Bitcoin and Ethereum return to study, ARIMA models provide better short-term predictions, and Neural Networks provide better long-term predictions, picking Kumar's forecast-horizon models. [27]. The researchers Wirawan, I.M et al. [28] studied using ARIMA (4,1,4) on Bitcoin data (2013-2019) demonstrated substantial short-term forecasting accuracy, with MAPE values of 0.87 for one day and 5.98 for seven-day predictions. The ARIMA model predicts Bitcoin values over three years [29]. ARIMA excels at short-term projections in stable periods but fails with long-term forecasts, especially in turbulent times like late 2017. The results indicate that model parameters and window size are crucial to prediction accuracy and that more characteristics are needed. Iqbal et al. The study [30] examines ARIMA, FBProphet, and XGBoost for Bitcoin price prediction. ARIMA was the most accurate model, with an RMSE of 322.4 and MAE of 227.3, providing cryptocurrency investors with helpful information. Latif et al. [31] compare ARIMA and LSTM Bitcoin price prediction models. In both tests, LSTM predicted price direction and value better than ARIMA, which monitored the trend. LSTM predicted Bitcoin price fluctuations better. The ARIMA model predicts Bitcoin's closing price well in stable sub-periods but suffers with big MSE owing to Bitcoin's volatility [32]. A high-resolution chart web service was constructed after testing different (p, q, d) values. ARIMA might be used with CNN or LSTM models to improve predictions. The study [33] describes a hybrid ARIMA-GARCH model for short-term Bitcoin price predictions. The ARIMA (12,1,12) model was chosen based on AIC, while GARCH (1,1) was utilized to represent volatility. The model is suitable for short-term projections but expects future conditions to follow historical trends, limiting its long-term predicting potential. Mittal et al. [34]. This article employs the ARIMA model to forecast the future values of over 1,500 cryptocurrencies, with an average accuracy of 86.42%, after confirming that the data remained stationary. Forecasts were created, and percentage price changes were determined. Feizian et al. [35] This investigation implements sentiment analysis and machine learning to forecast cryptocurrency prices. The LSTM model demonstrated enhanced accuracy ($P=0.045$) by weighting sentiment scores based on influencer impact. For Ethereum, EOS, and Cardano, the hybrid model outperformed others, while the weighted sentiment model was the most effective for Bitcoin and Ripple. This underscores that increased features do not necessarily result in improved accuracy. Yenidoğan, I. et al [36]. This article analyzes Bitcoin forecasting with PROPHET and ARIMA on a dataset spanning May 2016 to March 2018. After preprocessing and adding correlated variables, PROPHET surpassed ARIMA with an R^2 value of 0.94 vs 0.68. Hamayel et al. [37]. This article analyzes the GRU, LSTM, and bi-LSTM models for forecasting Bitcoin, Litecoin, and Ethereum values. GRU beat the others with the lowest MAPE (BTC: 0.2454%, ETH: 0.8267%, and LTC: 0.2116%), while bi-LSTM had the highest. The Novel Random Forest (RF) algorithm and the K-Nearest Neighbor (KNN) algorithm are compared in the author's [38] work to predict cryptocurrency prices. RF achieved an accuracy of 87.73%, while KNN attained an accuracy of 72.13%. The discrepancy in accuracy was statistically significant ($p=0.007$). Samson, T. K. [39] Gradient Boosting (GB), Random Forest (RF), and Bagging are tested in this study to estimate bitcoin values. GB was the most successful in Bitcoin and Solana, while RF outperformed Ethereum, USD, and XRP. The findings highlight the higher efficacy of RF in forecasting cryptocurrency values, offering investors helpful information. In their study [40], Oyedele et al. compared genetic algorithm-tuned deep learning models with boosted tree-based models for predicting the price of bitcoin. In terms of error and variance, CNN did the best, with 0.08 errors and 0.96 variances. Valencia et al. [41] applied machine learning and sentiment analysis to predict cryptocurrency prices, showing that neural networks outperform other models and Twitter data alone can predict certain markets. Akyildirim et al. [42] investigated the forecasting of 12 major cryptocurrencies with machine learning methodologies (SVM, logistic regression, neural networks, and random forests) grounded in historical prices and technical data. They achieved a 55–65% accuracy on daily and minute-level data, with SVM consistently exhibiting higher performance. Bagging and Gradient Boosting methods mitigate bias and improve accuracy in intricate linkages or unbalanced data scenarios. Nevertheless, RF amalgamates their respective capabilities. Consequently, it surpasses both of them. Due to the cryptocurrency series' time series data, this study uses the closing price's preceding lag values to create ML algorithms, unlike other review studies. Some research used RF regression, whereas others favored alternative ensemble ML techniques. The current crypto market necessitates recent research on projecting cryptocurrency closing prices.

3. Methodology

3.1. Source and Preprocess Data: Yahoo Finance(https://finance.yahoo.com/) provided Binance, Bitcoin, and Ethereum closing prices. The analysis examined data from January 1, 2020, to June 30, 2024. These three cryptocurrencies are among the top 10 most traded worldwide. Data was cleaned and checked for duplicates and missing values. This closing price was projected using the six days preceding closing price first, the characteristic, and then the target variable. The time-series-based, unsupervised cryptocurrency series is largely used for its unique features. Thus, the study thinks utilizing past data to predict current prices is trustworthy since it uses intrinsic knowledge. Data preparation is essential to ML projects. It converts data for machine-learning algorithms. Data preparation included normalization.

3.2. Normalization of Data: The time-series data for cryptocurrency is standardized to a uniform value while maintaining the variations in the price range. The Python Standard Scaler was employed for this objective. The data is transformed using Standard Scaler to provide a range of values from 0 to 1.

$$A_{t-normalize} = \frac{A_t - \min(A_t)}{\max(A_t) - \min(A_t)} \quad (1)$$

$$A_t = A_{t-normalize}[\max(A_t) - \min(A_t)] + \min(A_t) \quad (2)$$

3.3 ML Models

3.3.1 GB regression: This ensemble-supervised machine learning system uses multiple weak decision trees. The GB technique iteratively adjusts model weights based on previous failures to reduce prediction errors and improve accuracy. Each succeeding model is trained sequentially to correct the mistakes from the last model in GB regression. Figure 1 shows the gradient-boosted regression tree schematic.

3.3.2. RF: RF regression is supervised learning that combines bagging and boosting procedures. In Random Forests (RFs), the individual trees develop independently and concurrently, without any mutual influence or interaction. Random Forests (RFs) are robust and efficient machine learning models since they can efficiently handle input data with many dimensions, missing values, and outliers. In addition, they need minimum hyperparameter tuning and are straightforward to deploy. RF regression entails the creation of a Random Forest (RF) by randomly generating several trees. Each tree is constructed using a unique configuration of rows, and for every node, a separate set of features is selected for division.

Each tree offers a prediction combined to get a definitive result. The Random Forest (RF) technique outperforms a single DT by utilizing averaging, resulting in improved accuracy in the predictions made by RF regression. Each ML technique was evaluated using error measures, including MAPE, RMSE, MAE, and MSE.

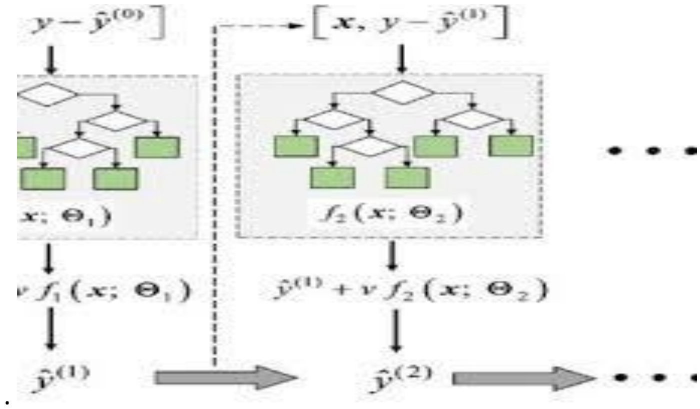

Figure 1. The GBR Schematic diagram

where A_t = Actual price, F_t = Predicted price, k = no of parameters, n = no of observations.

These ML algorithms were hyperparameter-tuned using Grid Search to increase performance. Each method has the maximum depth [5, 6] and 100,200,300, 500, 700, 900, and 1000 estimators. Grid SearchCV from sklearn. Model selection, a Python library, found the ideal hyperparameters. Grid SearchCV finds the optimal hyperparameters from a grid.

4. Evaluation Metrics:

$$\text{MAPE}=\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t-F_t}{A_t}\right| \quad (3)$$

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t-F_t)^2} \quad (4)$$

$$\text{MAE}=\frac{1}{n}\sum_{t=1}^{n}|A_t-F_t| \quad (5)$$

$$\text{MSE}=\frac{1}{n}\sum_{t=1}^{n}(A_t-F_t)^2 \quad (6)$$

5. Findings and Analysis: Results can be subdivided. It should clearly state the results, evaluate them, and draw tentative inferences. Table 1 summarizes descriptive information for the three cryptocurrencies. Bitcoin, Ethereum, and Binance had minimum prices of 4970.788 USD, 110.6059 USD, and 9.38605 USD." Bitcoin recorded the most significant standard deviation (17542.52) of the three cryptocurrencies, suggesting the highest risk. Figures 2-4 illustrate growing Bitcoin, Ethereum, and Binance prices. These three ML methods are compared in Table 2.

5.1. Results for BTC: The accuracies of these models for BTC coins are given in Table 2. The GB model's Mean Absolute Percentage Error (MAPE) is the lowest, with a value of 4.593971246. Additionally, the Root Mean Square Error (RMSE) is 3960.177425. Thus, GB has superior predictive capabilities for BTC movements compared to RF, but with a slight distinction between them. Figure 5 displays a graphical depiction that compares the absolute and forecasted values of the training dataset for BTC across the three models.

5.2. Results for ETH: The performance metrics of these models for ETH cryptocurrency are presented in Table 2. The GB model's MAPE (Mean Absolute Percentage Error) is the lowest, with a value of 3.612352523. Additionally, the MAE (Mean Absolute Error) is 115.065131. Thus, GB is more proficient in forecasting ETH trends than RF, but with a slight distinction between them. Figure 6 displays a graphical depiction that compares the actual and projected values of the training dataset for ETH across the three models.

5.3. Results for BNB: The performance metrics of these models for BNB coin are given in Table 2. The GB model's Mean Absolute Percentage Error (MAPE) is the lowest, with a value of 2.884169154, while the Root Mean Square Error (RMSE) is 22.49030183. Thus, GB exhibits more predictive capability for BNB trends than RF, with a slight distinction between them. Figures 7 display a graphical depiction that compares the absolute and forecasted values of the training dataset for the three BNB models.

ML Techniques were used to construct a graphic showing the actual and predicted prices of cryptocurrencies over 182 days. The resulting figures may be observed in Figure 5 to Figure 13. The graphs demonstrate the efficacy of these ML algorithms in predicting the daily closing price of cryptocurrencies, revealing a significant correlation between the test data prices and the expected data prices.

Table 1. Descriptive statistics for BTC, ETH, and BNB

Statistics	BTC-Close	BNB-Close	ETH-Close
count	1643	1643	1643
mean	32295.39	274.9599	1874.595
std	17542.52	179.7671	1149.953
min	4970.788	9.38605	110.6059
25%	18977.33	134.9396	1195.949
50%	29374.15	286.867	1805.205
75%	43975.53	381.0853	2706.377
max	73083.5	710.4641	4812.087

Figure 2. The closing price of BTC-USD (Train and Test)

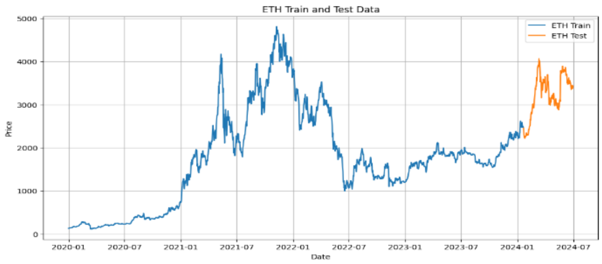

Figure 3. The closing price of ETH-USD (Train and Test)

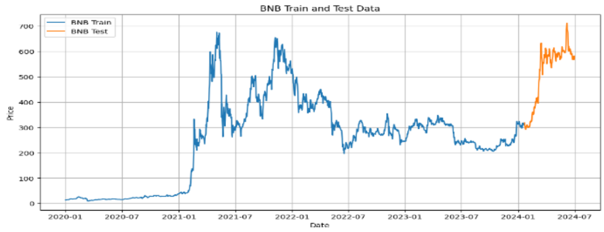

Figure 4. The closing price of BNB-USD (Train and Test)

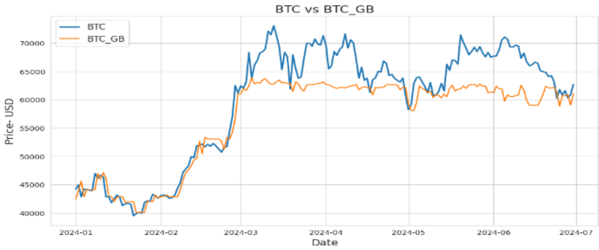

Figure 5. The closing price of BTC-USD and Predictions of GB

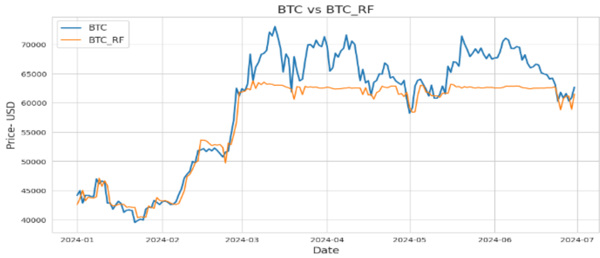

Figure 6. The closing price of BTC-USD and Predictions of RF

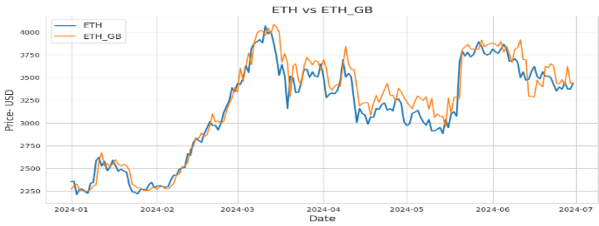

Figure 7. The closing price of ETH-USD and Predictions of GB

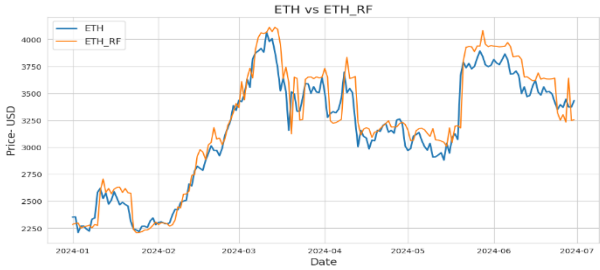

Figure 8. The closing price of ETH-USD and Predictions of RF

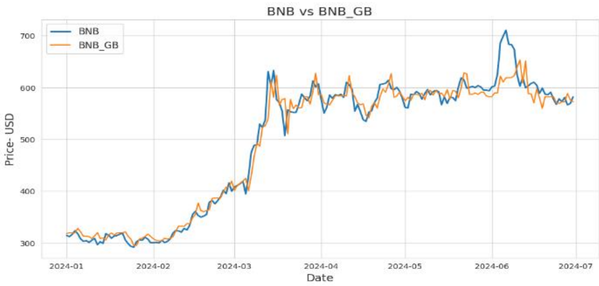

Figure 9. The closing price of BNB-USD and Predictions of GB

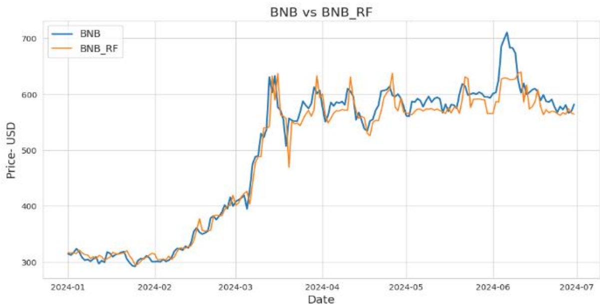

Figure 10. The closing price of BNB-USD and Predictions of RF

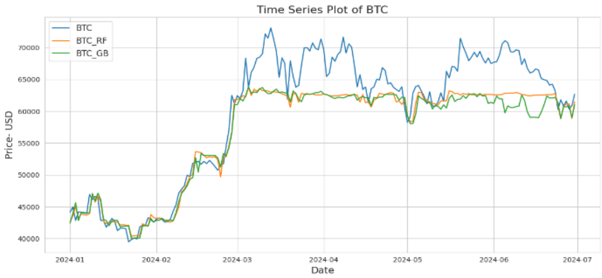

Figure 11. Test and predicted prices of BTC-USD

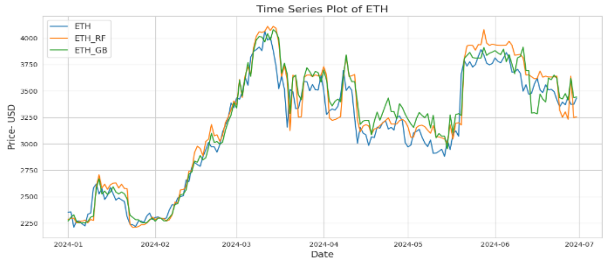

Figure 12. Test and predicted prices of ETH-USD

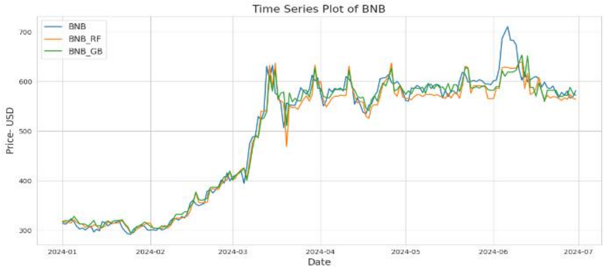

Figure 13. Test and predicted prices of BNB-USD

Table 2 describes the test error metrics of chosen cryptocurrencies, showing that the GB algorithm predicts cryptocurrency prices better than RF. However, all three models show better predictive capacity in predicting cryptocurrencies.

Table 2. Comparative performance (Metrics) of ML Algorithm

Cryptocurrency	ML Algorithm	MAPE	RMSE	MAE	MSE
Bitcoin-BTC	**RF**	4.706316987	4053.027643	3059.146743	16427033.08
	GB	**4.593971246**	**3960.177425**	**2981.979181**	**15683005.24**
Ethereum- ETH	**RF**	3.642470448	**150.8860273**	116.8280638	**22766.59323**
	GB	**3.612352523**	152.0570698	**115.065131**	23121.35247
Binance- BNB	**RF**	3.05621978	23.02133353	16.30256914	529.9818
	GB	**2.884169154**	**22.49030183**	**14.96510426**	**505.8137**

6. **Conclusions:** This study used three machine learning techniques, GB, and RF, to predict the daily closing price of three cryptocurrencies. The results demonstrated that the GB regression approach performed better than other machine learning algorithms for Bitcoin, Binance, and Ethereum. To improve the accuracy of bitcoin forecasts, it is crucial to consider using additional algorithms like LSTM, Bi-LSTM, and GRU. Additionally, it is critical to do similar examinations for cryptocurrencies that were not included in our analysis.

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