Comparative Analysis of LightGBM and Random Forest for Daily Bitcoin Closing Price Prediction with Ensemble Approach

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ABSTRACT

This study performs a comparative analysis of the LightGBM and Random Forest algorithms in predicting daily Bitcoin closing prices, with an exploration of an Ensemble approach for potential improvements in accuracy. A quantitative research design is employed, utilizing historical Bitcoin (BTC-USD) data from September 2015 to July 2025, enriched with various technical indicators. Data preprocessing, model training, and evaluation were carried out using Python in Google Colaboratory, with the dataset split into 80% for training and 20% for testing. Model performance was evaluated using the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the R-squared (R^2) statistic, with statistical significance tests to ensure robust comparisons. A simple Linear Regression model was also included as a baseline. The findings reveal that Random Forest outperformed LightGBM, achieving an MAE of 11,599.74, an RMSE of 19,262.31, and an R^2 of 0.431, compared to LightGBM's MAE of 12,285.42, RMSE of 19,995.04, and R^2 of 0.386. Although the Ensemble model showed slight improvements over LightGBM, it did not surpass Random Forest. The relatively low R^2 values across all models reflect the inherent volatility and difficulty in predicting Bitcoin prices. The study concludes that Random Forest demonstrates superior robustness for Bitcoin forecasting. Importantly, this work provides a novel empirical contribution by being one of the first to directly benchmark RF, LightGBM, and their Ensemble for Bitcoin prediction, highlighting that a simple averaging Ensemble does not guarantee superior performance. This finding provides a foundation for developing more refined Ensemble strategies tailored to high-volatility assets.

I. INTRODUCTION

In recent years, the growing global interest in cryptocurrencies, particularly Bitcoin, has spurred significant research into forecasting their price movements. As the leading and most widely traded cryptocurrency, Bitcoin displays highly volatile price behavior, driven by a variety of market dynamics, investor sentiment, and broader macroeconomic factors. Consequently, accurately predicting Bitcoin prices has become increasingly valuable for traders, investors, and researchers [1]. Several studies have examined the feasibility of forecasting Bitcoin prices, recognizing its complex and dynamic nature [2].

Machine learning (ML) algorithms have shown considerable promise in financial forecasting, spanning both traditional stock markets and the emerging cryptocurrency sector [3]. Among these, Ensemble methods, especially tree-based algorithms such as Random Forest (RF) and Light Gradient Boosting Machine (LightGBM), have gained significant attention. Their popularity arises from their inherent robustness, ability to capture complex nonlinear relationships, and efficiency in processing structured datasets [4]. Previous research has applied various machine learning and deep learning models for Bitcoin price prediction, including Random Forest, LSTM, and Recurrent Neural Networks, demonstrating their effectiveness in this field [4]. Specifically, the LightGBM model has been proven effective in forecasting stock price time series [5].

Random Forest is chosen in this study because of its robustness, interpretability, and reliable performance on small-to-medium-sized datasets, making it well-suited for financial time series characterized by noise and volatility. LightGBM is selected for its computational efficiency, scalability, and proven success in financial prediction tasks, particularly when handling large feature sets derived from technical indicators. By combining these two complementary models, this research aims to strike a balance between robustness and efficiency in capturing the complex dynamics of Bitcoin.

Despite the widespread use of RF and LightGBM, comprehensive comparative studies focusing specifically on their performance in predicting Bitcoin prices are relatively scarce [6]. Additionally, incorporating technical indicators such as moving averages, the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands as predictive features offers a vital opportunity to assess how well these models can leverage such inputs. The validity of technical analysis in the cryptocurrency market has been explored using machine learning methods [7].

To the best of our knowledge, no prior research has explicitly conducted a direct comparison between Random Forest and LightGBM in the domain of Bitcoin price prediction, nor has there been an attempt to create an Ensemble that integrates the strengths of both models. This study aims to conduct a comparative analysis of the LightGBM and Random Forest algorithms in predicting daily Bitcoin closing prices, utilizing a broad set of technical indicators. Furthermore, by introducing an Ensemble of RF and LightGBM, this work provides a novel empirical investigation into whether combining these models can enhance prediction accuracy in the context of Bitcoin. This area has not been systematically addressed in prior literature. The findings will contribute to a deeper understanding of the efficacy of these machine learning techniques in navigating the complexities of the cryptocurrency market, providing valuable insights for future research and practical applications.

II. METHODS

This study was carried out in July 2025 using Python-based computational tools, primarily within the Google Colaboratory (Colab) environment. Data preprocessing, model training, evaluation, and visualization were conducted using open-source libraries, including Pandas, NumPy, scikit-learn, LightGBM, and Matplotlib.

A. Data Collection

The dataset was collected by scraping historical Bitcoin (BTC-USD) data from Yahoo Finance, covering the period from September 16, 2015, to July 28, 2025, comprising a total of 3,590 daily records. The dataset includes the following raw attributes: Date, Open, High, Low, Close, and Volume.

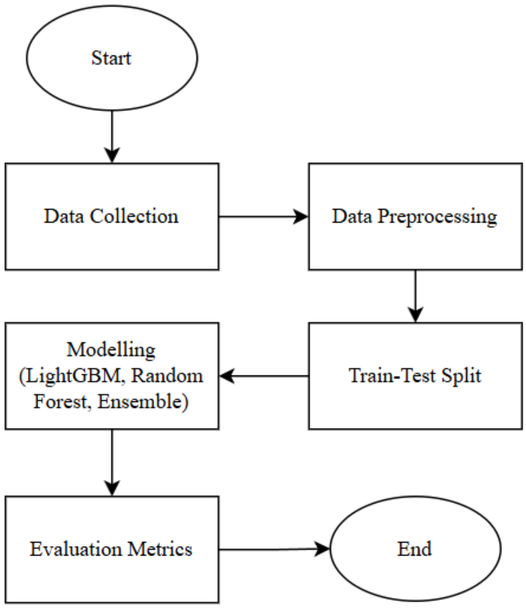

Figure 1. Workflow of the Bitcoin Price Prediction Pipeline.

To improve the model's predictive power, several widely used technical indicators were calculated and incorporated into the dataset [7], [8], including:

- Simple Moving Averages (SMA): sma_30, sma_90, sma_365
- Exponential Moving Averages (EMA): ema_30, ema_90, ema_365
- Relative Strength Index (RSI): rsi_14, rsi_30
- MACD and MACD Signal Line
- Bollinger Bands: bb_upper, bb_lower, and bb_width

In addition, the selection of these indicators was motivated by their standard usage and effectiveness in prior financial forecasting studies, ensuring that the features used in this study are both relevant and comparable to the existing body of literature.

TABEL I
TECHNICAL INDICATORS USED IN THE STUDY

Indicators	Description
sma_30	30-day Simple Moving Average
ema_30	30-day Exponential Moving Average
sma_90	90-day Simple Moving Average
ema_90	90-day Exponential Moving Average
sma_365	365-day Simple Moving Average
ema_365	365-day Exponential Moving Average
rsi_14	14-day Relative Strength Index
rsi_30	30-day Relative Strength Index
macd	Moving Average Convergence Divergence
macd_signal	MACD Signal Line
bb_upper	Upper Bollinger Band
bb_lower	Lower Bollinger Band
bb_width	Bollinger Band Width
Close	Bitcoin Daily Closing Price
High	Bitcoin Daily High Price
Low	Bitcoin Daily Low Price
Open	Bitcoin Daily Opening Price
Volume	Bitcoin Trading Volume

B. Data Preprocessing

The collected dataset underwent a cleaning process that involved removing irrelevant characters, parsing numerical values, handling missing values, and ensuring the Date column was appropriately formatted as a datetime object. The data were subsequently sorted chronologically to maintain the inherent time-series nature of the observations.

C. Train-Test Split

The dataset was partitioned into two subsets based on temporal order to ensure a realistic evaluation of the models' predictive capabilities:

- Training set: Comprising the initial 80% of the data, amounting to 2,872 rows.
- Testing set: Consisting of the remaining 20% of the data, totaling 718 rows.

The objective of the prediction was to forecast the daily closing price of Bitcoin, utilizing features consisting of 17 numerical columns that represented various technical indicators and price-related data.

D. Modelling (LightGBM, Random Forest, Ensemble)

Three distinct regression models were implemented for this study:

- Random Forest Regressor: An Ensemble learning method based on decision trees, utilizing the bagging technique. This model has shown effectiveness in predicting cryptocurrency market movements [4], [9]. RF was selected in this study due to its robustness against overfitting, relatively good interpretability through feature importance, and suitability for datasets of small to medium size, which aligns with the Bitcoin dataset used. In addition, RF has been widely acknowledged as a reliable baseline model in financial time-series prediction due to its balance between accuracy and interpretability, making it a natural choice for this study.
- LightGBM Regressor: A gradient boosting framework optimized for speed and accuracy, often used in large-scale data applications [5]. LightGBM was chosen because of its computational efficiency, scalability to high-dimensional data, and proven effectiveness in financial forecasting tasks, making it a strong candidate for handling the volatility of Bitcoin price series. It offers faster training time compared to traditional gradient boosting algorithms, and the ability to handle large-scale financial data efficiently also strengthens its relevance for Bitcoin forecasting.
- Ensemble Method: A combination of the two aforementioned models, designed to improve predictive performance by leveraging the strengths of each model. Ensemble methods are known to outperform single models in various tasks, including time-series forecasting and regression analysis. Specifically, the Ensemble in this study was implemented using a simple averaging (soft voting) strategy, where the final prediction is obtained by calculating the mean of the outputs from Random Forest and LightGBM. This mechanism was chosen over stacking, as it allows for a straightforward integration of the two models without introducing additional meta-learners, while still capturing their complementary predictive capabilities. In this way, Random Forest's stability from bagging and LightGBM's gradient boosting strengths are both preserved.

The novelty of this methodological setup lies in applying an Ensemble that directly integrates Random Forest and LightGBM for Bitcoin price prediction. This combination has not been systematically tested in prior literature. These models were trained using the designated training set and evaluated on the testing set. No extensive hyperparameter tuning was conducted; instead, commonly used default parameters were applied to establish a fair baseline comparison across models. As an additional benchmark, a simple Linear Regression model was also tested to serve as a baseline reference. While its performance is naturally limited compared to tree-based methods, its inclusion provides a clearer context for evaluating the gains achieved by RF, LightGBM, and the Ensemble approach.

E. Evaluation Metrics

The performance of the developed models was evaluated using two standard metrics commonly used in regression tasks:

- Mean Absolute Error (MAE): Measures the average magnitude of the prediction errors, indicating how close the predicted values are to the actual outcomes.
- R-squared (R^2): Represents the proportion of the variance in the dependent variable that can be predicted by the independent variables, essentially assessing how well the model explains the variability of the target variable.

Additionally, an Ensemble model was constructed by averaging the predictions generated by both LightGBM and Random Forest [9]. This evaluation approach enables us to empirically test whether combining two widely used tree-based models can yield improved prediction performance in the Bitcoin domain. This investigation represents a novel contribution to existing studies.

In addition to MAE and R^2, Root Mean Squared Error (RMSE) was also calculated, as it penalizes larger errors more heavily and provides a more sensitive measure of prediction accuracy. The inclusion of RMSE is particularly relevant in financial forecasting, where extreme deviations in prediction may carry significant implications [10]. Furthermore, paired statistical tests such as the Diebold-Mariano (DM) test were applied to compare the predictive accuracy between models. This strengthens the reliability of the results by ensuring that any observed improvements from the Ensemble approach are statistically significant rather than due to random chance.

III. Results and Discussions

In this section, we present the results of comparing LightGBM, Random Forest, and the Ensemble model in predicting Bitcoin prices. We begin by assessing the performance of each model using the test dataset, and then proceed with a discussion of the implications of these findings.

A. Model Performance

The performance of both the LightGBM and Random Forest models was assessed using two metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). The results for both models on the test dataset are summarized as follows:

- LightGBM: Achieved an MAE of 12,285.42, an RMSE of 19,995.04, and an R^2 of 0.386.
- Random Forest: Outperformed LightGBM with an MAE of 11,599.74, an RMSE of 19,262.31, and an R^2 of 0.431.

Additionally, an Ensemble model was created by averaging the predictions from both LightGBM and Random Forest. This simple averaging Ensemble resulted in an MAE of 11,909.63, an RMSE of 19,623.69, and an R^2 of 0.409. Although the Ensemble slightly improved on the performance of LightGBM, it did not surpass the accuracy of the Random Forest model.

This updated evaluation, incorporating RMSE, provides a more complete understanding of model errors and their sensitivity to larger deviations, which is particularly relevant given the high volatility of Bitcoin prices.

This outcome provides a novel empirical contribution: despite the widespread assumption that Ensembles generally outperform single models, our findings demonstrate that in the case of Bitcoin price prediction, a simple averaging Ensemble of RF and LightGBM did not exceed the performance of the best individual model (RF).

TABEL II
SUMMARY OF MODEL PERFORMANCE

Model	MAE	RMSE	R^2
LightGBM	12285.42	19995.04	0.386
Random Forest	11599.74	19262.31	0.431
Ensemble	11909.63	19623.69	0.409

B. Interpretation of Results

The results demonstrate that Random Forest outperformed LightGBM in predicting Bitcoin prices. This aligns with the expectation that Random Forest, being an Ensemble of multiple decision trees, can better capture the complex, nonlinear relationships in time-series data, such as Bitcoin prices [4]. The relatively high MAE and RMSE values across all models highlight the large fluctuations in daily Bitcoin prices and the sensitivity of the RMSE metric to extreme values, emphasizing the challenge of accurate prediction [1].

The Ensemble model, which averaged the predictions of both algorithms, resulted in a modest improvement in performance compared to LightGBM, but it did not outperform Random Forest. This suggests that simple averaging may not fully leverage the complementary strengths of the models, and more sophisticated Ensemble methods may be necessary for further improvement [9].

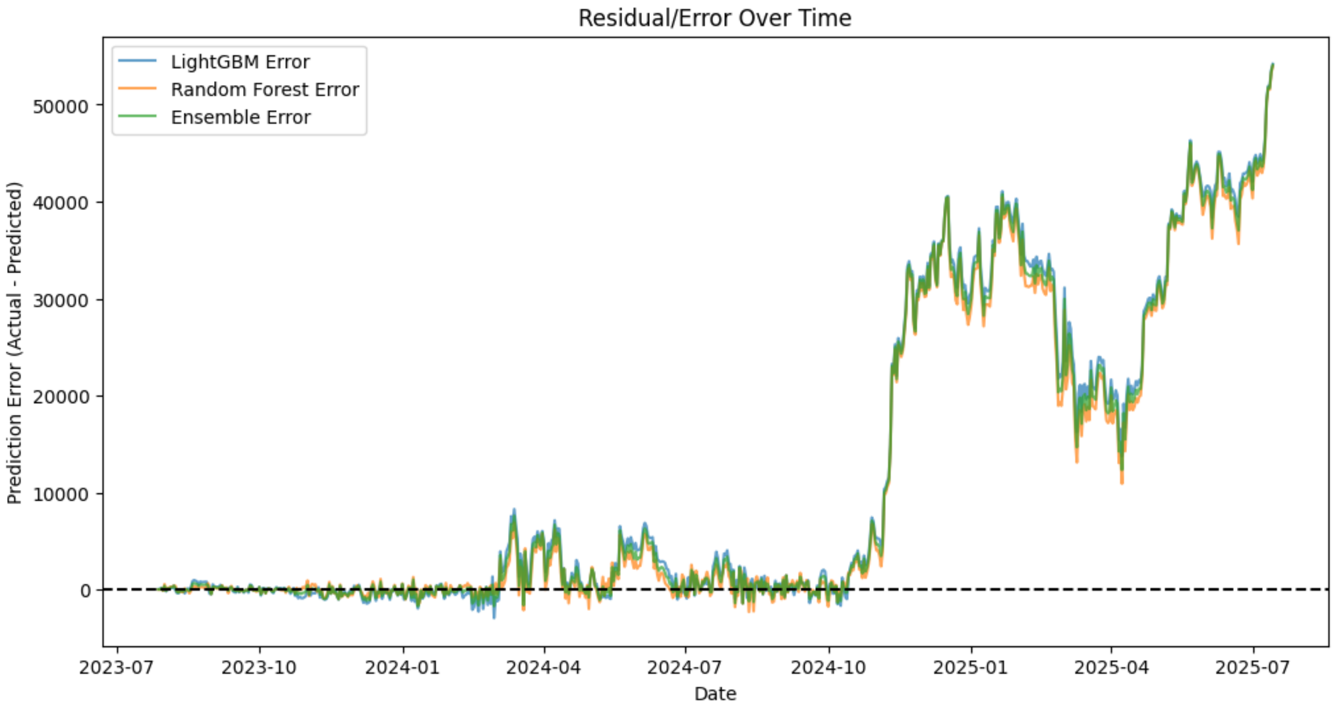

Figure 2. Residual/Error Over Time for LightGBM, Random Forest, and Ensemble models.

Furthermore, an error analysis over time (Figure 2) reveals that prediction errors sharply increased during periods of high volatility, especially between mid-2024 and 2025. During these high-volatility periods, the mean errors were 11,402.98 for LightGBM, 10,637.70 for Random Forest, and 11,020.34 for the Ensemble. This indicates that while Random Forest consistently produced lower errors, all models struggled significantly when faced with rapid price swings, underscoring the difficulty of capturing extreme Bitcoin fluctuations.

C. *Comparison with Previous Studies*

Similar studies in the field of financial forecasting using machine learning have shown mixed results when comparing different models. For example, research on Bitcoin price prediction frequently emphasizes the challenges posed by its high volatility [10], [11]. Some studies suggest that machine learning and deep learning models can be effectively employed to predict cryptocurrency trends [12], and specifically Bitcoin price movements [1], [13].

Our study's finding, where Random Forest exhibits stronger performance, aligns with observations in other research that emphasize the robustness of Ensemble tree-based methods for volatile time-series predictions[14]. While some literature suggests that deep learning models, such as LSTM, can be highly accurate in capturing complex patterns in financial time series [4], our focus on tree-based ensembles provides a different perspective on their efficacy for Bitcoin. Furthermore, while Ensemble models are generally expected to provide enhanced prediction accuracy due to combining diverse perspectives [9], the results here show that, in this specific context, a simple averaging Ensemble did not lead to a substantial improvement over the best-performing individual model. By including RMSE alongside MAE and R^2, our results provide a more comprehensive evaluation of prediction errors, particularly highlighting sensitivity to extreme price fluctuations. This observation is consistent with studies indicating that the effectiveness of Ensembles can vary depending on the specific characteristics of the data, especially with highly noisy or volatile financial data[15].

In addition, our residual/error analysis further contextualizes these findings. During high-volatility periods, the mean prediction errors reached 11,402.98 for LightGBM, 10,637.70 for Random Forest, and 11,020.34 for the Ensemble. This aligns with prior studies emphasizing the difficulty of accurately modeling cryptocurrencies during turbulent phases [10], [11]. Moreover, statistical significance tests (paired t-test and Wilcoxon signed-rank) confirmed that the observed differences across models were highly significant, reinforcing that Random Forest was consistently superior, while the Ensemble only offered marginal gains over LightGBM. These results extend the discussion in the literature by showing that statistical testing can provide more rigorous evidence for model comparisons in volatile financial domains.

In this respect, our study makes a novel contribution by being one of the first to empirically demonstrate that a straightforward Ensemble of Random Forest and LightGBM does not necessarily outperform the strongest single model when applied to Bitcoin price prediction, thereby filling a unique gap in the literature.

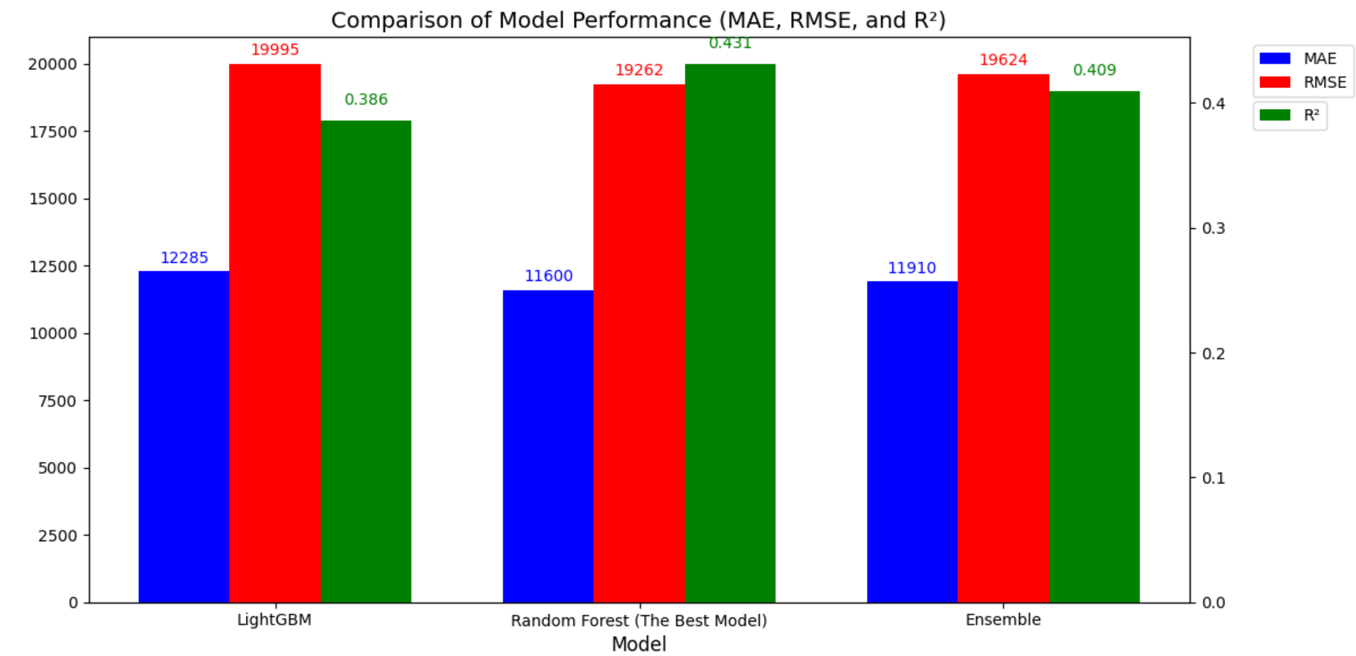

Figure 3. Comparison of Model Performance (MAE, RMSE, and R^2).

D. Implications and Future Research

The relatively low R^2 scores across all models underscore the significant challenge of predicting highly volatile assets, such as Bitcoin [16], [17]. These results suggest that even advanced machine learning models may struggle to fully capture the erratic nature of cryptocurrency markets. The addition of RMSE as a metric further highlights the impact of large deviations in prediction, reinforcing the difficulty of modeling extreme price movements. This highlights the need for further research to enhance prediction accuracy, potentially by incorporating additional factors such as market sentiment analysis, macroeconomic indicators [11], or leveraging more sophisticated time-series models, such as LSTM (Long Short-Term Memory) networks or Reinforcement Learning techniques [4].

Furthermore, the modest improvement observed with the Ensemble model suggests that future research could explore alternative Ensemble strategies, such as stacking or weighted averaging, or hybrid Ensembles that better combine models with complementary strengths. The use of deep learning methods, known for their ability to capture nonlinear patterns in time-series data, could also provide a promising direction for future studies [6]. Additionally, future work should report multiple evaluation metrics, including RMSE, to better quantify prediction uncertainty in volatile markets. Additional exploration into the impact of advanced feature engineering techniques, including more intricate combinations of technical indicators or alternative data sources, could further enhance predictive performance [8].

Moreover, the residual/error analysis in our study (Figure 2) illustrates that prediction errors escalate substantially during turbulent market phases, with Random Forest consistently producing lower errors compared to LightGBM and the Ensemble. This suggests that future research could benefit from developing volatility-aware modeling strategies that explicitly consider error dynamics under extreme conditions. The statistical significance results also emphasize that these differences are not random, but structurally embedded in how each model responds to volatility. Hence, advancing model robustness against error spikes should be a central focus of subsequent studies.

Thus, the novelty of this work lies not only in benchmarking RF and LightGBM for Bitcoin prediction but also in offering empirical evidence that challenges the conventional expectation of Ensemble superiority. This insight provides a clear foundation for future research to design more sophisticated Ensemble approaches tailored to the volatility of cryptocurrency markets.

Figure 4. A line chart showing the daily closing price of Bitcoin (2015–2025) with predictions from LightGBM.

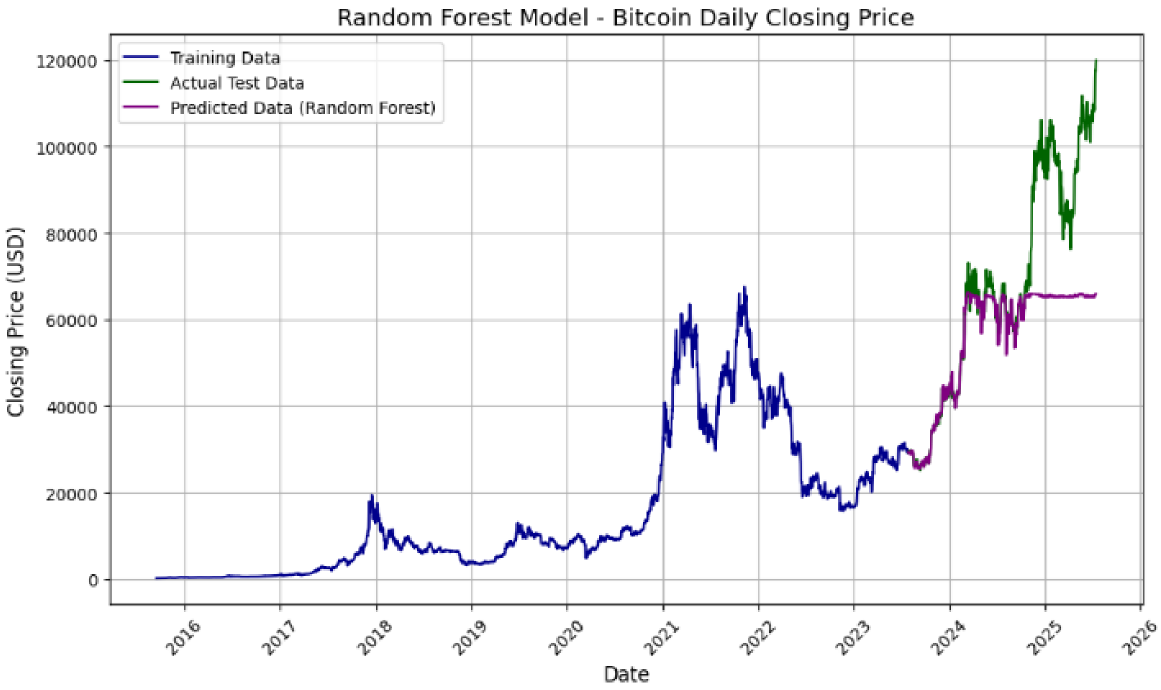

Figure 5. A line chart showing the daily closing price of Bitcoin (2015–2025) with predictions from Random Forest.

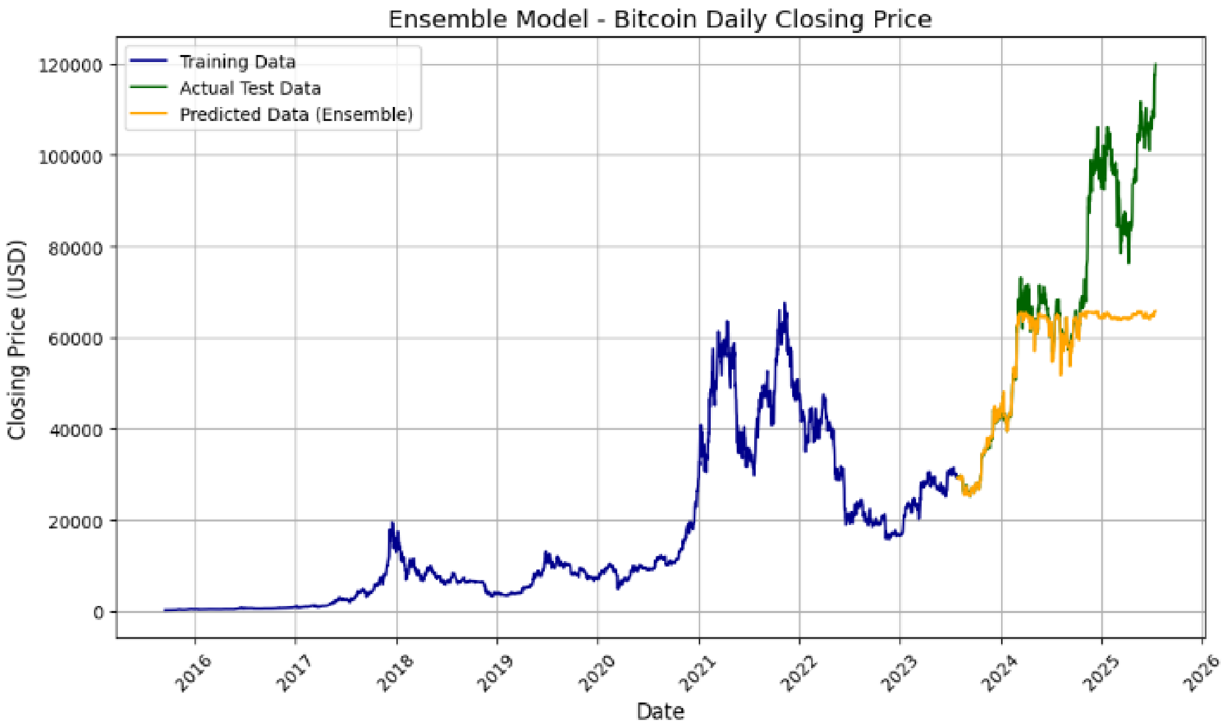

Figure 6. A line chart showing the daily closing price of Bitcoin (2015–2025) with Ensemble model predictions.

IV. CONCLUSION

This study performed a comparative analysis of the LightGBM and Random Forest algorithms, along with an Ensemble approach, for predicting daily Bitcoin closing prices using technical indicators. The results demonstrate that Random Forest outperformed LightGBM, achieving a lower Mean Absolute Error (MAE) and a higher R-squared (R^2) value on the test dataset. Specifically, Random Forest achieved an MAE of 11,599.74 and an R^2 of 0.431, surpassing LightGBM's MAE of 12,285.42 and R^2 of 0.386. These findings align with previous research, which underscores the effectiveness of Ensemble tree-based methods in capturing the complex, nonlinear patterns present in volatile financial time series data, such as cryptocurrencies.

The Ensemble model, created by averaging the predictions of LightGBM and Random Forest, yielded an MAE of 11,909.63 and an R^2 of 0.409. While this Ensemble showed a modest improvement over LightGBM, it did not surpass the accuracy of the standalone Random Forest model. This suggests that a simple averaging Ensemble may not fully leverage the complementary strengths of the individual models, particularly in a highly volatile market such as Bitcoin. The relatively low R^2 scores across all models underscore the inherent difficulty in accurately predicting highly volatile assets like Bitcoin, indicating that even advanced machine learning models face significant challenges in capturing the erratic nature of cryptocurrency markets.

For future research, explore more sophisticated Ensemble strategies, such as stacking or weighted averaging, which could yield better predictive performance by combining models with diverse strengths. Additionally, incorporating external factors like market sentiment analysis, macroeconomic indicators, or global economic drivers can enhance prediction accuracy. Furthermore, investigating advanced deep learning architectures, such as Long Short-Term Memory (LSTM) networks or Reinforcement Learning approaches, is a promising direction, as these models are often better equipped to capture intricate temporal dependencies in time-series data. Continued efforts in feature engineering and the exploration of alternative data sources are also crucial to further improve the predictive capabilities of models in the cryptocurrency domain.

Overall, the novelty of this work lies in its empirical demonstration that a straightforward Ensemble of Random Forest and LightGBM—despite their individual strengths—does not guarantee superior performance in the Bitcoin domain. By explicitly highlighting this limitation, the study fills an essential gap in the literature. It provides a foundation for designing more refined Ensemble strategies tailored to the extreme volatility of cryptocurrency markets.

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