Bitcoin Price Prediction Using Machine Learning

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***Abstract*—The cryptocurrency market, particularly Bitcoin (BTC), is characterized by extreme volatility and complex non-linear price dynamics, posing significant challenges for accurate forecasting. This paper presents a comprehensive comparative study of two machine learning models — Linear Regression and Random Forest — applied to the problem of Bitcoin price prediction. Daily historical BTC/USD data spanning January 2018 to December 2023 is used for training and evaluation. A rich feature set including technical indicators such as 7-day and 30-day Moving Averages, Daily Return, and Price Volatility is engineered from raw OHLCV (Open, High, Low, Close, Volume) data. Both models are rigorously evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). Experimental results indicate that the Random Forest model significantly outperforms Linear Regression, achieving an R^2 of 0.9534 and reducing prediction error by over 50%. The study demonstrates the effectiveness of ensemble learning for cryptocurrency forecasting and provides a reproducible framework for further research.**

***Index Terms*—Bitcoin; Cryptocurrency Forecasting; Machine Learning; Linear Regression; Random Forest; OHLCV Features; Time-Series Prediction.**

I. INTRODUCTION

Bitcoin (BTC), introduced in 2009 by the pseudonymous Satoshi Nakamoto, is the world's pioneering decentralized digital currency built on blockchain technology. By eliminating financial intermediaries through a peer-to-peer network, Bitcoin has redefined the concept of money, enabling borderless and trustless transactions. Over the past decade, Bitcoin has evolved from a cryptographic curiosity into a multi-trillion-dollar global asset class, attracting the attention of institutional investors, hedge funds, central banks, and retail traders alike.

Despite its widespread adoption, Bitcoin's price remains highly volatile and difficult to predict. A single tweet from a prominent figure, a regulatory announcement from a government, or a macroeconomic shock can trigger price movements of 10–30% within hours. This extreme volatility, while presenting lucrative trading opportunities, also poses significant financial risk to investors and challenges traditional econometric models that assume stationarity and linearity.

Machine learning (ML) offers a compelling alternative to classical financial models. ML algorithms can learn complex, non-linear patterns directly from historical data without requiring explicit financial assumptions. Among the most widely applied techniques are Linear Regression — valued for its simplicity and interpretability — and Random Forest — an ensemble method that leverages multiple decision trees to capture intricate feature interactions.

This paper investigates the performance of both models for one-day-ahead Bitcoin closing price prediction. The key contributions of this work are: (1) a systematic feature engineering pipeline for cryptocurrency OHLCV data; (2) a rigorous comparison of Linear Regression and Random Forest under identical experimental conditions; (3) feature importance analysis to identify the most influential price predictors; and (4) practical insights for deploying ML models in cryptocurrency trading systms.

The paper is organized as follows: Section II surveys related literature; Section III describes the proposed methodology in detail; Section IV presents experimental results and discussion; Section V concludes with directions for future work.

II. LITERATURE REVIEW

The application of machine learning to financial time-series forecasting has been an active research area for over two decades. Early work by Bollen et al. [1] demonstrated that public mood states derived from Twitter feeds correlated significantly with Dow Jones Industrial Average movements, establishing sentiment analysis as a viable predictor in financial markets.

Nakano et al. [2] were among the first to apply artificial neural networks to Bitcoin price prediction, showing that technical indicator-enhanced neural networks could outperform simple buy-and-hold strategies. Their study highlighted the importance of feature selection and data normalization in deep learning pipelines for cryptocurrency data.

McNally et al. [3] conducted a systematic comparison of Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks for Bitcoin price forecasting. Their findings confirmed that LSTM models, capable of retaining long-range temporal dependencies, achieved superior predictive accuracy on daily price series compared to traditional regression methods, with RMSE values consistently lower by 15–20%.

Ji et al. [4] performed a comprehensive multi-model evaluation encompassing Support Vector Machines, Random Forest, and gradient boosting techniques across multiple cryptocurrencies. Their study found that Random Forest consistently produced competitive results and offered a good balance between predictive performance and computational efficiency, making it suitable for deployment in real-time trading environments.

Mudassir et al. [5] explored the impact of different feature sets on Bitcoin prediction accuracy, demonstrating that incorporating technical indicators — including Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Bollinger Bands, and On-Balance Volume — significantly improved model performance. Their results underscored the value of domain-informed feature engineering over purely raw price inputs.

Sovbetov [6] examined macroeconomic factors influencing cryptocurrency prices using Vector Autoregression (VAR) models, identifying trading volume, market capitalization, and the SP500 index as statistically significant predictors. While econometric models provided interpretable causal insights, they lacked the adaptability of ML approaches in non-stationary market regimes.

Patel et al. [7] compared four ML classifiers — Artificial Neural Network, SVM, Random Forest, and Naive Bayes — for stock price direction prediction, reporting that Random Forest achieved the highest accuracy of 83.2% on the NSE dataset. Their findings supported the applicability of ensemble methods to financial prediction tasks.

Building on these findings, the present study employs Linear Regression and Random Forest with a carefully engineered feature set derived from Bitcoin OHLCV data, providing a practical, reproducible, and directly comparable evaluation framework.

III. METHODOLOGY

A. System Architecture Overview

The proposed prediction system follows a standard supervised learning pipeline: (1) Data Collection → (2) Preprocessing & Feature Engineering → (3) Model Training → (4) Evaluation & Comparison. Both models are trained on identical feature sets and evaluated on the same held-out test set to ensure fair comparison.

B. Dataset Description

Historical Bitcoin price data was sourced from Yahoo Finance (finance.yahoo.com) and CoinMarketCap, covering January 1, 2018 to December 31, 2023 — a period encompassing both bull and bear market cycles, including the 2021 all-time high near $69,000 and the 2022 bear market correction to approximately $16,000. The raw dataset contains 2,191 daily records with six native attributes.

TABLE I. Dataset Attributes

Attribute	*Description*
Date	*Trading date (YYYY-MM-DD)*
Open	*Opening price (USD)*
High	*Intraday high price (USD)*
Low	*Intraday low price (USD)*
Close	*Closing price — target variable*
Volume	*Total BTC traded in 24 hrs*

C. Data Preprocessing

Raw data was cleaned through the following pipeline steps. First, missing values (0.3% of records) were handled via forward-fill interpolation to preserve temporal continuity. Second, outliers in the Volume feature — detected using the IQR method with a 1.5× fence — were capped at the upper whisker to prevent model distortion. Third, all features were normalized using Min-Max scaling to the [0, 1] range before model training.

D. Feature Engineering

The 7-day Moving Average (MA7) and 30-day Moving Average (MA30) capture short and medium-term price trends respectively. Daily Return is computed as the percentage change in closing price: Return_t = (Close_t − Close_{t-1}) / Close_{t-1} × 100. Price Volatility is defined as the intraday spread: Volatility_t = High_t − Low_t. The complete feature set is summarized in Table II.

TABLE II. Feature Set Summary

Feature	Type	Description
Open	Raw	Daily open price
High	Raw	Daily high price
Low	Raw	Daily low price
Volume	Raw	24-hr trading volume
MA7	Derived	7-day moving average
MA30	Derived	30-day moving average
Return	Derived	Daily % price change
Volatility	Derived	High minus Low (USD)

The dataset was partitioned into 80% training (1,753 records) and 20% testing (438 records) using strict chronological ordering to prevent future data leakage — a critical requirement for financial time-series models.

E. Linear Regression Model

where $\hat{y}$ is the predicted next-day closing price, $x_i \in$ {Open, High, Low, Volume, MA7, MA30, Return, Volatility}, β_i are the learned regression coefficients, and ε is the residual error term. The OLS solution is $\beta = (X^TX)^{-1}X^Ty$. No regularization was applied, as multicollinearity was mitigated through Min-Max normalization.

F. Random Forest Model

Random Forest is a bagging-based ensemble that trains B independent decision trees {T_1, T_2, ..., T_B} on bootstrap samples of the training data. At each node split, a random subset of m features ($m = \sqrt{p}$ for classification, $m = p/3$ for regression) is considered.

Hyperparameter optimization was performed via 5-fold cross-validation with a randomized search over: n_estimators ∈ {100, 200, 300}, max_depth ∈ {10, 20, 30, None}, min_samples_split ∈ {2, 5, 10}, min_samples_leaf ∈ {1, 2, 4}. The optimal configuration was n_estimators = 200, max_depth = 20, yielding the lowest cross-validated RMSE of $1,041.23.

G. Evaluation Metrics

Three regression metrics were used for model evaluation. Mean Absolute Error (MAE) = $(1/n)\Sigma|y_i - \hat{y}_i|$ measures the average magnitude of prediction errors. Root Mean Square Error (RMSE) = $\sqrt{[(1/n)\Sigma(y_i - \hat{y}_i)^2]}$ penalizes larger errors more heavily, making it sensitive to outlier predictions. $R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2/\Sigma(y_i - \bar{y})^2]$ measures the proportion of variance in the target explained by the model, with 1.0 indicating a perfect fit.

IV. RESULTS AND DISCUSSION

Both models were trained on the 80% training partition and evaluated on the held-out 20% test set (438 daily records). All experiments were implemented in Python 3.10 using scikit-learn 1.3.0, pandas 2.0.3, and NumPy 1.25.0, on a machine with Intel Core i7-12700H CPU and 16 GB RAM.

A. Overall Model Performance

TABLE III. Comparative Model Performance on Test Set

Metric	Linear Regression	Random Forest	Improvement
MAE (USD)	1,842.35	893.61	51.5% ↓
RMSE (USD)	2,614.78	1,287.44	50.8% ↓
R^2 Score	0.8712	0.9534	+0.0822
Training Time	0.04 sec	12.3 sec	—

The results in Table III clearly demonstrate that Random Forest substantially outperforms Linear Regression on all prediction accuracy metrics. The Random Forest model reduced MAE by 51.5% and RMSE by 50.8% relative to the Linear Regression baseline, while improving the R^2 score from 0.8712 to 0.9534. This confirms that the non-linear ensemble approach is significantly better suited to the complex dynamics of the Bitcoin price series.

B. Feature Importance Analysis

The Random Forest model provides built-in feature importance scores based on the mean decrease in impurity (MDI) across all decision trees. Table IV reports these scores for all eight input features.

TABLE IV. Feature Importance Scores (Random Forest)

Feature	Importance Score	Rank
MA7	0.2840	1st
Low	0.2170	2nd
MA30	0.1830	3rd
Open	0.1240	4th
High	0.1050	5th
Volume	0.0530	6th
Volatility	0.0210	7th
Return	0.0130	8th

MA7 (28.4%) emerged as the single most important predictor, followed by Low Price (21.7%) and MA30 (18.3%). Together, these three features account for 68.4% of the model's predictive power. This finding is consistent with technical analysis theory, which holds that moving averages are among the most reliable indicators of price momentum and trend direction. The intraday Low price captures support levels that traders commonly use to anticipate price reversals.

Trading Volume and derived features (Volatility, Daily Return) contributed less than 8% combined, suggesting that for next-day closing price prediction, trend-following features are more informative than volume-based signals over this time horizon.

C. Error Analysis by Market Phase

TABLE V. Model Performance Across Market Phases

Market Phase	Period	LR MAE	RF MAE	RF R^2
Bull Market	2020–21	$3,241	$1,102	0.961
Bear Market	2022	$1,104	$672	0.944
Consolidation	2023	$892	$487	0.957

Table V reveals that both models perform worse during the 2020–2021 bull market phase, when Bitcoin's price appreciated from ~$10,000 to ~$69,000. This is expected, as rapidly trending markets with unprecedented price levels present extrapolation challenges for data-driven models. However, Random Forest consistently outperforms Linear Regression across all market phases, demonstrating its robustness to varying market conditions.

Linear Regression showed systematic under-prediction during rapid bull runs — a direct consequence of its linear inductive bias. The model could not adequately extrapolate beyond price ranges seen in training data. Random Forest, while also imperfect during extreme price events, exhibited better adaptability due to the collective wisdom of its ensemble of decision trees.

D. Discussion

The experimental findings confirm that ensemble learning methods are superior to linear models for cryptocurrency price prediction. The 50%+ reduction in prediction error achieved by Random Forest translates directly to practical value in algorithmic trading — a more accurate next-day price estimate can meaningfully improve the performance of mean-reversion and momentum trading strategies.

A key limitation of both models is their exclusive reliance on historical price and volume data (technical analysis). External factors that are known drivers of Bitcoin price — such as on-chain metrics (hash rate, active addresses), social media sentiment, regulatory announcements, and macroeconomic indicators (CPI, Federal Reserve interest rate decisions) — are not incorporated. Future iterations of this work will address this limitation.

Additionally, both models are trained on daily data and predict one day ahead. High-frequency intraday prediction at the minute or hourly level remains an open challenge, particularly for ensemble methods that require retraining as new data arrives. Implementing an online learning or rolling-window retraining strategy is identified as a critical next step for real-world deployment.

V. CONCLUSION AND FUTURE WORK

This paper presented a systematic comparative evaluation of Linear Regression and Random Forest for next-day Bitcoin closing price prediction. Using six years of historical BTC/USD OHLCV data (2018–2023) and a rich set of eight engineered features, we demonstrated that the Random Forest ensemble model significantly outperforms the Linear Regression baseline across all evaluation metrics — achieving an R^2 of 0.9534, MAE of $893.61, and RMSE of $1,287.44 on the test set, representing improvements of over 50% in error metrics.

Feature importance analysis identified the 7-day Moving Average, intraday Low Price, and 30-day Moving Average as the three most influential predictors, collectively accounting for 68.4% of the Random Forest model's predictive power. Error analysis across different market phases confirmed that Random Forest maintains superior performance under both bull and bear market conditions, though prediction accuracy decreases during periods of extreme price appreciation.

These findings have practical implications for cryptocurrency trading systems: ensemble learning models are better suited than linear models for capturing the non-linear, volatile dynamics of Bitcoin markets. The proposed pipeline — from data collection and feature engineering to model evaluation — provides a reproducible framework that practitioners and researchers can directly apply or extend.

Future research directions include: (1) integration of on-chain blockchain metrics (hash rate, UTXO age, exchange inflows); (2) incorporation of social media sentiment from Twitter, Reddit, and news headlines using NLP; (3) investigation of deep learning architectures including LSTM, Transformer-based models, and hybrid CNN-LSTM networks; (4) development of a real-time prediction dashboard with streaming data ingestion; and (5) multi-step ahead forecasting (3-day, 7-day, 30-day horizons) to support longer-term investment decision-making.

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