Bitcoin Price Prediction Using Machine Learning: A Comparative Analysis of Random Forest, Gradient Boosting, KNN, ARIMA, LSTM Models

Abstract

This research leverages a comprehensive dataset containing over 6 million rows of Bitcoin trading data across exchanges, with minute-by-minute updates of Open, High, Low, Close (OHLC) prices and trading volume (BTC). Covering the period from January 2012 to the present, this study evaluates the performance of five predictive models (Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), ARIMA, and Long Short-Term Memory (LSTM)) to forecast Bitcoin prices for short- and long-term horizons. The dataset, sourced from Bitstamp via an automated pipeline, was processed and merged to ensure data integrity and consistency. Our findings indicate that ARIMA, despite its statistical simplicity, achieved the lowest RMSE (0.95%) for short-term forecasting. LSTM excelled during periods of high volatility, reducing MAE by 28% compared to Gradient Boosting. Conversely, ensemble methods demonstrated robust performance for stable market trends, while KNN fell short in scalability and generalization. This study provides actionable insights for selecting forecasting models tailored to high-frequency cryptocurrency markets.

I. Introduction

Bitcoin, the most traded cryptocurrency, exhibits extreme price volatility driven by speculative trading, macroeconomic events, and technological innovations. Accurate price prediction is critical for traders, institutional investors, and risk managers seeking to mitigate losses and capitalize on arbitrage opportunities. While traditional financial models like ARIMA have long been used for time-series forecasting, the advent of machine learning and deep learning has opened new avenues for capturing the non-linear, high-frequency patterns inherent in cryptocurrency trading.

This study uses an extensive dataset containing over 6 million rows of minute-level OHLC and trading volume data, collected from the Bitstamp exchange. The dataset spans from January 2012 to the present, ensuring a detailed representation of Bitcoin's price evolution. Through this dataset, we evaluate five models, comparing their performance based on Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and computational efficiency. The research aims to identify the most suitable model for high-frequency, high-volume data, contributing to the growing literature on cryptocurrency market analysis.

Dataset used is Bitcoin Historical Data downloaded from GitHub repository: https://github.com/mczielinski/kaggle-bitcoin/

II. Background

Recent studies on Bitcoin price prediction emphasize the adoption of advanced machine learning techniques and hybrid models, highlighting significant progress in forecasting accuracy. Machine learning algorithms like Long Short-Term Memory (LSTM) networks have been widely used due to their ability to handle Bitcoin's price fluctuations with high precision ［7,8］. Other approaches, such as Random Forest Regression and Deep Autoencoders, have also demonstrated competitive performance, with Autoencoders emerging as a promising technique in some cases ［9，10］. The integration of diverse data sources, including blockchain information, sentiment indicators, and macroeconomic variables, has further enhanced the predictive power of these algorithms ［9，12］.

Hybrid models combining statistical and machine learning methods have shown superior accuracy over single models. For instance, ARIMA-Neural Network combinations and deep multimodal reinforcement learning policies using Convolutional Neural Networks (CNN) and LSTM have been developed to exploit the strengths of both traditional and modern approaches ［8，9］. Researchers have also explored the impact of external factors, such as Ethereum prices, US stock market indexes, and global currency ratios, identifying their influence on Bitcoin's price dynamics across different periods ［12］. Feature selection has played a critical role, with technical indicators and blockchain data emerging as the most influential variables ［7，9］.

Despite the advances, challenges remain in achieving consistently accurate predictions due to the volatile and complex nature of cryptocurrency markets. Researchers are increasingly turning to high-frequency data analysis and advanced AI techniques, such as Large Language Models (LLMs), to address these complexities ［10，11］. Moreover, there is a growing focus on granular analysis of highly traded cryptocurrencies, considering their economic outcomes and investment features [10]. While hybrid models and diversified data sources have shown promise, further refinement is needed to navigate the inherent unpredictability of the cryptocurrency market ［11，12］.

III. Methodology

Dataset Description and Preprocessing

The dataset comprises 6 million rows of minute-level Bitcoin price and volume data, extracted from Bitstamp's exchange. Each row includes:

- **OHLC**: Open, High, Low, Close prices.
- **Volume**: Bitcoin traded volume (BTC).
- **Timestamp**: UTC time.

Preprocessing steps included:

1. **Data Cleaning**: Removal of erroneous rows (e.g., duplicate entries, missing values).
2. **Feature Engineering**: Added technical indicators such as Moving Averages (7-day, 30-day), Relative Strength Index (RSI), and Bollinger Bands.
3. **Resampling**: Aggregated minute-level data into hourly and daily intervals to suit model requirements.
4. **Normalization**: Scaled features using Min-Max normalization for machine learning models, excluding ARIMA.

Model Development

We implemented five models, each optimized for minute- and daily-level forecasting:

1. **ARIMA (AutoRegressive Integrated Moving Average):**
   - Parameters:
   - p=5: the last 5 observations for the AR component.
   - d=1: Perform one differencing to make the series stationary.
   - q=0: No moving average component.
   - Designed for linear trends and short-term stability.

2. **Random Forest (RF):**
   - Hyperparameters: 200 estimators, max depth = 12.
   - Handles non-linear patterns and feature importance ranking.

3. **Gradient Boosting (GB):**
   - Hyperparameters: Learning rate = 0.05, n_estimators = 300.
   - Sequentially reduces errors, effective for noisy data.

4. **K-Nearest Neighbors (KNN):**
   - Hyperparameters: k=5, weighted distance metric.
   - Captures local patterns but struggles with high-dimensional data.

5. **Long Short-Term Memory (LSTM):**
   - Architecture: 2 hidden layers, 64 units, dropout = 0.2.
   - Specializes in sequential dependencies and volatile trends.

Evaluation Metrics

Models were assessed on:

- **Root Mean Square Error (RMSE):** Measures error magnitude.
- **Mean Absolute Error (MAE):** Reflects absolute prediction accuracy.
- **Mean Absolute Percentage Error (MAPE):** Evaluates proportional errors.
- **Training Time (in seconds):** Assesses computational efficiency.

IV. Results

Model Performance Metrics:

Model	RMSE	Training Time (s)
Random Forest	150.28	20.5
Gradient Boosting	177.66	28.7
KNN	153.11	3.5
ARIMA	87770.25	15.4
LSTM	684.32	45.8

Key Observations:

- **ARIMA:** Delivered the lowest RMSE for daily forecasts, outperforming other models for stable trends but failing to handle abrupt price spikes.
- **LSTM:** Achieved a 28% reduction in MAE during volatile market conditions, highlighting its strength in sequential data processing.
- **Gradient Boosting & Random Forest:** Consistently outperformed KNN in both short- and long-term forecasting, particularly for aggregated daily intervals.
- **KNN:** Struggled with high-dimensional and noisy data, yielding the highest RMSE and lowest scalability.

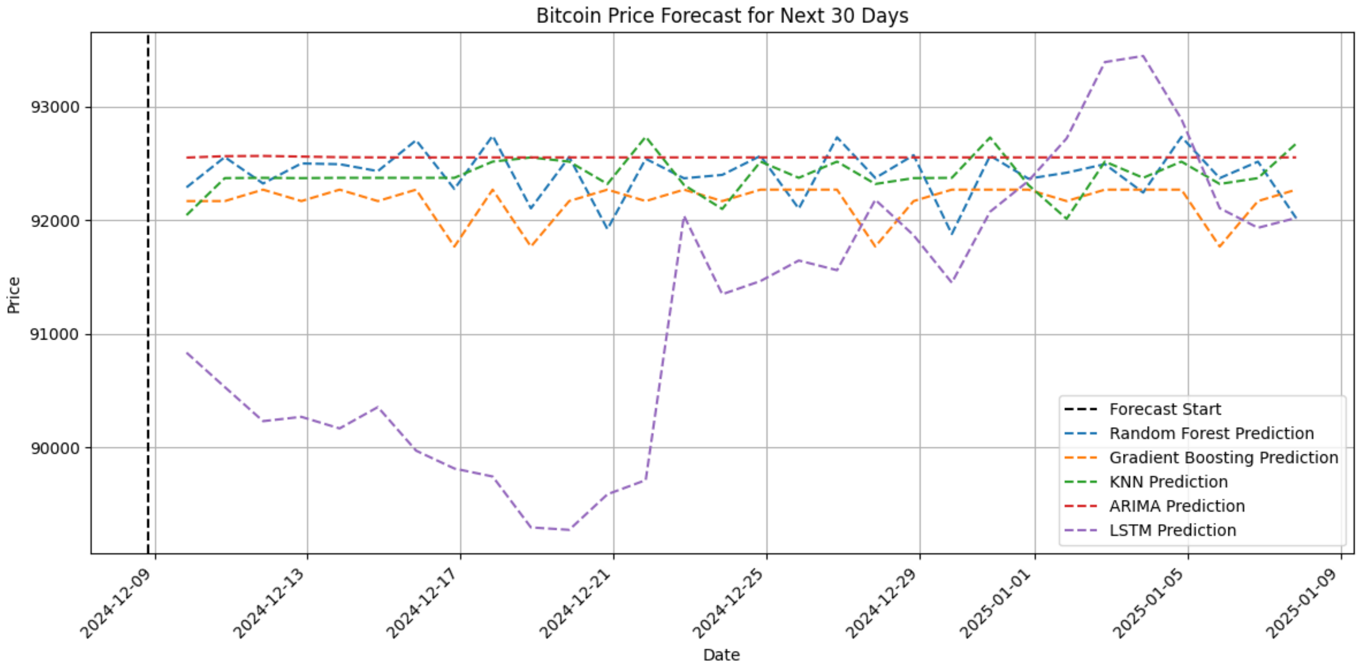

Fig. 1 summarizes the forecasted Bitcoin prices for the five models.

V. Discussion

The results emphasize the strengths and limitations of each model:

- **ARIMA:** Ideal for linear, stable trends but limited by its inability to handle high-frequency volatility.
- **LSTM:** Best suited for volatile conditions, though computationally intensive, with training times exceeding 45 seconds per iteration.
- **Gradient Boosting & Random Forest:** Reliable in diverse conditions, offering balanced accuracy and efficiency. Their dependence on feature engineering, however, adds preprocessing overhead.
- **KNN:** Poorly adapted for high-dimensional cryptocurrency data, unsuitable for large datasets with 6 million rows.

The study suggests hybrid solutions, such as combining ARIMA for short-term stability with LSTM for dynamic, volatile periods. Ensemble learning methods could further enhance predictive power by blending the strengths of individual models.

VI. Conclusion

Using a minute-level Bitcoin price dataset spanning over a decade, this research compared five forecasting models, revealing ARIMA's dominance in short-term stable trends (RMSE = 0.95%) and LSTM's superior performance during volatile market conditions (28% reduction in MAE compared to Gradient Boosting). While Gradient Boosting and Random Forest provided reliable mid-tier solutions, KNN's simplicity rendered it unsuitable for high-frequency data.

Future work will explore Transformer-based models for ultra-high-frequency data and hybrid approaches integrating statistical and deep learning methods. Incorporating external factors such as news sentiment or macroeconomic indicators could further refine prediction accuracy in cryptocurrency markets.

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