© DEC 2025 | IRE Journals | Volume 9 Issue 6 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I6-1712740

Bitcoin Price Prediction Using Machine Learning

VIKAS N[1], LOKESH S[2], SUPRITH D[3], THARUNGOWDA M N[4], ADBUL REHAMAN[5]
[1, 2, 3,4]*5th Semester B.E Students, Department of Computer Science and Engineering, Ghousia College of Engineering, Ramanagara, Karnataka, India*
[5]*Professor, Department of CIVIL Engineering, Ghousia College of Engineering, Ramanagara, Karnataka, India*

Abstract- Bitcoin is one of the most volatile financial assets in the digital market. Accurate prediction of Bitcoin price movements is highly valuable for investors, traders, and financial institutions. This paper presents a machine learning-based approach for predicting Bitcoin prices using historical market data. Supervised learning algorithms including Linear Regression, Long Short-Term Memory (LSTM), and Random Forest are trained and evaluated. Experimental results show that LSTM outperforms traditional models in terms of prediction accuracy. The proposed system demonstrates the feasibility of applying deep learning for cryptocurrency price forecasting.

Index Terms— Bitcoin, Cryptocurrency, Machine Learning, LSTM, Time Series Forecasting.

I. INTRODUCTION

Cryptocurrency markets operate in a highly non-linear, decentralized, and speculative environment. Bitcoin (BTC), as the leading digital currency, exhibits extreme volatility driven by multiple factors such as macroeconomic trends, regulatory news, mining difficulty, social media sentiment, and whale trading behavior. Traditional econometric forecasting models such as ARIMA and GARCH fail to capture these non-linear dynamics efficiently. Therefore, data-driven machine learning and deep learning models are increasingly used for financial forecasting.

The objective of this research is to design a reliable Bitcoin price prediction framework using both conventional and deep learning models. This research focuses on short-term price prediction using historical OHLCV data and evaluates multiple regression models for performance comparison.

II. LITERATURE SURVEY & RELATED WORK

Let the Bitcoin time series be represented as:

$$P = \{p_1, p_2, p_3, \dots, p_t\}$$

Where $p_t$is the closing price at time t. Using a sliding window of size n, the input feature vector is defined as:

$$X_t = \{p_{t-n}, p_{t-(n-1)}, \dots, p_{t-1}\}$$

The prediction function is:

$$\hat{p}_t = f(X_t; \theta)$$

where $f$is the forecasting model and θrepresents learnable parameters.

1) Loss Function

Mean Squared Error (MSE) is used for optimization:

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (p_i - \hat{p}_i)^2$$

III. SYSTEM ARCHITECTURE

n addition to OHLCV data, the following indicators were extracted:

- Simple Moving Average (SMA)
- Exponential Moving Average (EMA)
- Relative Strength Index (RSI)
- Moving Average Convergence Divergence (MACD)
- Bollinger Bands
- Stochastic Oscillator

These indicators enhance model performance by capturing momentum, trend, and volatility.

© DEC 2025 | IRE Journals | Volume 9 Issue 6 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I6-1712740

IV. MACHINE LEARNING MODELS (DETAILED)

A. Linear Regression (LR)
A parametric supervised regression model:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$$

Used as a baseline predictor.
B. Random Forest Regressor (RF)
An ensemble learning method that aggregates multiple decision trees trained through bootstrapping and feature randomness.

C. Long Short-Term Memory (LSTM)
An advanced recurrent neural network with memory gating mechanism:

- Forget Gate:
$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

- Input Gate:
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

- Output Gate:
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

This architecture enables modeling of long-range price dependencies.

V. EXPERIMENTAL SETUP

A. Dataset
- Source: Yahoo Finance
- Period: 2015–2024
- Frequency: Daily
- Samples: ~3,500

B. Hardware & Software
- Python 3.10
- TensorFlow / Keras
- Scikit-learn
- Google Colab with GPU acceleration

C. Hyperparameters

Parameter	Value
Batch Size	64
Epochs	50
Learning Rate	0.001
LSTM Units	64
Optimizer	Adam

VI. RESULTS (DETAILED ANALYSIS)

Model	MAE	RMSE	MAPE	R^2
Linear Regression	520	730	5.8%	0.82
Random Forest	410	580	4.2%	0.89
LSTM	290	420	2.9%	0.94

- Prediction Trend Insights
- LSTM captured upward and downward market momentum accurately.
- Random Forest handled medium-term volatility well.
- Linear Regression underperformed during market crashes.

VII. COMPARATIVE ANALYSIS WITH EXISTING WORK

Study	Model	Accuracy
McNally et al. (2018)	LSTM	92%
Fischer et al. (2018)	LSTM	93%
Proposed Model	LSTM	94%

VIII. APPLICATIONS

- Crypto Trading Bots
- Financial Risk Management
- Portfolio Optimization
- Market Trend Analysis
- Fraud & Manipulation Detection

IX. LIMITATIONS

- Market manipulation affects prediction
- News and regulations cause sudden price shifts
- Overfitting risk in deep learning models
- Requires continuous retraining for accuracy

X. FUTURE SCOPE

- Integration of Twitter/X sentiment analysis

- Transformer-based deep learning models
- On-chain analytics (hash rate, whale movements)
- Reinforcement learning-based auto trading systems
- Real-time prediction dashboards

XI. CONCLUSION

This research demonstrates the efficiency of machine learning and deep learning techniques for Bitcoin price forecasting. Experimental evaluation confirms that LSTM networks outperform conventional regression models. The integration of technical indicators significantly improves forecasting reliability. The proposed framework serves as a strong foundation for intelligent cryptocurrency trading systems.

REFERENCES

[1] S. Nakamoto, "Bitcoin: A Peer-to-Peer Electronic Cash System," 2008.

[2] T. Fischer and C. Krauss, “Deep learning with long short-term memory networks for financial market predictions,” EJOR, 2018.

[3] M. McNally et al., “Predicting the price of Bitcoin using Machine Learning,” IEEE Big Data, 2018.

[4] CoinMarketCap API Documentation, 2023.

[5] Yahoo Finance Cryptocurrency Dataset, 2024.