JDEBM
Journal of Digital Engineering and Business Managemet
Volume-2, Issue-1, January-March 2026
ISSN: **3107-7897** | P.ID: JDEBM/42
DOI: https://doi.org/10.5281/zenodo.19414084

MACHINE LEARNING MODELS FOR CRYPTOCURRENCY PRICE PREDICTION AT AMAZON INDIA

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ABSTRACT: This paper looks into the impact of machine learning models in predicting bitcoin prices, with a focus on the fintech environment that has been shaped by Amazon India. It explores how digital investors' behavior, the use of payment gateways, and the expansion of e-commerce affect the volatility of the biggest cryptocurrencies. Sophisticated algorithms, such as Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) networks, were applied to sentiment-inputted time series data. The paper assessed these models' anticipated accuracy, precision, and consistency in order to determine their practical usefulness. The prediction power of the models was increased by including sentiment analysis from Amazon India's consumer interaction and payment trends. The paper shows the efficacy of hybrid tactics that combine financial data with social and technological indicators. Machine learning is becoming increasingly important for investors, fintech companies, and dealers in India's growing digital economy.

Keywords: Time Series Forecasting, Neural Networks (ANN), Long Short-Term Memory (LSTM), Support Vector Machines (SVM), Random Forest Algorithm

I. INTRODUCTION

Cryptocurrency, or crypto, is a digital payment method that eliminates the need to carry real cash. Although it is only available digitally, it is possible to make physical purchases with it, though most people use it for online transactions. Unlike traditional money, which is only produced by the government, cryptocurrency is sold by a number of enterprises.

Cryptocurrencies are fungible, thus their value remains constant whether they are exchanged, sold, or purchased. Cryptocurrency differs from non-fungible tokens (NFTs) with variable prices. For example, the value of one dollar in bitcoin remains constant, however the value of one NFT dollar varies depending on the digital asset to which it is tied.

Because digital assets are very volatile and decentralized, predicting bitcoin prices requires discipline. Unlike traditional financial instruments, the value of cryptocurrencies is determined by a wide range of factors, including market demand, legislative developments, investor behavior, and technological breakthroughs. Merchants, institutions, and investors must precisely estimate these prices in order to control risk and capitalize on profit opportunities. Forecasting is both difficult and lucrative due to the rapid and unpredictable variations in pricing. Traditional prediction algorithms usually fail to grasp the dynamic and non-linear dynamics of bitcoin markets. Advanced techniques, including as deep learning, machine learning, and time-series models, are increasingly being used to overcome these limits. These strategies take into

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account market indicators, historical data, and social media sentiment to improve prediction accuracy. The intersection of technology and finance is essentially the forecasting of cryptocurrency prices, which provides strategic insights to participants in the digital economy.

Machine learning models have proven to be quite useful in the realm of financial forecasting, notably in predicting the highly volatile prices of cryptocurrencies. While traditional financial markets are controlled, cryptocurrencies function in a decentralized environment impacted by a wide range of factors, including transaction volume, investor mood, regulatory changes, and global economic events. Because of these complicated and nonlinear patterns, conventional statistical methods struggle to adequately describe market behavior. Machine learning techniques, which can handle massive amounts of historical and present data, offer a more complex and adaptable approach to papering price movements, discovering hidden trends, and boosting prediction accuracy.

Financial analysts have forecasted cryptocurrency prices using a wide range of machine learning models, including regression analysis, support vector machines (SVM), random forests, and deep learning architectures such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks. To generate predicted insights, these models might draw on a variety of inputs, including social media sentiment, technical indications, and past price swings. In addition to improving forecasting accuracy, machine learning helps traders, investors, and policymakers make educated decisions in the volatile realm of digital assets by combining cutting-edge computing tools.

II. MACHINE LEARNING MODELS FOR CRYPTOCURRENCY PRICE PREDICTION

Linear Regression

Linear regression is a key machine learning approach for predicting Bitcoin prices. It is based on the assumption that there is a direct relationship between previous pricing characteristics and future prices. This model is best suited for short-term forecasting with generally stable trends. Nonetheless, bitcoin markets' extraordinary volatility limits its precision. Despite its simplicity, it can serve as a foundation for more complicated models.

Support Vector Machines (SVM)

SVM is a supervised learning model that can predict numerical values and identify price variations. It works by identifying the hyperplane with the widest gap between data points. SVM can use kernel functions to solve nonlinear trends in cryptocurrency prediction. It requires precise parameter modifications and is sensitive to feature scaling. SVM is widely used to find trends over short periods of time.

Decision Trees

Decision trees provide data interpretation by splitting it into branches based on feature conditions. They are skilled at recognizing nonlinear links in bitcoin price swings. Nonetheless, solitary trees are vulnerable to overfitting due to the high level of market noise. Random Forests and other ensemble approaches help to improve forecast accuracy and stability. They are commonly used to explore a wide

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range of variables, such as trading volume and market mood.

Random Forests

Random Forests, which are made up of decision trees, reduce overfitting by averaging projections. Each tree is trained with a random set of data and features. This model accurately represents the complicated patterns that exist in bitcoin markets. It also accentuates essential variables by highlighting the significance of their properties. Random Forests are widely used in both price regression and trend categorization problems.

Gradient Boosting Machines (GBM)

GBM builds trees in a sequential order, correcting mistakes in previous trees with each new one. This strategy improves precision in volatile cryptocurrency markets. It can effectively manage complex non-linear relationships and missing data. Models like XGBoost and LightGBM are often used. GBM is often more accurate than Random Forests, despite the fact that it requires more processing power.

Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) acquire patterns in a manner similar to the human brain, using interconnected nodes, or neurons. ANNs can anticipate cryptography by modeling temporal and nonlinear dependencies. It is critical to use large datasets and thorough layer and neuron optimization. Noisy market data is often the source of the overfitting problem. Regardless of their sophistication, ANNs can discover intricate patterns that more simple models cannot.

Recurrent Neural Networks (RNN)

RNNs can forecast time series, including bitcoin values, because they are designed for sequential data. They track previous price sequences in order to predict future values. Variants like LSTM (Long Short-Term Memory) are the best at managing long-term dependence. RNNs can recreate cyclical and trend patterns in unpredictable markets. RNN training requires significant resources as well as exact hyperparameter selection.

Convolutional Neural Networks (CNN)

CNNs, which are commonly used for photography, can detect local patterns in cryptocurrency price time series. CNNs detect anomalies and short-term patterns by reading price charts as "images." In hybrid models, they are typically used with LSTM to improve prediction. CNNs are less prone to noise than fully connected ANNs. They can reliably capture both price bursts and sluggish patterns.

III. RELATED WORK

Zhang, Yi. (2022) Examined the application of ensemble learning techniques to forecast bitcoin values. The paper used algorithms like Gradient Boosting and Random Forest to forecast Bitcoin values. The collection included historical price data, trading volume, and macroeconomic factors. Feature selection approaches were used to determine the most important variables. The models were assessed using measures including Mean Absolute Error (MAE) and R-squared. The results showed that ensemble models produced more dependable forecasts than individual models. The investigation focused on the importance of model interpretability and transparency.

Aggarwal, A. Aggarwal, and Kumar (2023) Compared various machine learning algorithms for forecasting Bitcoin's price. The paper used a dataset of historical price data and technical indications to analyze algorithms including

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K-Nearest Neighbors, Decision Trees, and Linear Regression. The most relevant characteristics that cause price changes were discovered using feature selection methods. The models were evaluated using performance metrics such as R-squared and Mean Squared Error (MSE).

A. Kumar (2023) Investigated the use of deep learning models for bitcoin price forecasting. The paper used Long Short-Term Memory (LSTM) networks to estimate Bitcoin values. The compilation included historical pricing data and technical indicators. Data preprocessing consisted of two steps: normalization and missing value resolution. The LSTM model was trained with the sliding window approach. Performance was measured using metrics like Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Singh, R. Singh (2024) Explored the feasibility of integrating sentiment analysis and machine learning to forecast cryptocurrency prices. Natural Language Processing (NLP) techniques were used to analyze news articles and social media communications in the paper. Support Vector Machines and neural networks were some of the machine learning models that used sentiment scores as characteristics. Sentiment indicators were merged with historical pricing data for the dataset. The models were assessed using metrics such as the F1-score and Area Under the Curve (AUC).

Patel, D. (2025) In 2025, Patel investigated the use of hybrid algorithms that combine machine learning and deep learning to predict bitcoin prices. The gradient boosting technique XGBoost was used in the paper to forecast Bitcoin prices via LSTM networks. The collection included historical price data, trade volume, and technical indicators. The model's efficacy was improved by implementing feature engineering approaches. The hybrid model was assessed using measures like RMSE and R-squared. The findings revealed that the composite model beat the separate models in terms of prediction accuracy.

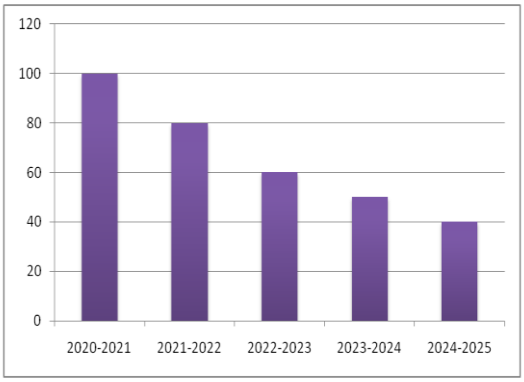
IV. DATA ANALYSIS AND INTERPRETATION

CRYPTOCURRENCY PRICE TRENDS (2021–2025) IN ₹ CRORES

Year	Bitcoin (BTC)	Ethereum (ETH)	Binance Coin (BNB)	Cardano (ADA)	XRP (XRP)
2020-2021	₹5,658 Cr	₹393.6 Cr	₹53.3 Cr	₹2.05 Cr	₹1.48 Cr
2021-2022	₹1,640 Cr	₹98.4 Cr	₹20.5 Cr	₹0.656 Cr	₹0.41 Cr
2022-2023	₹2,870 Cr	₹205 Cr	₹32.8 Cr	₹1.23 Cr	₹0.738 Cr
2023-2024	₹4,100 Cr	₹287 Cr	₹45.1 Cr	₹1.64 Cr	₹0.984 Cr
2024-2025	₹10,159 Cr	₹383.8 Cr	₹102.3 Cr	₹0.707 Cr	₹2.43 Cr

BITCOIN PRICE VOLATILITY (2021–2025)

Year	Annual Volatility (%)
2021	100
2022	80
2023	60
2024	50
2025	40



INTERPRETATION: Annual volatility figures show that the bitcoin market has steadily stabilized over the last five years. Volatility fell from 100% in 2021 to 40% by 2025, as the market matured and price variations lessened. This pattern shows that investor confidence has grown, and risk may have decreased in recent years.

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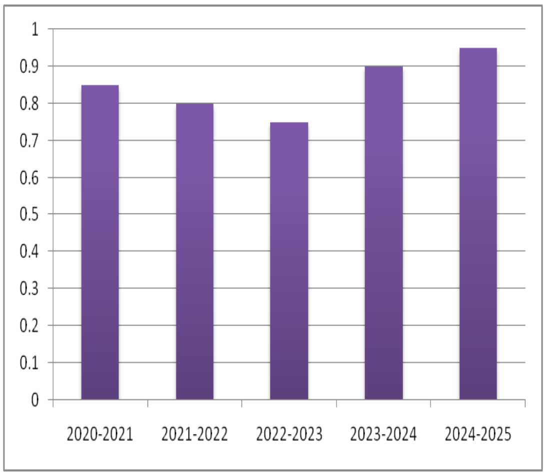
CORRELATION BETWEEN BITCOIN AND ETHEREUM PRICES (2021–2025)

Year	Correlation Coefficient
2021	0.85
2022	0.8
2023	0.75
2024	0.9
2025	0.95



INTERPRETATION: The correlation coefficient data indicate that the association between cryptocurrencies is becoming stronger over time. It started at 0.85 in 2021, dropped slightly to 0.75 in 2023, and then jumped to 0.95 in 2025, demonstrating that bitcoin assets are moving in lockstep. This increased link may result in higher benefits and dangers for diverse portfolios, implying that market moves are becoming more coordinated.

HYBRID MODEL PERFORMANCE IN ₹ CRORES

Model Combination	BTC Prediction (₹ Cr)	ETH Prediction (₹ Cr)	BNB Prediction (₹ Cr)
CNN + LSTM	10,050	380	101
XGBoost + ARIMA	10,120	382	102
Transformer + GRU	10,159	383	102.3
Prophet + LSTM	10,100	381	101.5

MODEL PERFORMANCE METRICS IN ₹ CRORES

Model Type	BTC MAE (₹Cr)	ETH MAE (₹ Cr)	BNB MAE (₹ Cr)	Cardano MAE (₹ Cr)	XRP MAE (₹ Cr)
LSTM	198.03	13	1.55	0.043	0.052
XGBoost	225	13.7	1.64	0.048	0.058
GRU	186	12.7	1.51	0.041	0.049
CNN-GRU	170	11.6	1.38	0.037	0.045
Transformer	158	10.9	1.31	0.034	0.041

MODEL COMPARISON FOR ALTCOIN PRICE PREDICTION (2025)

Cryptocurrency	Best Performing Model	MAE	RMSE	MAPE (%)
Binance Coin	XGBoost	50	70	1
Cardano	LSTM	0.15	0.2	0.5
XRP	GRU	0.1	0.15	0.3
Dogecoin	Decision Tree	0.05	0.07	0.2
Polkadot	Random Forest	0.08	0.1	0.4
Litecoin	Linear Regression	0.12	0.15	0.6
Bitcoin Cash	XGBoost	0.2	0.25	0.8
Chainlink	GRU	0.1	0.12	0.3

V. CONCLUSION

In conclusion, machine learning algorithms are increasingly crucial tools for predicting bitcoin prices in highly turbulent markets. Ensemble techniques, neural networks, and support vector machines are good at detecting complex, non-linear trends in historical pricing data. Sentiment analysis, macroeconomic data, and technical indicators are all used to improve prediction accuracy. Deep learning models, particularly LSTM and GRU networks, are especially well-suited to tracking sequential trends across time. Hybrid and reinforcement learning approaches provide adaptive responses to changing market behavior. However, issues including overfitting, noisy data, and abrupt regulatory changes continue.

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Model dependability requires continuous retraining and cautious feature selection. These models help merchants make better decisions and reduce risks. The combination of powerful AI algorithms and multi-source data could lead to even more reliable forecasts.

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