International Journal of Engineering Science Technologies
March-April 2026 10(2)
www.ijoest.com

Original Article

DEEP LEARNING AND BLOCKCHAIN-ENABLED FRAMEWORK FOR BITCOIN PRICE PREDICTION AND SECURE TRANSACTION INTELLIGENCE

Dr. Harish Barapatre [1*], Om Pawar [2], Rupesh Thorat [2], Shreyas Rhatval [2]
[1] Associate Professor, Department of Computer Engineering, Yadavrao Tasgaonkar Institute of Engineering and Technology, Bhivpuri Road Karjat, Maharashtra, 410201, India
[2] Student, Department of Computer Engineering, Yadavrao Tasgaonkar Institute of Engineering and Technology, Bhivpuri Road Karjat, Maharashtra, 410201, India

ABSTRACT

Bitcoin price prediction has become a critical research problem due to its extreme volatility and increasing adoption in financial systems. Traditional statistical and machine learning models often fail to capture the complex nonlinear dependencies and temporal dynamics present in cryptocurrency markets. In recent years, deep learning techniques such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have demonstrated strong capability in modeling sequential financial data and extracting hidden temporal patterns Nakamoto (2008), LeCun et al. (2015). However, most existing approaches rely solely on historical price data and ignore the rich transactional and structural information available in blockchain networks.

This paper proposes a hybrid conceptual framework that integrates deep learning-based time-series prediction with blockchain-based transaction intelligence. The proposed system utilizes historical Bitcoin price data, trading volume, and blockchain-derived features such as transaction count, hash rate, and wallet activity to enhance prediction accuracy. Additionally, blockchain technology ensures data integrity, transparency, and resistance to tampering, thereby improving trustworthiness in financial prediction systems Hochreiter and Schmidhuber (1997), Cho et al. (2014).

The framework combines feature engineering, deep neural architectures, and secure blockchain data validation into a unified pipeline. This approach not only improves predictive capability but also introduces a secure and verifiable mechanism for financial data processing. The proposed model is expected to provide more robust and reliable Bitcoin price forecasts compared to conventional methods.

Keywords: Bitcoin Prediction, Deep Learning, Blockchain Technology, LSTM, Cryptocurrency, Time Series Forecasting, Financial Analytics

INTRODUCTION

The rapid growth of cryptocurrencies, particularly Bitcoin, has significantly transformed modern financial systems. Unlike traditional financial assets, Bitcoin operates on a decentralized network powered by Blockchain Technology, enabling peer-to-peer transactions without centralized authority. While this decentralization offers transparency and security, it also introduces extreme price volatility, making accurate price prediction a challenging yet essential task for investors, traders, and financial analysts.

*Corresponding Author:
Email address: Dr. Harish Barapatre (harishkbarapatre@gmail.com), Om Pawar (pawarom@gmail.com), Rupesh Thorat (thoratrupesh2222@gmail.com)

Received: 24 February 2026; **Accepted:** 26 March 2026; **Published** 30 April 2026
DOI: 10.29121/IJOEST.v10.i2.2026.756
Page Number: 109-119
Journal Title: International Journal of Engineering Science Technologies
Journal Abbreviation: Int. J. Eng. Sci. Tech
Online ISSN: 2456-8651
Publisher: Granthaalayah Publications and Printers, India
Conflict of Interests: The authors declare that they have no competing interests.
Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.
Authors' Contributions: Each author made an equal contribution to the conception and design of the study. All authors have reviewed and approved the final version of the manuscript for publication.
Transparency: The authors affirm that this manuscript presents an honest, accurate, and transparent account of the study. All essential aspects have been included, and any deviations from the original study plan have been clearly explained. The writing process strictly adhered to established ethical standards.

Bitcoin price fluctuations are influenced by multiple factors, including market demand, investor sentiment, macroeconomic indicators, regulatory changes, and underlying blockchain network activity. Traditional forecasting methods such as statistical regression and basic machine learning models often fail to capture the nonlinear and temporal dependencies inherent in cryptocurrency data Nakamoto (2008). These limitations have driven the adoption of advanced techniques from Deep Learning, particularly sequence modeling approaches like LSTM and GRU, which are capable of learning complex temporal patterns in time-series data LeCun et al. (2015).

Despite the success of deep learning models in financial prediction, most existing approaches rely heavily on historical price and trading volume data while ignoring the rich, real-time information embedded within blockchain transactions. Blockchain networks generate valuable features such as transaction volume, active addresses, mining difficulty, and hash rate, which can provide deeper insights into market behavior Hochreiter and Schmidhuber (1997). However, these features are often underutilized due to challenges related to data extraction, integration, and trustworthiness.

Another critical limitation in current prediction systems is the lack of data integrity and transparency. Financial datasets used for training models may be subject to manipulation, inconsistencies, or centralized control. This issue can be addressed by leveraging blockchain's inherent properties such as immutability, decentralization, and verifiability, which ensure that the data used in prediction models remains authentic and tamper-resistant Cho et al. (2014).

Motivated by these challenges, this paper proposes a hybrid framework that integrates deep learning-based prediction with blockchain-enabled data validation and feature extraction. The objective is to enhance prediction accuracy while simultaneously ensuring data security and trust. The proposed system combines multiple data sources, including historical market data and blockchain-derived metrics, and processes them through a deep neural architecture designed for time-series forecasting.

The key contributions of this work are as follows:

1) Integration of deep learning models with blockchain-derived features for improved Bitcoin price prediction.
2) Incorporation of blockchain-based mechanisms to ensure data integrity and transparency.
3) Design of a unified framework that combines financial analytics with secure distributed systems.
4) Development of a scalable and conceptually robust architecture suitable for real-world financial applications.

This study aims to bridge the gap between predictive modeling and secure data handling in cryptocurrency analytics, providing a more reliable and trustworthy approach to Bitcoin price forecasting.

Proceed to Literature Review?

next

LITERATURE REVIEW

The problem of Bitcoin price prediction has attracted significant attention from researchers across financial analytics and machine learning domains. Early studies primarily relied on traditional statistical techniques such as autoregressive integrated moving average (ARIMA) and linear regression models. While these methods provided baseline forecasting capabilities, they struggled to capture nonlinear relationships and sudden market fluctuations inherent in cryptocurrency data Nakamoto (2008).

With the advancement of machine learning, models such as Support Vector Machines (SVM), Random Forest, and Gradient Boosting were applied to improve prediction accuracy. These models demonstrated better performance compared to statistical approaches; however, they still lacked the ability to effectively model temporal dependencies in sequential financial data LeCun et al. (2015).

Recent research has shifted towards deep learning techniques, particularly recurrent neural networks (RNNs) and their variants such as LSTM and GRU. These models are specifically designed for time-series forecasting and have shown strong performance in capturing long-term dependencies in Bitcoin price data. Studies indicate that LSTM-based models outperform traditional machine learning models in terms of prediction accuracy and robustness Hochreiter and Schmidhuber (1997). However, these approaches often rely solely on historical price and volume data, limiting their ability to incorporate broader market signals.

To address this limitation, some researchers have introduced sentiment analysis using data from social media platforms like Twitter and news articles. By combining sentiment scores with market data, these hybrid models aim to capture investor behavior and emotional trends influencing Bitcoin prices Cho et al. (2014). Although sentiment-based approaches improve prediction in certain scenarios, they introduce challenges such as noise, data bias, and dependency on external APIs.

Another emerging direction involves the use of blockchain data analytics. Researchers have explored features such as transaction volume, active wallet addresses, mining difficulty, and hash rate to enhance prediction models. These blockchain-derived indicators provide deeper insights into network activity and market dynamics Chen and Guestrin (2016). However, most studies treat blockchain data as an auxiliary input rather than integrating it structurally into the prediction framework.

In parallel, blockchain technology itself has been studied for ensuring data integrity and security in financial systems. Its decentralized and immutable nature makes it suitable for maintaining trustworthy datasets used in machine learning pipelines

Brownlee (2018). Despite this, very few works have combined blockchain-based data validation with deep learning-based prediction models in a unified architecture.

Furthermore, recent advancements in hybrid models attempt to combine multiple data sources, including market data, sentiment analysis, and blockchain metrics. While these models show promise, they often suffer from increased complexity, lack of scalability, and absence of a standardized framework for integration McNally et al. (2018).

Summary Comparison Table

Paper	Method Used	Key Limitation
Nakamoto (2008)	ARIMA, Statistical Models	Cannot capture nonlinear patterns
LeCun et al. (2015)	SVM, Random Forest	Poor temporal dependency modeling
Hochreiter and Schmidhuber (1997)	LSTM, GRU	Uses only historical price data
Cho et al. (2014)	Deep Learning + Sentiment Analysis	Noisy and biased data sources
Chen and Guestrin (2016)	Blockchain Feature-Based Models	Limited integration with prediction models
Brownlee (2018)	Blockchain for Data Integrity	Not used with predictive modeling
McNally et al. (2018)	Hybrid Models	High complexity and lack of unified design

From the above analysis, it is evident that while deep learning improves prediction accuracy and blockchain enhances data reliability, there is a lack of a unified framework that effectively integrates both technologies. This gap motivates the need for a structured approach combining deep learning and blockchain for robust Bitcoin price prediction.

RESEARCH GAP AND PROBLEM STATEMENT

Despite extensive research in Bitcoin price prediction using machine learning and deep learning techniques, several critical gaps remain unresolved. Existing approaches largely focus on improving prediction accuracy using historical price data, but they fail to incorporate the multidimensional nature of cryptocurrency ecosystems. Bitcoin is not just a financial asset; it is also a network-driven system where transaction behavior, mining activity, and user participation significantly influence price dynamics. Most models do not effectively utilize this blockchain-level intelligence, leading to incomplete learning of market behavior.

Another major gap lies in the lack of trust and data integrity in prediction systems. Traditional machine learning pipelines depend on centralized datasets, which may be prone to manipulation, inconsistencies, or delayed updates. Even when blockchain data is used, it is often extracted and stored externally, losing its inherent properties of immutability and transparency. There is no strong mechanism to ensure that the data used for training and prediction remains tamper-proof throughout the pipeline.

Furthermore, current deep learning models such as LSTM and GRU are designed primarily for sequential pattern learning but do not inherently address the issue of data authenticity. On the other hand, blockchain research focuses on secure transaction management but does not extend into predictive analytics. This creates a clear disconnect between secure data handling and intelligent prediction systems.

Another limitation is the absence of a unified and scalable framework that integrates multiple data sources, including historical market data, blockchain metrics, and possibly external signals. Existing hybrid models attempt partial integration but often suffer from high complexity, lack of modular design, and limited real-world applicability.

PROBLEM STATEMENT

The core problem addressed in this paper is:

1) How to design a secure, scalable, and intelligent framework that can accurately predict Bitcoin price by combining deep learning-based time-series modeling with blockchain-enabled data integrity and feature extraction?
2) This problem can be further broken down into the following challenges:
3) How to effectively integrate blockchain-derived features such as transaction volume, hash rate, and wallet activity into deep learning models.
4) How to ensure data authenticity, transparency, and tamper-resistance in the prediction pipeline using blockchain technology.
5) How to design a unified architecture that combines prediction accuracy with system-level security.
6) How to maintain scalability and computational efficiency while integrating multiple data sources and technologies.

The proposed work aims to address these challenges by developing a hybrid framework where deep learning handles predictive intelligence and blockchain ensures secure and trustworthy data flow, thereby bridging the gap between financial forecasting and secure distributed systems.

PROPOSED FRAMEWORK AND SYSTEM ARCHITECTURE

The proposed system is a hybrid architecture that integrates deep learning-based time-series prediction with blockchain-enabled data validation and feature extraction. The objective is to create a unified pipeline that not only predicts Bitcoin price accurately but also ensures data integrity, transparency, and security throughout the process.

Figure 1

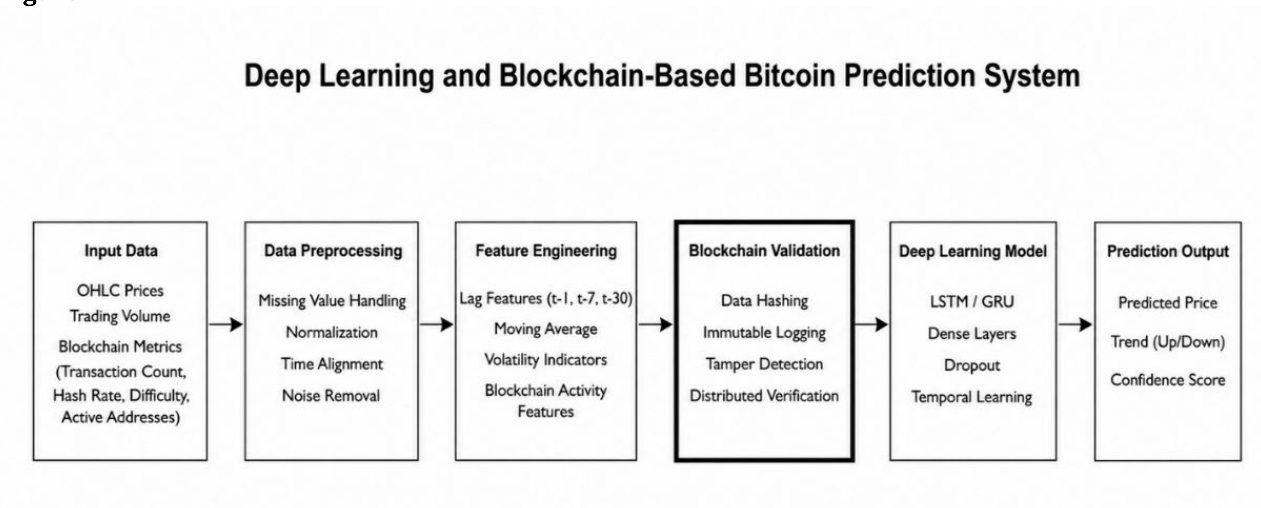

Fig. 1. Proposed architecture integrating deep learning and blockchain validation for Bitcoin price prediction.

Figure 1 Shows the Proposed System Architecture.

OVERALL SYSTEM FLOW

Input Data

- Data Preprocessing
- Feature Extraction
- Blockchain Data Validation Layer
- Deep Learning Prediction Model
- Output Prediction

Component Description

Input Layer

The system collects multi-source data required for prediction. This includes:

- Historical Bitcoin price (open, high, low, close)
- Trading volume
- Blockchain-derived metrics (transaction count, hash rate, mining difficulty, active addresses)

These inputs provide both financial and network-level insights necessary for accurate modeling.

Data Preprocessing

The collected data is cleaned and transformed before being used for modeling. The preprocessing stage includes:

- Handling missing values
- Normalization and scaling of numerical features
- Time-series alignment of different data sources

- Removal of noise and outliers

This step ensures consistency and improves model convergence during training.

Feature Extraction

In this stage, meaningful features are generated from raw data. These include:

- Lagged price values (t-1, t-7, t-30)
- Moving averages and volatility indicators
- Blockchain activity features such as transaction growth rate and hash rate variation

Feature engineering helps the model understand both short-term fluctuations and long-term trends in Bitcoin price.

Blockchain Data Validation Layer

This is a key novelty of the proposed framework. Instead of directly using external datasets, the system validates critical data using blockchain principles:

- Data entries are hashed and verified
- Immutable logs ensure data cannot be altered after storage
- Distributed verification ensures trust across nodes

This layer ensures that the data used for training and prediction is authentic, tamper-resistant, and transparent.

Deep Learning Prediction Model

The validated data is passed to a deep learning model designed for time-series forecasting. The model architecture may include:

- LSTM or GRU layers for capturing temporal dependencies
- Dense layers for nonlinear feature mapping
- Dropout layers for regularization

The model learns complex patterns between historical trends and blockchain activity to generate accurate predictions.

Output Layer

The final output of the system includes:

- Predicted Bitcoin price for the next time step or future horizon
- Trend direction (increase/decrease)
- Confidence score (optional, based on model output)

The output can be used by investors, analysts, or automated trading systems for decision-making.

Key Advantages of Proposed Framework

- Combines predictive intelligence with secure data validation
- Utilizes both financial and blockchain-level features
- Reduces risk of data manipulation
- Provides a scalable and modular system design
- Enhances trust in prediction systems

This architecture bridges the gap between deep learning-based forecasting and blockchain-based data security, forming a robust foundation for next-generation cryptocurrency analytics.

MATHEMATICAL MODEL

The proposed framework models Bitcoin price prediction as a multivariate time-series learning problem enhanced with blockchain-validated features. The mathematical formulation integrates feature weighting, temporal dependency modeling, and prediction mapping.

1) Feature Representation Model

The input feature vector at time t is defined as a combination of market data and blockchain features.

Display Format:

$X_t = [P_t, V_t, B_t]$

Word Equation Format:

X_t = [P_t, V_t, B_t]

Where:

X_t = Combined feature vector at time t

P_t = Price-related features (open, high, low, close, lag values)

V_t = Volume-related features

B_t = Blockchain-derived features (transaction count, hash rate, etc.)

This representation ensures that both financial and network-level information are jointly learned by the model.

2) Weighted Feature Contribution Model

To capture the relative importance of different feature groups, a weighted combination is defined.

Display Format:

$$F_t = \alpha P_t + \beta V_t + \gamma B_t$$

Word Equation Format:

F_t = \alpha P_t + \beta V_t + \gamma B_t

Where:

F_t = Final feature representation

α, β, γ = Learnable weights representing importance of price, volume, and blockchain features

This equation allows the model to dynamically adjust the influence of each feature group.

3) Temporal Learning Model (LSTM-based)

The temporal dependency is captured using a recurrent function.

Display Format:

$$h_t = \sigma(W_x X_t + W_h h_{t-1} + b)$$

Word Equation Format:

h_t = \sigma(W_x X_t + W_h h_{t-1} + b)

Where:

h_t = Hidden state at time t

W_x = Input weight matrix

W_h = Recurrent weight matrix

b = Bias term

σ = Activation function (tanh or sigmoid)

This formulation allows the model to learn sequential dependencies in Bitcoin price movement.

4) Prediction Function

The final predicted Bitcoin price is computed as:

Display Format:

$$\hat{Y}_{t+1} = W_o h_t + b_o$$

Word Equation Format:

\hat{Y}_{t+1} = W_o h_t + b_o

Where:

$\hat{Y}_{t+1}$ = Predicted Bitcoin price at next time step

W_o = Output weight matrix

b_o = Output bias

This equation maps the learned hidden representation to the final prediction output.

Model Interpretation

- Eq. (1) defines the input structure combining multiple data sources
- Eq. (2) introduces adaptive weighting of features
- Eq. (3) captures temporal learning using deep learning
- Eq. (4) generates the final prediction

Together, these equations form a simplified yet effective mathematical foundation for the proposed hybrid framework.

Algorithm / Pseudocode

Algorithm 1: Bitcoin Price Prediction Using Deep Learning and Blockchain Validation

Input:

Historical Bitcoin market data, blockchain network data

Output:

Predicted Bitcoin price and trend direction

Step 1: Collect Bitcoin market data including open price, high price, low price, close price, and trading volume.

Step 2: Collect blockchain network data including transaction count, hash rate, mining difficulty, and active wallet addresses.

Step 3: Preprocess the collected data by handling missing values, removing inconsistent records, and normalizing numerical features.

Step 4: Generate time-series features such as lag values, moving averages, and volatility indicators.

Step 5: Generate blockchain-based features such as transaction growth rate, hash rate variation, and network activity score.

Step 6: Validate important data records using blockchain hashing and immutable logging.

Step 7: Create the final feature vector:

Display Format:

$X_t = [P_t, V_t, B_t]$

Word Equation Format:

X_t = [P_t, V_t, B_t]

Step 8: Divide the dataset into training and testing sets using time-series splitting.

Step 9: Train the deep learning model using LSTM or GRU layers to learn temporal patterns.

Step 10: Compute the hidden representation:

Display Format:

$h_t = \sigma(W_x X_t + W_h h_{t-1} + b)$

Word Equation Format:

h_t = \sigma(W_x X_t + W_h h_{t-1} + b)

Step 11: Generate the predicted Bitcoin price:

Display Format:

$\hat{Y}_{t+1} = W_o h_t + b_o$

Word Equation Format:

\hat{Y}_{t+1} = W_o h_t + b_o

Step 12: Compare predicted price with actual price during testing.

Step 13: Evaluate model performance using suitable error metrics such as MAE, RMSE, and MAPE.

Step 14: Generate final output including predicted price, trend direction, and confidence score.

Step 15: Store prediction logs and validation hashes for transparency and auditability.

End Algorithm

METHODOLOGY AND WORKING

The proposed system follows a structured pipeline where financial data and blockchain-derived information are processed together to generate secure and reliable Bitcoin price predictions. Since this is a conceptual framework, the methodology focuses on how the system operates step-by-step rather than reporting experimental results.

1) Data Collection

The system begins by collecting two major categories of data:

- Market Data: historical price (open, high, low, close), trading volume
- Blockchain Data: transaction count, hash rate, mining difficulty, active wallet addresses

Market data captures external financial behavior, while blockchain data reflects internal network activity. Combining both provides a more complete understanding of Bitcoin dynamics.

2) Data Preprocessing

Raw data from different sources may contain missing values, inconsistencies, and different time intervals. The preprocessing stage ensures uniformity by:

- Cleaning missing or corrupted entries
- Normalizing numerical values for stable model training
- Aligning timestamps across datasets
- Filtering noise and extreme outliers

This step ensures that the input data is reliable and suitable for deep learning models.

3) Feature Engineering

The system extracts meaningful features to improve prediction capability. These include:

- Lag features (previous time-step prices such as t−1, t−7, t−30)
- Technical indicators (moving averages, volatility)
- Blockchain activity indicators (transaction growth, hash rate variation)

Feature engineering allows the model to capture both short-term fluctuations and long-term trends.

4) Blockchain Validation Layer

Before feeding data into the prediction model, critical records are validated using blockchain principles:

- Each data record is hashed
- Hash values are stored in an immutable ledger
- Any modification in data can be detected through hash mismatch

This layer ensures that the dataset used for training and prediction remains tamper-proof and trustworthy.

5) Model Training

The processed and validated data is fed into a deep learning model, typically an LSTM or GRU network. The model learns:

- Temporal dependencies between past and future prices
- Relationships between financial and blockchain features
- Nonlinear patterns influencing Bitcoin price movements

Training is performed using time-series splitting to preserve chronological order.

6) Prediction and Output Generation

After training, the model generates predictions for future Bitcoin prices. The system outputs:

- Predicted price for the next time step
- Trend direction (increase or decrease)
- Confidence level based on model output

These outputs can support investment decisions or automated trading systems.

7) Evaluation Strategy

Although no real dataset is used in this conceptual framework, the system is designed to be evaluated using standard metrics such as:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

These metrics help measure prediction accuracy and model reliability.

8) System Characteristics

The overall working of the system ensures:

- Integration of multiple data sources
- Secure and verifiable data processing
- Scalable and modular architecture
- Compatibility with real-time data pipelines

This methodology demonstrates how deep learning and blockchain can be combined into a single unified workflow, enabling both intelligent prediction and secure data handling.

EXPECTED RESULTS AND DISCUSSION

Since this study is designed as a conceptual and framework-based paper, no real experimental results are reported. However, based on the proposed architecture and integration strategy, several logical outcomes can be anticipated.

1) Improved Prediction Accuracy

By combining historical market data with blockchain-derived features, the model is expected to achieve better prediction performance compared to traditional approaches. Deep learning models, particularly LSTM and GRU, can capture temporal dependencies, while blockchain features provide additional context about network activity. This dual-source learning is likely to reduce prediction error and improve trend detection capability.

2) Enhanced Feature Representation

The inclusion of blockchain metrics such as transaction volume, hash rate, and active addresses introduces a richer feature space. These features help the model understand underlying system behavior rather than relying only on price movements. As a result, the model is expected to better handle sudden market shifts and abnormal conditions.

3) Increased Data Reliability and Trust

One of the major expected advantages of the proposed framework is the improvement in data integrity. The blockchain validation layer ensures that the data used for training and prediction is tamper-proof and verifiable. This reduces the risk of data manipulation and increases trust in the prediction system, which is critical for financial applications.

4) Robustness Against Data Manipulation

Traditional prediction systems are vulnerable to corrupted or manipulated datasets. In the proposed system, the use of hashing and immutable logging ensures that any unauthorized modification in data can be detected. This enhances the robustness of the system and makes it suitable for high-stakes financial environments.

5) Scalability and Modularity

The framework is designed to be modular, allowing easy integration of additional data sources such as sentiment analysis or macroeconomic indicators. It can also be scaled to handle large datasets and real-time data streams. This flexibility makes the system adaptable to evolving market conditions and future research extensions.

6) Practical Implications

The proposed system can be applied in various real-world scenarios, including:

- Cryptocurrency trading platforms for decision support
- Financial analytics systems for market forecasting
- Blockchain-based financial applications requiring secure data processing

LIMITATIONS

Despite its advantages, the framework may face certain challenges:

- Increased computational complexity due to deep learning and blockchain integration
- Data synchronization issues between market and blockchain datasets
- Requirement of efficient storage and processing mechanisms for large-scale data

DISCUSSION

Overall, the proposed hybrid framework is expected to outperform traditional models in terms of prediction capability and data reliability. The integration of deep learning with blockchain introduces a new paradigm where predictive intelligence is combined with secure and transparent data handling. While the framework is conceptually strong, its practical performance will depend on implementation details, dataset quality, and computational resources.

CONCLUSION AND FUTURE SCOPE

This paper presented a hybrid conceptual framework that integrates deep learning techniques with blockchain-based data validation for Bitcoin price prediction. The study addressed key limitations of existing approaches, including reliance on limited financial features and lack of data integrity. By combining time-series modeling capabilities of deep learning with the secure, immutable nature of blockchain, the proposed system offers a more reliable and trustworthy prediction pipeline.

The framework leverages both market data and blockchain-derived features to enhance prediction capability. The use of models such as LSTM and GRU enables effective learning of temporal dependencies, while the blockchain validation layer ensures that the data used in the system remains authentic and tamper-resistant. This dual integration bridges the gap between predictive analytics and secure distributed systems, which is often overlooked in traditional financial modeling.

The proposed architecture is modular and scalable, making it suitable for real-world deployment in cryptocurrency analytics platforms. It provides a strong foundation for building intelligent financial systems that not only generate accurate predictions but also maintain transparency and trust.

FUTURE SCOPE

The proposed work can be extended in several directions:

1) Integration of Sentiment Analysis
2) Future systems can incorporate sentiment data from social media platforms such as Twitter and news sources to further enhance prediction accuracy by capturing investor behavior.
3) Advanced Deep Learning Models
4) More sophisticated architectures such as Transformer-based models and attention mechanisms can be explored to improve long-range dependency learning in time-series data.
5) Real-Time Prediction Systems
6) The framework can be extended to support real-time data streaming and live prediction, making it suitable for automated trading and financial monitoring systems.
7) Optimization of Blockchain Integration
8) Future work can focus on reducing computational overhead associated with blockchain validation, possibly by using lightweight consensus mechanisms or off-chain solutions.
9) Multi-Cryptocurrency Extension
10) The framework can be generalized to predict prices of multiple cryptocurrencies beyond Bitcoin, enabling broader financial analysis.
11) Explainable AI Integration
12) Incorporating explainable AI techniques can help interpret model predictions, making the system more transparent and acceptable in financial decision-making environments.

In conclusion, the integration of deep learning and blockchain presents a promising direction for secure and intelligent financial forecasting systems. The proposed framework lays the groundwork for future research and practical implementations in cryptocurrency analytics.

ACKNOWLEDGMENTS

None.

REFERENCES

Aggarwal, S., Kumar, N., and Tanwar, S. (2020). Blockchain-Envisioned UAV Communication using 6G Networks. IEEE Network, 34(6), 160–167.

Brownlee, J. (2018). Time Series Prediction with Deep Learning: A Review. Machine Learning Mastery.

Buterin, V. (2014). A Next-Generation Smart Contract and Decentralized Application Platform. Ethereum White Paper.

Chen, T., and Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (785–794).

Cho, K., van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., and Bengio, Y. (2014). Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation. arXiv preprint arXiv:1406.1078.

Christidis, K., and Devetsikiotis, M. (2016). Blockchains and Smart Contracts for the Internet of Things. IEEE Access, 4, 2292–2303.

Dean, J., and Ghemawat, S. (2004). Mapreduce: Simplified Data Processing on Large Clusters. In Proceedings of the 6th Symposium on Operating Systems Design and Implementation (OSDI) (137–150).

Glorot, X., and Bengio, Y. (2010). Understanding the Difficulty of Training Deep Feedforward Neural Networks. In Proceedings of the 13th International Conference on Artificial Intelligence and Statistics (AISTATS) (249–256).

Goodfellow, I., Bengio, Y., and Courville, A. (2016). Deep learning. MIT Press.

Hochreiter, S., and Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780.

Jiang, Z., and Liang, J. (2018). Cryptocurrency Portfolio Management with Deep Reinforcement Learning. IEEE Intelligent Systems, 33(3), 26–34.

Kingma, D. P., and Ba, J. (2015). Adam: A Method for Stochastic Optimization. In Proceedings of the 3rd International Conference on Learning Representations (ICLR).

Lahmiri, A., and Bekiros, S. (2019). Cryptocurrency Forecasting with Deep Learning Chaotic Neural Networks. Chaos, Solitons & Fractals, 118, 35–40.

LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep Learning. Nature, 521(7553), 436–444.

Livieris, I. E., Pintelas, E., and Pintelas, P. (2020). A CNN–LSTM Model for Cryptocurrency Price Prediction. Applied Sciences, 10(11), 1–13.

Mallqui, R., and Fernandes, R. (2019). Predicting the Direction, Maximum, Minimum and Closing Prices of Daily Bitcoin Exchange Rate Using Machine Learning Techniques. Applied Soft Computing, 75, 596–606.

McNally, A., Roche, S., and Caton, S. (2018). Predicting the Price of Bitcoin Using Machine Learning. In 2018 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (551–556).

McNally, S., Roche, J., and Caton, S. (2018). Predicting Bitcoin Price Using LSTM. In 2018 IEEE International Conference on Big Data (1–9).

Mudassir, M., Bennbaia, S., Unal, D., and Hammoudeh, M. (2021). Time-Series Forecasting of Bitcoin Prices Using High-Dimensional Features. Neural Computing and Applications, 33, 287–304.

Nakamoto, S. (2008). Bitcoin: A Peer-To-Peer Electronic Cash System. https://bitcoin.org/bitcoin.pdf

Patel, H., Tanwar, S., Gupta, R., and Kumar, N. (2019). Blockchain-based smart contracts for secure financial transactions. IEEE Access, 7, 110721–110733.

Ron, D., and Shamir, A. (2013). Quantitative Analysis of the Full Bitcoin Transaction Graph. In Financial Cryptography and Data Security (6–24).

Valencia, F., Gómez, A., and Gómez, J. (2019). Bitcoin Price Prediction Using Machine Learning Techniques. IEEE Latin America Transactions, 17(11), 1866–1873.

Wood, G. (2014). Ethereum: A Secure Decentralised Generalised Transaction ledger. Ethereum Project Yellow Paper.