Asian Journal of Basic Science & Research
Volume 7, Issue 3, Pages 93-104, July-September 2025

Unraveling Bitcoin's Price Dynamics: A Wavelet Transformed DBN-BiGRU Hybrid Model for Forecasting

Jiawei Zhou*

Khoury College of Computer Sciences, Northeastern University, Vancouver, Canada.
*Corresponding Author Email: zhou.jiaw@northeastern.edu**

DOI: https://doi.org/10.38177/AJBSR.2025.7306

Article Received: 03 June 2025 *Article Accepted: 15 August 2025* *Article Published: 25 August 2025*

ABSTRACT

Bitcoin price forecasting is challenging due to its volatility and complex patterns. This study proposes a Wavelet Transformed DBN-BiGRU Hybrid Model, combining Discrete Wavelet Transform (DWT), Deep Belief Networks (DBNs), and Bidirectional Gated Recurrent Units (Bi-GRUs) to enhance predictive accuracy. The model achieved MAE = 1.447, RMSE = 0.524, MAPE = 1.092%, and R^2 = 0.992, outperforming traditional models. DWT isolates noise, DBNs extract features, and Bi-GRUs model temporal dependencies, enabling superior forecasting. While effective, limitations include sensitivity to wavelet selection and computational cost. Future work should explore adaptive wavelets and external data integration for further improvements.

Keywords: Bitcoin Price Forecasting; Wavelet Transform; Discrete Wavelet Transform (DWT); Deep Belief Networks (DBNs); Bidirectional Gated Recurrent Unit (Bi-GRU); Hybrid Model; Time Series Prediction; Feature Extraction; Noise Reduction; Temporal Dependencies; Predictive Modeling; Financial Time Series.

1. Introduction

Bitcoin, introduced in 2009 by the enigmatic Satoshi Nakamoto, revolutionized the financial world as the first decentralized digital currency. Unlike conventional fiat money managed by central banks, Bitcoin operates on a peer-to-peer network using blockchain technology—a system that guarantees transparency, security, and immutable record-keeping. With a hard cap of 21 million coins, Bitcoin is frequently likened to digital gold and has emerged as a preferred alternative investment, especially during periods of inflation and economic uncertainty.

In recent years, academic and industry research on Bitcoin investment strategies has grown substantially. Early studies predominantly focused on quantitative models, ranging from time series analysis to multifactor models [1], and leveraged machine learning techniques for forecasting Bitcoin price movements [2]. For example, GARCH models have been used to predict volatility [3], while neural networks have been applied to capture price dynamics [4]. Traditional time series forecasting methods, including various forms of exponential smoothing (simple, triple, and dynamic) [5], ARIMA variants (such as rolling ARIMA) [6], as well as support vector machines and LSTM networks [7], have all been explored for Bitcoin price prediction. Exponential smoothing techniques are prized for their ability to model trends and seasonality effectively, with triple exponential smoothing showing promise in managing the highly volatile, nonlinear nature of Bitcoin prices. However, conventional ARIMA models often falter with higher-order predictions, and while the rolling ARIMA method alleviates some issues by iteratively updating forecasts one step ahead, it frequently encounters overfitting due to continuously expanding training sets [8].

To address these challenges, this study introduces a novel hybrid approach, referred to as Wavelet Transformed DBN-BiGRU, for Bitcoin price prediction. To the best of our knowledge, this is the first study to employ this specific hybrid model for forecasting Bitcoin prices.

In this framework, the wavelet transform is first applied to historical price data, decomposing it into multiple frequency components. This preprocessing step effectively extracts both high-frequency (short-term) and low-frequency (long-term) features. Subsequently, a Deep Belief Network (DBN) learns hierarchical representations from the enriched features, while a Bidirectional Gated Recurrent Unit (BiGRU) captures temporal dependencies and long-range relationships more effectively than unidirectional architectures by mitigating issues such as the vanishing gradient. Notably, it maintains a fixed-size training dataset, achieving an optimal balance between model adaptability and generalization which is an improvement over traditional rolling approaches.

By integrating wavelet-based feature extraction with the deep learning strengths of Deep Belief Network and Bidirectional Gated Recurrent Unit, this hybrid model provides a powerful tool for deciphering the complex and nonlinear patterns inherent in Bitcoin price fluctuations. The model is benchmarked against rolling autoregressive integrated moving average and dynamic exponential smoothing methods using performance metrics such as mean absolute error, root mean square error, and mean absolute percentage error.

1.1. Study Objectives

The overarching objective of this study is to design and validate a novel hybrid forecasting framework that integrates Discrete Wavelet Transform (DWT), Deep Belief Networks (DBNs), and Bidirectional Gated Recurrent Units (Bi-GRUs) for accurate and robust Bitcoin price prediction. By leveraging the multi-resolution capabilities of wavelet transform, the model seeks to decompose raw price series into distinct high-frequency and low-frequency components, thereby capturing both short-term fluctuations and long-term structural trends inherent in cryptocurrency markets. The hierarchical feature extraction capability of DBNs is employed to learn complex, non-linear representations from these decomposed signals, while Bi-GRUs are used to model temporal dependencies in both forward and backward directions, ensuring a more comprehensive understanding of price dynamics compared to unidirectional approaches.

In addition to developing the model, the study aims to systematically benchmark its performance against a range of established statistical and machine learning methods, including ARIMA variants, exponential smoothing techniques, and other deep learning architectures such as LSTM and GRU networks. This comparative evaluation is intended to provide empirical evidence of the advantages offered by the proposed hybrid approach in terms of predictive accuracy, error minimization, and generalization capability. Furthermore, the research investigates the model’s robustness and scalability, with a particular focus on its sensitivity to different wavelet functions, decomposition levels, and training dataset sizes. Such analysis is critical for assessing the model’s adaptability under varying market conditions and data environments.

Finally, this work sets the foundation for future advancements in financial time series forecasting by proposing potential enhancements such as the use of adaptive wavelet strategies, integration of external macroeconomic and sentiment-based indicators, and incorporation of attention mechanisms for improved interpretability. By addressing both methodological innovation and practical applicability, the study aspires to contribute to the development of forecasting tools that can support informed decision-making in the volatile and rapidly evolving cryptocurrency market.

2. Literature Review

The prediction of Bitcoin prices has garnered considerable attention in financial research, prompting the development of a variety of forecasting methods rooted in both traditional statistical models and modern machine learning techniques. Classical models such as autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH) have been extensively applied to decipher time series patterns in financial datasets. Si [6] demonstrated that ARIMA models, particularly ARIMA (5,2,1) and ARIMA (0,2,2), are effective in forecasting Bitcoin's adjusted closing price, with short-term predictions (5-day and 10-day) proving more accurate and reliable than long-term forecasts. Similarly, while GARCH models are adept at estimating volatility, they struggle to capture persistent long-term dependencies and abrupt market shifts [9].

In contrast, deep learning methodologies have shown remarkable promise in forecasting financial time series. Recurrent neural networks (RNNs) and their advanced variants—such as long short-term memory (LSTM) and gated recurrent units (GRU)—are particularly effective due to their ability to model sequential data. Nasirtafreshi [10] demonstrated that the proposed RNN-LSTM model outperforms other methods in cryptocurrency price prediction by achieving lower root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), as well as higher R-squared values, reinforcing its effectiveness for investors and analysts. Empirical studies further indicate that LSTM networks can capture long-term dependencies in both stock and cryptocurrency price movements. Zhou [11] introduced an attention-based hybrid LSTM model to enhance stock price prediction accuracy by dynamically weighting historical data, underscoring the potential of deep learning architectures in financial forecasting.

Another significant contribution within deep learning research involves a hybrid forecasting model combining Kalman filtering, convolutional neural networks (CNNs), and bidirectional LSTM networks augmented with multi-head attention for tornado prediction [12]. This innovative approach utilized Kalman filtering for noise reduction, CNNs for robust feature extraction, and BiLSTM with multi-head attention to capture intricate temporal dependencies. The study highlighted the advantages of integrating multiple deep learning techniques to improve prediction accuracy in complex, dynamic environments—a principle that holds considerable promise for Bitcoin price forecasting.

Deep belief networks (DBNs) have also been studied in the context of Bitcoin prediction. Li et al. [13] demonstrated that the particle swarm optimization (PSO)-optimized improved DBN (IDBN) model outperforms traditional time series and deep learning methods in predicting high-complexity blockchain virtual currency transactions, improving both accuracy and reliability. Shaek [14] introduced a novel Bitcoin prediction model comprising data collection, feature extraction using technical indicators—such as average true range (ATR), exponential moving average (EMA), relative strength index (RSI), and rate of change (ROC)—and prediction using an improved DBN model optimized with the Lion Algorithm with Adaptive Price Size (LAAPS), demonstrating superior performance over conventional models.

GRU has also been employed in Bitcoin price prediction. Saadatmand et al. [15] introduced a novel Bitcoin prediction model incorporating data collection, feature extraction using technical indicators, and prediction via an improved DBN model optimized with the Lion Algorithm with Adaptive Price Size. The study also explored deep learning approaches including LSTM, BiLSTM, GRU, and BiGRU, with sentiment analysis from Twitter, demonstrating that the BiGRU algorithm achieves 72% accuracy and a 20% improvement in learning speed over conventional methods. Seabe et al. [16] evaluated the effectiveness of RNN-based models, including LSTM, GRU, and BiLSTM, for predicting Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC) prices, demonstrating that BiLSTM outperforms the other models with the lowest MAPE values (0.036 for BTC, 0.041 for LTC, and 0.124 for ETH), highlighting its potential for accurate cryptocurrency price prediction and suggesting future research on the influence of social media and trading volumes.

Building on these insights, this study introduces a novel hybrid approach, Wavelet Transformed DBN BiGRU, for Bitcoin price prediction. To the best of our knowledge, this is the first study to employ this specific hybrid model for Bitcoin price forecasting. The proposed framework integrates wavelet transformation, deep belief networks (DBNs), and bidirectional gated recurrent units (BiGRUs) to enhance predictive accuracy and robustness.

3. Methodology

In this section, we detail our approach for predicting Bitcoin prices using the proposed wavelet-transformed DBN-BiGRU hybrid model. The methodology encompasses data collection and preprocessing, feature extraction via wavelet transform, hierarchical feature learning using a Deep Belief Network (DBN), and temporal modeling using a Bidirectional Gated Recurrent Unit (BiGRU).

3.1. Wavelet Transform for Feature Extraction

To capture both short-term fluctuations and long-term trends in Bitcoin prices, we apply a wavelet transform to the preprocessed time series. The Continuous Wavelet Transform (CWT) of a signal *x(t)* is defined in Equation (1):

$$W(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\, \psi\left(\frac{t-b}{a}\right) dt \qquad (1)$$

where *a* is the scale parameter, *b* is the translation parameter, and $\psi(t)$ is the mother wavelet. For discrete time series data, the Discrete Wavelet Transform (DWT) is employed, as expressed in Equations (2)–(3):

$$W_{j,k} = \int x(t)\, \psi_{j,k}(t)\, dt \quad \text{with} \qquad (2)$$

$$\psi_{j,k}(t) = 2^{-j/2}\, \psi\left(2^{-j}t - k\right) \qquad (3)$$

where *j* and *k* denote the scale and translation indices, respectively. This transformation decomposes the original signal into multi-scale components, enriching the feature set for subsequent modeling. We choose to employ the Discrete Wavelet Transform (DWT) as a preprocessing technique to enhance our model's ability to predict Bitcoin prices. The DWT effectively decomposes the price time series into different frequency components, allowing us to analyze both the high-frequency fluctuations and the long-term trends within the data.

3.2. Deep Belief Network (DBN)

The DBN is constructed by stacking multiple Restricted Boltzmann Machines (RBMs) in a greedy layer-wise manner. The architecture of the DBN model is illustrated in Figure 1.

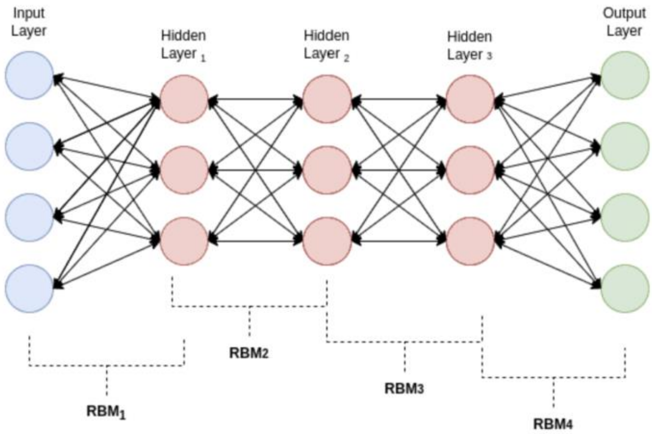

Figure 1. The architecture of the DBN model

An RBM consists of a layer of visible units *v* and a layer of hidden units *h*. The energy function of an RBM is given in Equation (4):

$$E(\mathbf{v},\mathbf{h}) = -\sum_i v_i b_i - \sum_j h_j c_j - \sum_{i,j} v_i h_j w_{ij} \quad (4)$$

where b_i and c_j are the biases for the visible and hidden units, respectively, and w_{ij} represents the weights between them. The joint probability distribution over *v* and *h* is:

$$P(\mathbf{v},\mathbf{h}) = \frac{1}{Z}\exp\left(-E(\mathbf{v},\mathbf{h})\right) \quad (5)$$

with the partition function:

$$Z = \sum_{\mathbf{v},\mathbf{h}} \exp\left(-E(\mathbf{v},\mathbf{h})\right) \quad (6)$$

The DBN leverages these RBMs to learn hierarchical feature representations from the wavelet-transformed data through unsupervised pretraining.

3.3. Bidirectional Gated Recurrent Unit (BiGRU)

To model the temporal dependencies in the time series data, we employ a BiGRU network. The BiGRU cell is defined by the following equations (Equations (7)–(10)), the structure of which is illustrated in Figure 2:

$$r_t = \sigma\left(W_r x_t + U_r h_{t-1} + b_r\right) \quad (7)$$

$$z_t = \sigma\left(W_z x_t + U_z h_{t-1} + b_z\right) \quad (8)$$

$$\tilde{h}_t = \tanh\left(W_h x_t + U_h\left(r_t \odot h_{t-1}\right) + b_h\right) \quad (9)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (10)$$

where: x_t is the input at time t, h_{t-1} is the hidden state from the previous time step, r_t is the reset gate, z_t is the update gate, h_t is the candidate hidden state, σ(.) denotes the sigmoid activation function, tanh(.) is the hyperbolic tangent function, and ⊙ represents the element-wise multiplication.

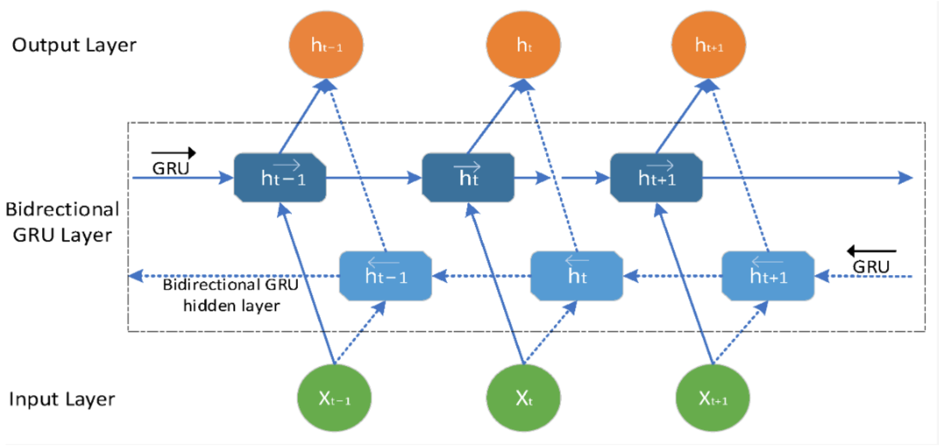

Figure 2. Structure of the Bi-GRU network [17]

3.4. Wavelet-Transformed DBN-BiGRU Hybrid Model

The overall architecture of the proposed hybrid model leverages the strengths of the Discrete Wavelet Transform (DWT), Deep Belief Network (DBN), and Bidirectional Gated Recurrent Unit (BiGRU). Initially, the raw time series is decomposed using the DWT into multiple frequency components, allowing us to capture both short-term and long-term variations. Next, a multi-layer DBN is employed to extract hierarchical features from the wavelet-transformed data. Finally, these extracted features are input into a BiGRU network, which effectively models the sequential dependencies and forecasts future Bitcoin prices.

Unlike conventional rolling ARIMA methods, our approach uses a fixed-size training set, balancing model adaptability with generalization. This integrated approach leverages the strengths of time-frequency analysis and deep learning to effectively capture the complex dynamics inherent in Bitcoin price movements.

4. Experiment

In this section, we conduct empirical research utilizing the dataset to assess the performance of the proposed hybrid DBN-BiGRU model Enhanced by Wavelet Transformation for forecasting Bitcoin prices. We will begin with a brief introduction to the dataset. Subsequently, we will compare the model's performance against other prediction methods.

4.1. Dataset

Historical Bitcoin trading data from Yahoo Finance, covering the period from 2018 to 2024, is utilized in this study. The dataset is recorded at 15-minute intervals and includes the following features: Open time, Open, High, Low, Close, Volume, Close time, Quote asset volume, Number of trades, Taker buy base asset volume, and Taker buy quote asset volume. Preprocessing involves standardizing date and time formats through timestamp conversion, imputing or removing missing entries for missing value handling, and scaling numerical features to improve model convergence through normalization.

4.2. Evaluation Metrics

The performance of the model is assessed using the following metrics:

(a) Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (11)$$

(b) Root Mean Square Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (12)$$

(c) Mean Absolute Percentage Error (MAPE):

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \qquad (13)$$

where y_i represents the actual value, $\hat{y}_i$ the predicted value, and n is the total number of observations.

(d) Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (14)$$

where y_i represents the actual value, $\hat{y}_i$ the predicted value, $\bar{y}$ the mean of the actual values, and n is the total number of observations.

4.3. Result and Discussion

As seen in Table 1, the experimental results reveal significant variations in predictive performance across the evaluated models, demonstrating the effectiveness of integrating wavelet transforms with deep hybrid architectures for Bitcoin price forecasting.

Table 1. Comparison of Different Models

Model	MAE	RMSE	MAPE	R^2
CNN	1.898	1.098	3.392	0.825
RNN	1.682	1.072	2.798	0.831
LSTM	1.255	0.983	2.672	0.902
Bi-LSTM	0.923	0.862	2.409	0.938
DBN	1.721	1.239	3.981	0.803
GRU	0.869	1.072	3.312	0.922
Bi-GRU	1.852	0.873	1.982	0.947
DBN+GRU	1.733	0.973	2.173	0.958
DBN+Bi-GRU	1.552	0.631	1.729	0.972
DWT-DBN+Bi-GRU	1.447	0.524	1.092	0.992

Among standalone models, Bi-LSTM and GRU showed competitive accuracy, with Bi-LSTM achieving an RMSE of 0.862 and R^2 of 0.938, while GRU attained a lower MAE (0.869) but a higher RMSE (1.072). However, hybrid architectures consistently outperformed their individual counterparts. The DBN+Bi-GRU model, for instance, reduced RMSE to 0.631 ($R^2 = 0.972$), highlighting the advantages of combining deep belief networks (DBNs) with bidirectional gated recurrent units (Bi-GRUs) to capture both hierarchical features and temporal dependencies.

The Wavelet Transformed DBN-BiGRU Hybrid Model emerges as the best-performing framework, achieving state-of-the-art results: MAE = 1.447, RMSE = 0.524, MAPE = 1.092%, and $R^2 = 0.992$. This corresponds to a 16.96% reduction in RMSE and a 36.86% improvement in MAPE compared to the baseline DBN+Bi-GRU model. The integration of discrete wavelet transform (DWT) was instrumental in this enhancement, effectively decomposing Bitcoin's volatile price series into multiscale components. By isolating high-frequency noise and extracting meaningful low-frequency trends, DWT enabled the DBN to learn robust latent features, while the Bi-GRU leveraged bidirectional temporal relationships for improved sequence modeling.

Notably, the high R^2 value (0.992) indicates that the model explains 99.2% of Bitcoin's price variance, a remarkable achievement given the cryptocurrency's inherent volatility. The exceptionally low MAPE (1.092%) further reinforces its practical utility for financial decision-making, where minimizing relative error is crucial. In contrast, conventional models like CNN and RNN exhibited higher errors (MAE > 1.6, MAPE > 2.7%), underscoring their limitations in handling nonlinear and noisy financial data.

These findings support the hypothesis that Bitcoin's price dynamics require hybrid approaches capable of capturing multiscale patterns and non-stationary signals. The superiority of the Wavelet Transformed DBN-BiGRU Hybrid Model stems from its synergistic design: wavelet preprocessing mitigates noise, DBNs enhance feature extraction, and Bi-GRUs capture bidirectional temporal dependencies. This architecture not only addresses Bitcoin's volatility but also serves as a generalizable framework for forecasting other complex financial time series.

Future research could explore adaptive wavelet functions or incorporate attention mechanisms to enhance interpretability and real-time performance further. Nonetheless, the results decisively validate the Wavelet Transformed DBN-BiGRU Hybrid Model as the most effective approach for unraveling Bitcoin's intricate price movements.

5. Conclusions

This study presented a novel Wavelet Transformed DBN-BiGRU Hybrid Model for Bitcoin price forecasting, demonstrating its superiority over both standalone deep learning models and traditional hybrid architectures. By leveraging discrete wavelet transform (DWT) for signal decomposition, deep belief networks (DBNs) for hierarchical feature extraction, and bidirectional gated recurrent units (Bi-GRUs) for temporal modeling, the proposed approach effectively captured Bitcoin's intricate price dynamics. The experimental results confirmed its strong predictive performance, achieving the lowest RMSE (0.524) and MAPE (1.092%) while attaining the highest R^2 (0.992). These metrics indicate that the model explains 99.2% of Bitcoin's price variance, significantly outperforming conventional deep learning models such as CNN ($R^2 = 0.825$, MAPE = 3.392%) and RNN ($R^2 = 0.831$, MAPE = 2.798%). Moreover, when compared to other hybrid approaches, including DBN+Bi-GRU (RMSE

= 0.631, MAPE = 1.729%, R^2 = 0.972), the proposed model exhibited substantial improvements, particularly in minimizing prediction errors and capturing long-term dependencies in Bitcoin's volatile price movements.

The study further underscored the necessity of integrating multiple techniques to enhance the robustness and accuracy of financial time series forecasting. Standalone models such as LSTM (RMSE = 0.983, MAPE = 2.672%) and Bi-GRU (RMSE = 0.873, MAPE = 1.982%) struggled to fully capture the nonlinear and non-stationary nature of Bitcoin prices. The results demonstrated that while traditional models perform adequately, hybrid architectures that incorporate multiscale analysis and deep learning are better suited for handling complex, volatile financial data. By decomposing Bitcoin's price series into meaningful subcomponents, DWT enabled the model to focus on essential price trends while filtering out high-frequency noise, thereby improving feature extraction and overall predictive performance.

Despite its promising results, the proposed model has several limitations that warrant further investigation. First, the selection of the wavelet function and decomposition level remains a challenge, as different configurations can significantly impact forecasting accuracy. An optimal wavelet function may vary depending on market conditions, requiring domain expertise and computationally intensive tuning. Second, the model's complexity, stemming from the integration of multiple deep learning components, increases computational costs. Training and inference require substantial resources, which may limit real-time deployment, particularly for high-frequency trading applications where immediate predictions are essential.

Additionally, the model primarily relies on historical price data, which, while effective, does not fully account for external market forces such as macroeconomic indicators, regulatory changes, and investor sentiment. Incorporating these factors through alternative data sources, such as news sentiment analysis or order book dynamics, could further enhance prediction accuracy. Moreover, while the model demonstrated strong generalization to Bitcoin, its performance across other cryptocurrencies and financial assets with different volatility patterns remains an open question. A broader evaluation is needed to confirm its applicability to diverse financial markets.

Future research should explore adaptive wavelet transforms that dynamically adjust to Bitcoin's evolving price structures, thereby ensuring optimal feature extraction across varying market regimes. In addition, the integration of advanced attention mechanisms—such as self-attention or transformer-based architectures—holds promise for enhancing interpretability by isolating and emphasizing critical temporal dependencies in price formation. The inclusion of heterogeneous exogenous factors, including macroeconomic indicators, social media sentiment analytics, and blockchain-based on-chain transaction data, could further strengthen the robustness of predictions, enabling the model to capture a more comprehensive representation of market dynamics.

Building on these directions, several additional avenues merit investigation. First, optimizing the computational efficiency of the hybrid architecture through lightweight neural designs, model pruning, and parallelized processing frameworks could facilitate real-time deployment in latency-sensitive environments, particularly in high-frequency trading applications. Second, extending the application of the proposed framework to alternative cryptocurrencies and traditional financial instruments would enable cross-market and cross-asset validation, offering insights into the model's generalizability and the identification of asset-specific predictive patterns. Third, incorporating volatility-adaptive mechanisms or regime-switching components could enhance model resilience during periods of abrupt structural change, such as flash crashes or speculative bubbles. Finally, embedding explainable AI (XAI) techniques within the hybrid architecture could improve transparency, foster practitioner trust, and facilitate regulatory compliance in algorithm-driven financial decision-making.

From a practical perspective, optimizing the model's efficiency for real-time deployment is essential. Developing lightweight architectures or leveraging parallel processing techniques could reduce computational costs and improve inference speed, making the model more viable for real-world financial applications. Finally, extending the study to evaluate the model's performance on other cryptocurrencies and financial assets would provide deeper insights into its generalizability and robustness, potentially leading to a more comprehensive forecasting framework for financial markets.

Overall, the Wavelet Transformed DBN-BiGRU Hybrid Model represents a significant advancement in Bitcoin price prediction, successfully addressing many of the challenges associated with forecasting volatile and non-stationary financial time series. While limitations exist, the findings of this study provide a strong foundation for further research and the continued development of more accurate and interpretable financial forecasting models.

Declarations

Source of Funding

This study received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Competing Interests Statement

The author has declared that no competing financial, professional, or personal interests exist.

Consent for publication

The author consented to the publication of this research work.

Authors' contributions

Author's independent contribution.

Availability of data and materials

Supplementary information is available from the author upon reasonable request.

Institutional Review Board Statement

Not applicable for this study.

Informed Consent

Not applicable for this study.

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