A Comparative Study of CEEMDAN–Attention-Based CNN and RNN Models for Bitcoin Price and Trading Signal Prediction

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Abstract. Accurate Bitcoin price and trading signal prediction remains challenging due to the pronounced noise, nonlinearity, and non-stationary characteristics of cryptocurrency markets. This study conducts a comprehensive comparative analysis of convolutional neural network (CNN)–based and recurrent neural network (RNN)–based models under a unified CEEMDAN–Attention framework for Bitcoin forecasting. Specifically, vanilla CNN, GRU, LSTM, and Bi-LSTM architectures are examined and enhanced by integrating Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and attention mechanisms. Daily Bitcoin price data from 17 September 2014 to 11 October 2025 are used for empirical evaluation. CEEMDAN is first employed to decompose the original price series into multi-scale intrinsic mode functions, enabling effective noise reduction and feature separation, while attention mechanisms further improve the models' ability to focus on informative temporal components. Forecasting performance is evaluated using multiple error metrics, and statistical significance is rigorously assessed through the Diebold–Mariano test. In addition, the economic value of the forecasts is examined via trading signal backtesting. The results demonstrate that CEEMDAN–Attention-enhanced CNN and RNN models consistently and significantly outperform their baseline counterparts in terms of forecasting accuracy, with DM test results confirming the statistical significance of these improvements. Moreover, the proposed models yield substantially higher cumulative trading profits, highlighting both their predictive superiority and practical applicability in cryptocurrency markets.

Keywords: Attention mechanism, Bitcoin price forecasting, CEEMDAN, Deep learning, Trading signal prediction.

1 Introduction

The rapid expansion of cryptocurrency markets has intensified the demand for precise forecasting models to support trading strategies and risk management. Within this domain, Bitcoin (BTC) serves as the primary benchmark for digital assets; however, its price dynamics exhibit pronounced volatility, strong nonlinearity, and non-stationary behavior [1]. These intrinsic properties pose substantial challenges for conventional time-series forecasting techniques. Current literature suggests that such complexities often lead to unstable predictions, thereby limiting the practical applicability of many existing models in trading-oriented scenarios where predictive accuracy and economic value are paramount [2].

Traditional statistical approaches rely on restrictive assumptions of linearity and stationarity, which are frequently violated in cryptocurrency data. To address these limitations, deep learning models have emerged as a powerful alternative. Specifically, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) architectures, such as Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM), have been widely adopted. Previous studies [3], [4], [5], [6] have demonstrated that CNN-based models effectively extract local temporal patterns, while RNN-based models are more effective for capturing long-term sequential dependencies. Despite these advancements, standard CNN and RNN models remain sensitive to noise and multi-scale fluctuations when trained directly on raw price series. This sensitivity frequently results in degraded forecasting accuracy and suboptimal trading performance.

To mitigate these issues, this study proposes a unified framework integrating signal decomposition and attention mechanisms. Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is employed to decompose complex time series into intrinsic mode functions, facilitating noise reduction. Simultaneously, attention mechanisms are integrated to enable models to selectively focus on informative temporal features. While prior research has explored these components in isolation, a systematic comparison of CNN and RNN architectures under a combined CEEMDAN–Attention framework remains limited. This study addresses this research gap by providing a rigorous evaluation of both architectures for Bitcoin price and trading signal prediction.

The main contributions of this paper are threefold. First, we develop a unified and systematic CEEMDAN–Attention framework that is applicable to both CNN-based and RNN-based architectures, enabling effective multi-scale feature extraction from volatile financial data. Second, a comprehensive comparative analysis is conducted using a longitudinal dataset of daily Bitcoin prices from 17 September 2014 to 11 October 2025, with the Diebold–Mariano test [7] employed to rigorously validate the statistical significance of the performance improvements. Finally, this study provides an empirical backtesting of trading signals, which demonstrates the practical economic utility of the proposed models and offers insights beyond standard predictive error metrics.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 details the proposed methodology. Section 4 presents the experimental setup and analyzes the results. Finally, Section 5 concludes the paper and discusses future work.

2 Related work

The forecasting of financial time series, particularly for high-volatility assets such as Bitcoin, presents significant challenges due to the data's inherent non-linearity, non-stationarity, and noise [8]. Although traditional econometric models such as ARIMA and GARCH have been extensively applied in financial forecasting, their capability to capture complex non-linear dependencies remains limited in the context of cryptocurrency markets [8], [9]. Consequently, recent studies have increasingly shifted toward deep learning (DL) paradigms, signal decomposition techniques, and attention mechanisms to enhance predictive accuracy and robustness.

Deep learning architectures have become the dominant approach for financial forecasting. Convolutional Neural Networks (CNNs) are widely adopted to extract local features and spatial patterns from time-series data [5], [10]. Meanwhile, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, were developed to address the vanishing gradient problem, making them suitable for capturing long-term temporal dependencies [8], [9]. Variations such as Gated Recurrent Units (GRU) offer computational efficiency [5], while Bidirectional LSTMs (Bi-LSTM) enhance performance by processing data in both forward and backward directions [10], [11].

Hybrid models combining these architectures, such as CNN-LSTM, have demonstrated superior performance over single models by simultaneously extracting features and modeling temporal dynamics [12], [13]. Nevertheless, a common limitation of these approaches lies in their direct utilization of raw and noisy financial signals, which may adversely affect learning stability and generalization performance [5].

To mitigate the impact of noise and non-stationarity, signal decomposition has emerged as a critical preprocessing step. Empirical Mode Decomposition (EMD) and Ensemble EMD (EEMD) were early attempts to decompose signals into Intrinsic Mode Functions (IMFs) [14], [15], [16]. However, these methods suffer from mode mixing and reconstruction errors [6], [17].

Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) was introduced to resolve these limitations by adding adaptive white noise, ensuring better spectral separation and reconstruction accuracy [10], [18]. Recent studies have successfully applied CEEMDAN to forecast various time series, including carbon prices [19], exchange rate volatility [10], and stock indices [18]. Despite these advancements, many studies usually pair CEEMDAN with a single model type (e.g., only LSTM) without systematically comparing how different DL architectures handle the decomposed components in the highly volatile crypto market.

The Attention Mechanism (AM) has been introduced to address the limitation of RNNs in processing long sequences, where critical information may be lost [5], [8]. By assigning dynamic weights to different time steps or features, AM enables models to focus on the most salient information [10], [18]. Research indicates that integrating attention with models like LSTM or CNN can significantly improve forecasting accuracy by highlighting relevant features and suppressing noise [6], [13].

Despite the extensive literature, several critical gaps remain. First, while CEEMDAN and Attention mechanisms have been used individually or in specific hybrids (e.g., for passenger flow [13] or specific commodities [18]), there is a lack of a unified framework that systematically compares CNN-based models against multiple RNN variants (GRU, LSTM, Bi-LSTM) under the exact same CEEMDAN-Attention conditions for Bitcoin. Most existing studies rely on a single hybrid architecture (e.g., only CEEMDAN-LSTM [1] or CNN-LSTM [20]), failing to provide a rigorous comparative analysis of which deep learning architecture best exploits the decomposed, attention-weighted features.

Second, the majority of prior works focus heavily on statistical error metrics (RMSE, MAE) [2], [9], often neglecting the economic significance of the predictions. There is a scarcity of research that rigorously evaluates these advanced hybrid models using both statistical significance tests, such as the Diebold-Mariano test [8], and practical trading signal profitability. This study aims to bridge these gaps by proposing a comprehensive comparative study of CEEMDAN-Attention-based CNN and RNN models, specifically tailored to handle the volatility of Bitcoin and validate their practical utility in generating trading signals.

3 CEEMDAN–Attention-Based Soft Computing Framework for Bitcoin Price Forecasting

This section presents the proposed soft computing methodology for Bitcoin price forecasting. The framework integrates signal decomposition, deep learning, and attention mechanisms into a unified predictive architecture. The main objective is to effectively address the noise, nonlinearity, and non-stationarity inherent in cryptocurrency price dynamics. The overall structure of the proposed framework is illustrated in Fig. 1.

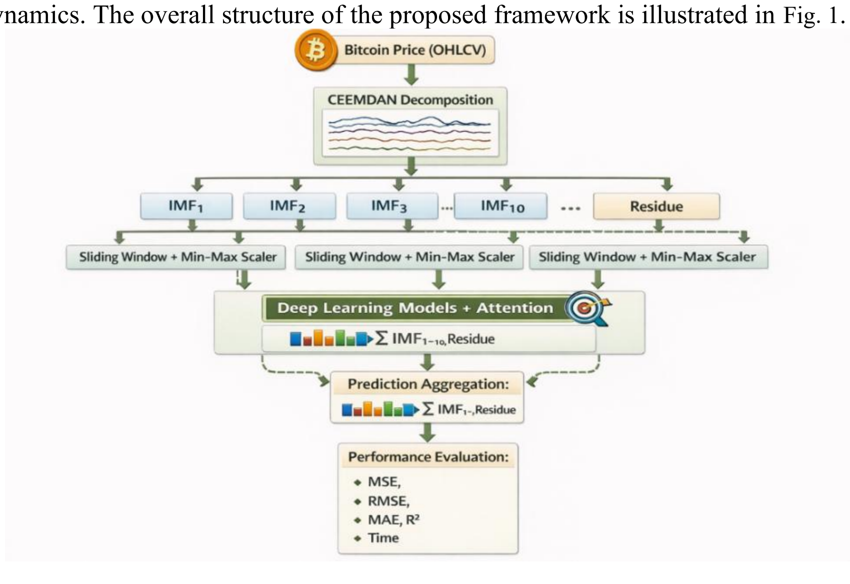

Fig. 1. Proposed CEEMDAN–Attention-Based Deep Learning Framework for Bitcoin Price Forecasting.

3.1 Framework Overview

The proposed methodology follows a decomposition–learning–reconstruction paradigm, which has proven effective in modeling complex financial time series. Instead of learning directly from the raw Bitcoin price series, the framework first decomposes the signal into multiple intrinsic components using CEEMDAN. Each component is then modeled independently using deep learning architectures enhanced with an attention mechanism. Finally, the individual forecasts are aggregated to obtain the final Bitcoin price prediction.

Formally, the framework consists of seven sequential layers:

1. Bitcoin OHLCV (Open, High, Low, Close, Volume) price series as input data,
2. CEEMDAN-based signal decomposition,
3. Multi-scale intrinsic mode functions (IMFs) and residual component,
4. Signal-wise normalization and sliding-window transformation,
5. Deep learning models with attention mechanisms,
6. Prediction aggregation and price reconstruction,
7. Performance evaluation using statistical and computational metrics.

This modular structure allows the framework to flexibly combine different deep learning models while preserving interpretability at the signal-component level.

3.2 CEEMDAN-Based Signal Decomposition

Let $C = \{C_t\}_{t=1}^{T}$ denote the Bitcoin closing price series. Due to strong volatility clustering and non-stationary behavior, direct modeling of Ct often leads to unstable predictions. To alleviate this issue, the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is applied as a preprocessing step.

CEEMDAN decomposes the original series into a finite set of intrinsic mode functions (IMFs) and a residual term:

$$C_t = \sum_{k=1}^{K} \mathrm{IMF_k}(t) + r(t)(1)$$

where $\mathrm{IMF}_k(t)$ represents oscillatory components at different frequency scales and $r(t)$ captures the long-term trend.

Compared with classical EMD and EEMD, CEEMDAN introduces adaptive white noise during the decomposition process, which significantly reduces mode mixing and improves reconstruction accuracy. As a result, high-frequency IMFs capture short-term market fluctuations, while low-frequency IMFs and the residual reflect medium- and long-term price movements. This multi-scale representation provides a structured and noise-reduced input for subsequent learning stages.

3.3 Signal-Wise Normalization and Sliding Window Construction

Each decomposed component $s_k(t) \in \{\mathrm{IMF}_1, \ldots, \mathrm{IMF}_K, r(t)\}$ is processed independently to preserve its scale-specific characteristics.

To stabilize neural network training and ensure numerical consistency across components, Min–Max normalization is applied to each signal:

$$\widetilde{s_k}(t) = \frac{s_k(t) - \min(s_k)}{\max(s_k) - \min(s_k)} \quad (2)$$

This signal-wise normalization prevents high-amplitude components from dominating the learning process and enhances convergence stability.

The normalized signal is converted into supervised learning samples using a sliding window of length L:

$$X_k^{(i)} = [\widetilde{s_k}(i), \widetilde{s_k}(i+1), \ldots, \widetilde{s_k}(i+L-1)] \quad (3)$$
$$y_k^{(i)} = \widetilde{s_k}(i+L) \quad (4)$$

This transformation allows the models to learn temporal dependencies within each frequency component while maintaining a consistent input structure across all IMFs.

3.4 Deep Learning Models

To evaluate how different architectures exploit the decomposed signals, four deep learning models are employed: CNN (to extract local temporal patterns), along with GRU, LSTM, and Bi-LSTM (to capture long-term temporal and bidirectional dependencies). Each model is trained independently on each IMF and the residual component, ensuring a fair and architecture-agnostic comparison under the same CEEMDAN-based preprocessing conditions.

3.5 Attention Mechanism

While deep learning models can extract temporal features, not all time steps contribute equally to future price movements. To address this limitation, an attention mechanism is integrated after the feature extraction layers of each model.

Let $H = [h1, h2, \ldots, hL]$ denote the hidden representations produced by a CNN or RNN-based model. The attention weights are computed as:

$$e_t = v^\top \tanh(W h_t + b) \quad (5)$$
$$\alpha_t = \frac{\exp(e_t)}{\sum_{j=1}^{L} \exp(e_j)} \quad (6)$$

The context vector is then obtained by:

$$z = \sum_{t=1}^{L} \alpha_t h_t \quad (7)$$

This mechanism allows the model to dynamically emphasize informative time steps while suppressing less relevant fluctuations, thereby improving robustness against residual noise and abrupt market movements.

3.6 Prediction Aggregation and Price Reconstruction

After forecasting all IMFs and the residual component, the final Bitcoin price prediction is reconstructed through linear aggregation:

$$\hat{C}_{t+1} = \sum_{k=1}^{K} \widehat{IMF}_k(t+1) + \hat{r}(t+1) \quad (8)$$

This reconstruction preserves the additive structure of CEEMDAN and ensures that information from all frequency scales contributes to the final prediction. The aggregation step is model-independent and can be applied uniformly across CNN- and RNN-based architectures.

3.7 Performance Evaluation

To assess both predictive accuracy and practical usability, forecasting performance is evaluated using standard metrics including MSE, RMSE, MAE, MAPE, R^2, and Directional Accuracy (DA)

4 Experiments

The experimental analysis was conducted using daily Bitcoin closing price data covering the period from 17 September 2014 to 11 October 2025, comprising 4,041 observations. The dataset was divided chronologically into a training set of 3,232 samples and a testing set of 809 samples to avoid look-ahead bias. A sliding-window scheme was applied to construct supervised learning samples for all models.

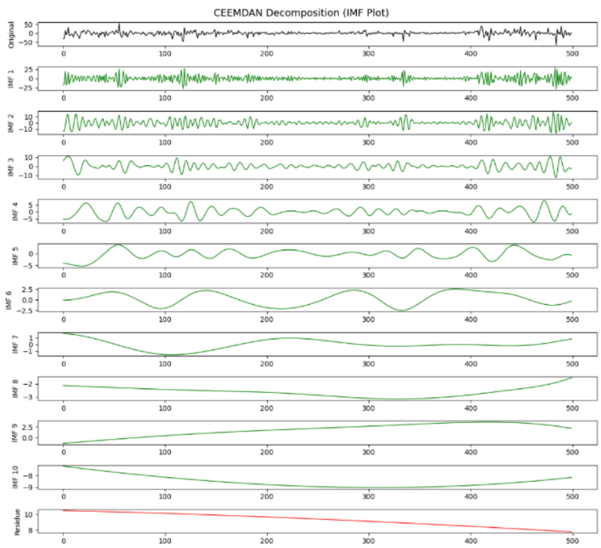

Fig. 2. CEEMDAN decomposition of the Bitcoin price series into intrinsic mode functions (IMFs) and residual component.

Four deep learning architectures were considered: a one-dimensional convolutional neural network (CNN) and three recurrent neural network (RNN)–based models, namely GRU, LSTM, and Bi-LSTM. For each architecture, a baseline model trained on the raw price series was compared with a proposed model integrating Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and an attention mechanism. All models were trained using identical hyperparameter settings, optimization procedures, and stopping criteria to ensure a fair comparison. In addition to statistical accuracy, the economic implications of the forecasts were assessed through trading signal backtesting.

CEEMDAN was applied to decompose the original Bitcoin price series into multiple intrinsic mode functions (IMFs) and a residual component. As illustrated in Fig. 2, high-frequency IMFs mainly capture short-term market fluctuations and noise, whereas lower-frequency components and the residual preserve smoother long-term market dynamics.

To qualitatively examine the forecasting behavior, zoomed-in comparisons between actual prices and predicted values were analyzed for all architectures over selected test intervals. For CNN, GRU, LSTM, and Bi-LSTM models, baseline predictions exhibit noticeable lag and larger deviations around local extrema. In contrast, the CEEMDAN–Attention-based models more closely follow the observed price dynamics, particularly during periods of rapid price changes. Fig. 3, Fig. 4, Fig. 5, and Fig. 6 consistently show that the proposed CEEMDAN–Attention models reduce prediction lag and better capture local extrema across both CNN- and RNN-based architectures.

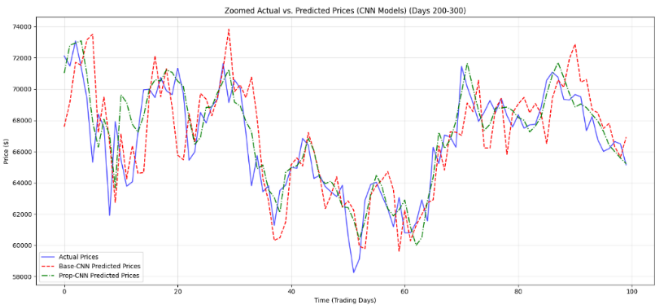

Fig. 3. Actual versus predicted Bitcoin prices for CNN models over a selected test window.

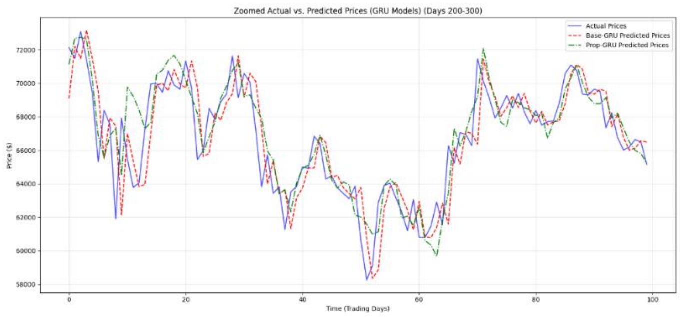

Fig. 4. Actual versus predicted Bitcoin prices for GRU models over a selected test window.

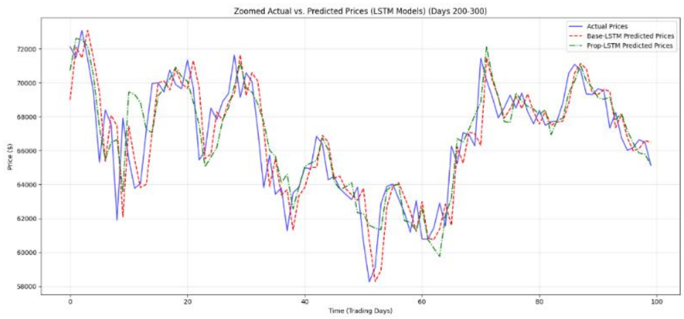

Fig. 5. Actual versus predicted Bitcoin prices for LSTM models over a selected test window.

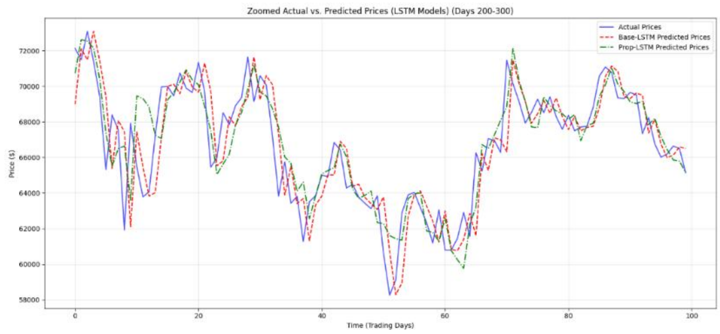

Fig. 6. Actual versus predicted Bitcoin prices for Bi-LSTM models over a selected test window.

Table 1 presents a comprehensive comparison of forecasting accuracy and trading performance between baseline models and the proposed CEEMDAN–Attention-enhanced architectures on the test set. The results indicate consistent reductions in forecasting errors when CEEMDAN and attention mechanisms are incorporated.

Table 1. Forecasting performance comparison between baseline and CEEMDAN–Attention-based models.

Model	RMSE	MAE	MAPE (%)	R^2	DA (%)	Final Profit ($)
Base-CNN	2331.87	1687.21	2.3124	0.9929	47.04	6.27×10^3
Prop-CNN	1391.40	1022.70	1.4363	0.9975	56.94	1.28×10^8
Base-GRU	1863.29	1275.43	1.7518	0.9955	48.59	1.36×10^4
Prop-GRU	1454.31	1080.97	1.5126	0.9973	54.50	7.59×10^7
Base-LSTM	1862.24	1274.24	1.7517	0.9955	48.07	5.30×10^3
Prop-LSTM	1534.25	1129.80	1.5801	0.9969	54.76	3.07×10^7
Base-Bi-LSTM	1860.55	1274.85	1.7523	0.9955	48.20	2.72×10^4
Prop-Bi-LSTM	1482.27	1063.10	1.4711	0.9971	55.66	5.18×10^7

For the CNN architecture, RMSE decreases from 2331.87 to 1391.40, corresponding to a reduction of approximately 40.3%. MAE decreases from 1687.21 to 1022.70, and

MAPE decreases from 2.31% to 1.44%. For RNN-based models, RMSE reductions of 21.9%, 17.6%, and 20.3% are observed for GRU, LSTM, and Bi-LSTM, respectively. Across all architectures, DA increases from values below 49% for baseline models to values exceeding 54% for the proposed models.

The convergence behavior of all models was examined using training loss curves. Baseline models converge rapidly within the first 10 epochs and stabilize at loss values around 0.011–0.012. The proposed models exhibit higher initial loss values (approximately 0.037) due to the increased input dimensionality introduced by CEEMDAN decomposition, but show stable and monotonic convergence toward lower final loss values around 0.027–0.028.

Although baseline models achieve lower training loss, the proposed models demonstrate lower forecasting errors on the test set, indicating improved generalization performance.

The Diebold–Mariano (DM) test was applied to compare the predictive accuracy of each baseline model with its corresponding proposed model. The null hypothesis of equal predictive accuracy was tested using forecast error series from the test set.

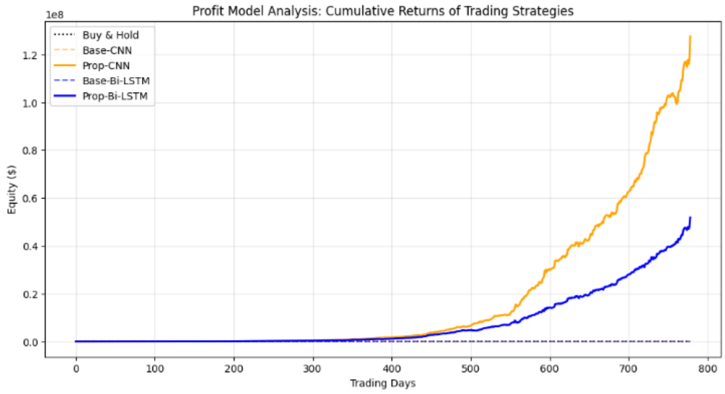

Fig. 7. Cumulative returns of trading strategies based on baseline and CEEMDAN–Attention-based forecasts.

For all architectures, the DM test yields p-values strictly below 10^{-7}, strongly rejecting the null hypothesis of equal predictive accuracy. These results indicate that the observed reductions in forecasting errors are statistically significant.

To assess the economic relevance of the forecasting models, a trading strategy based on predicted price direction was implemented. Cumulative returns of the resulting trading strategies were compared against baseline models and a buy-and-hold benchmark. As shown in Fig. 7, the proposed models exhibit substantially steeper cumulative return trajectories, indicating superior profitability and more stable trading performance over time.

Baseline models generate limited cumulative profits ranging from approximately 5.3×10^3 USD to 2.7×10^4 USD. In contrast, the proposed CNN model achieves a cumulative profit of 1.28×10^8 USD, while the proposed GRU, LSTM, and Bi-LSTM models yield profits of 7.59×10^7 USD, 3.07×10^7 USD, and 5.18×10^7 USD, respectively.

These results indicate that improvements in forecasting accuracy are reflected in trading performance under the evaluated strategy.

The experimental results demonstrate that the integration of CEEMDAN and attention mechanisms consistently improves forecasting accuracy, statistical robustness, and trading outcomes across both CNN-based and RNN-based architectures. The findings are supported by quantitative error metrics, statistical hypothesis testing, and cumulative return analysis, aligning with the evaluation criteria typically adopted in Applied Soft Computing.

5 Conclusion

This study demonstrated that integrating CNN and RNN architectures within a unified CEEMDAN-Attention framework significantly improves Bitcoin forecasting accuracy over baseline models. Diebold–Mariano tests confirmed the statistical significance of these gains, and backtests yielded substantially higher trading profits. While CEEMDAN successfully isolated multi-scale components and attention mechanisms optimized feature extraction, several limitations remain. First, focusing solely on Bitcoin restricts generalizability. Second, relying only on historical prices ignores valuable macroeconomic, sentiment, trading volume, or on-chain data. Third, the framework lacks an adaptive update mechanism for continuous market changes. Future research will address these by extending to multi-asset portfolios, integrating multi-modal data, and developing adaptive learning mechanisms for highly dynamic environments.

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