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Revolutionizing Bitcoin price forecasts: A comparative study of advanced hybrid deep learning architectures

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Abstract

This paper employs a deep learning network with a comprehensive architecture to forecast Bitcoin prices, enhancing accuracy by integrating two meta-heuristic optimization algorithms, INFO and NRBO. Empirical results demonstrate that the hybrid model significantly outperforms the LSTM in both fit and predictive accuracy across in-sample and out-of-sample data. Notably, the NRBO-CNN-BiLSTM-Attention model substantially improves accuracy in 5-day and 15-day forecasts, reducing the MAPE by over 50% compared to the LSTM model, thereby significantly enhancing overall predictive performance. The robustness of our results is supported by the MCS tests. Furthermore, strategically modifying time steps in data analysis optimizes model performance.

Keywords: Bitcoin price; Price forecast; Meta-heuristic optimization algorithms; Hybrid models

1. Introduction

Bitcoin, a decentralized digital currency based on blockchain technology, has been a prominent topic in financial technology since its introduction in 2008. The significant price volatility of cryptocurrencies is a defining characteristic of the cryptocurrency market (Risius and Spohrer, 2017; Brauneis and Mestel, 2018). As an essential asset class in global finance, Bitcoin has revolutionized various investment and trading strategies. However, the recent severe volatility in Bitcoin prices has posed significant challenges to the market, drawing the attention of both academic researchers and market participants (Ahmed, 2021; Zeng et al., 2020). Since Bitcoin's volatility is strongly correlated with traditional financial markets, movements in the price of Bitcoin not only affect the decisions of investors and hedgers (Li and Wang, 2017; Patel et al., 2023) but can also lead to pricing errors in Bitcoin derivatives, potentially triggering a financial crisis (Liu et al., 2022). Consequently, a deep understanding, modeling, and prediction of Bitcoin's price are crucial for portfolio optimization, risk management and the minimization of potential financial losses (Li et al., 2022).

In current academic research, scholars have employed empirical asset pricing theory to analyze the various factors affecting Bitcoin prices. Several factors contribute to Bitcoin's price trends and volatility, including supply-demand dynamics (Buchholz et al., 2012), trading volume (Feng et al., 2018), daily price fluctuations (Baek and Elbeck, 2015), trade adoption (Hakim das Neves, 2020), the Economic Policy Uncertainty Index (Wang et al., 2019), and technical, scale, and momentum effects (Bâra and

Oprea, 2024). These factors, intrinsic to Bitcoin's unique nature, significantly shape its market behavior.

Forecasting Bitcoin prices requires the utilization of a variety of analytical techniques, each offering distinct insights. The traditional econometric models, such as ARIMA and GARCH, predict future values by examining historical trends, seasonality and volatility (Aras, 2021; Malladi and Dheeriya, 2021; Xia et al., 2023). Recently, advances in machine learning and artificial intelligence have profoundly influenced academic research. Advanced algorithms such as ANN, Fb-Prophet, and LSTM have been widely employed to analyze large datasets, revealing intricate nonlinear relationships to enhance prediction accuracy (Cheng et al., 2024; Ahmad et al., 2018; Wang et al., 2022; Chen et al., 2017). For instance, Mallqui and Fernandes (2019) employed ANN and SVM, demonstrating a 10% improvement in predictive accuracy through machine learning models. Ortu et al. (2022) utilized four deep learning algorithms—MLP, CNN, LSTM, and attention LSTM— to assess and forecast price fluctuations, significantly enhancing the predictive precision of all algorithms by integrating various trading and technical indicators. Comparative analyses have shown that nonlinear deep learning methods outperform traditional ARIMA models (McNally et al., 2018; Phaladisailoed and Numnonda, 2018).

However, current academic models for Bitcoin price prediction remain relatively simplistic. Given that Bitcoin prices are influenced by a variety of complex factors and are highly volatile, simple prediction models often struggle to accurately capture their price movements. While deep learning can capture non-linear features, few academics have proposed models to predict the price of bitcoin using deep learning methods. An effective solution is the use of deep learning architectures capable of multi-level nonlinear operations. Based on prior research, this paper utilizes the LSTM as the foundational prediction model and further explores the use of CNN-BiLSTM and CNN-BiLSTM-Attention as composite machine learning methods for predicting Bitcoin prices. Given the sensitivity of deep learning models to parameter selection, this study introduces the INFO optimization algorithm (Ahmadianfar et al., 2022) to optimize the CNN-BiLSTM model and employs the Newton-Raphson Backpropagation Optimizer (NRBO) (Sowmya et al., 2024) to optimize the CNN-BiLSTM-Attention model. Through this process, we have developed optimized INFO-CNN-BiLSTM and NRBO-CNN-BiLSTM-Attention models for Bitcoin price prediction. Validation through multiple loss functions demonstrates that these composite machine learning approaches significantly outperform the standalone LSTM model. Notably, the CNN-BiLSTM-Attention model optimized with the NRBO algorithm shows a well-balanced performance in both in-sample and out-of-sample predictions, exhibiting the best out-of-sample

61 prediction capability among all models.

2. Data and Variables

2.1. Data

We collected Bitcoin data spanning 120 months from April 1, 2014, to April 1, 2024, including daily closing (Clsprc) and opening prices (Opnprc), highest (High) and lowest prices (Low), and trading volume (Vol). These data were obtained from investing.com. In this study, these Bitcoin data serve as the primary transaction variables. Moreover, according to research by Bâra and Oprea (2024), incorporating technical indicators can significantly enhance the accuracy of Bitcoin price predictions. Nouir and Hamida (2023) examined the impact of the Economic Policy Uncertainty Index (EPU) and the Geopolitical Risk Index (GPRD) on Bitcoin volatility, finding that the U.S. EPU and GPRD have a short-term impact, while China's EPU and GPRD have a long-term effect. Xia et al. (2023) also demonstrated that including the EPU in the prediction model significantly improves forecasts of Bitcoin volatility. Research by Jareño et al. (2020) revealed a positive and statistically significant correlation between Bitcoin and gold prices. Consequently, this paper incorporates the GPRD, EPU, and gold spot prices (Goldprc) into the model to enhance its predictive performance. Precise definitions of the variables used in this paper can be found in Table A1 of the online appendix.

Table 1

Descriptive statistics.

variable	Obs.	Mean	Median	S.D.	Min	Max
Opnprc	2923	18521	10340	17337	415.6	73067
Clsprc	2923	18544	10342	17360	415.6	73066
High	2923	18979	10614	17772	416.9	73741
Low	2923	18032	10071	16872	412.4	71338
Vol	2923	204678	106600	228347	260	999530
Pct_change	2923	0	0	0.0400	-0.390	0.260
MA	2923	18207	10236	16916	414.0	68115
EMA	2923	18217	10327	16867	415.1	66342
OBV	2923	1.430e+07	1.660e+07	6.247e+06	3.487e+06	2.510e+07
MACD	2923	155.8	18.36	1114	-5068	5501
signal	2923	147.1	16.72	973.8	-3675	4382
PSAR	2923	17553	9435	15860	392.1	53750
GRPD	2923	104.0	95.46	55.06	3.570	540.8
EPU	2923	138.6	109.6	104.0	4.050	1026
Goldprc	2923	1739	1779	236.9	1174	2250

2.2. Technical indicators

The price trends of Bitcoin are analyzed using technical indicators commonly applied in the stock

market. This paper incorporates several technical indicators based on the study by Bâra and Oprea (2024) into our model. These indicators include the Moving Average (MA), Exponential Moving Average (EMA), On-Balance Volume (OBV), Moving Average Convergence Divergence (MACD), and Parabolic Stop and Reverse (PSAR). The calculations for these technical indicators are detailed in Appendix B online.

2.3. Descriptive statistics

As illustrated in Table 1, our sample encompasses 2923 observations for all three groups of variables. The closing prices exhibited a range of 415.6 to 73066, with an average of 18544. And the standard deviation of the closing price is 17,360, which reflects the high volatility of the bitcoin price.

2.4. Models

We use the first 70% of the dataset for training and the remaining 30% for testing, allowing us to evaluate the models' prediction performance under varying conditions. These models examined include a basic LSTM model, hybrid neural network models (comprising CNN-BiLSTM and CNN-BiLSTM-Attention), and optimized hybrid neural network models (including INFO-CNN-BiLSTM and NRBO-CNN-BiLSTM-Attention). All these models use Bitcoin's closing price (Clsprc) as the predictive target, with the other variables serving as inputs. Specially, the basic LSTM model consists of two layers: the first layer with 64 neurons and the second layer with 32 neurons, incorporating a dropout rate of 0.2 to mitigate overfitting. The parameters for the hybrid neural network models are detailed in Tables 2 and 3. Table 4 provides the initial ranges for three key hyperparameters adjusted by the optimization algorithms—initial learning rate, regularization coefficient, and the number of nodes in the BiLSTM hidden layers. These optimized parameter settings, consistent with those in Tables 2 and 3, are used for further predictive analysis. Moreover, to explore the impact of different forecasting step lengths on the results, we tested the predictive performance with both 5-day and 15-day step lengths.

Table 2

Hyperparameters of CNN-BiLSTM.

Hyperparameter	Value	Hyperparameter	Value
num-filters	32	filter-size	10×1
num-bilstm-layer	2	input-lstm-dim	100
output-lstm-dim	64	L2Regularization	0.001
decay-rate	0.8	optimizer	Adam
learning-rate	0.01	dropout	0.25
miniBatchSize	256	maxEpochs	500

Note: "num-filters" refers to the number of convolutional kernels, "filter-sizes" denotes the various kernel scales used in convolution, "num-bilstm-layer" indicates the number of BiLSTM layers, "lstm1-dim" and "lstm2-dim"

4

109 represent the dimensions of the first and second unidirectional LSTM layers, respectively. "learning-rate" and
110 "decoration-rate" are optimizer parameters, with the initial learning rate set to 0.01. "miniBatchSize" denotes the
111 batch size, set to 256. Finally, "maxEpochs" specifies the maximum number of iterations, set to 500.

112

113 **Table 3**
114 Hyperparameters of CNN-BiLSTM-Attention.

Hyperparameter	Value	Hyperparameter	Value
num-convolutional-layers	2	filter-size	3×1; 3×1
num-fiters	96	num-bilstm-layers	2
num-lstm-dim	$6\times2=12$	num-attention-head	3
attention-dim	64	L2Regularization	0.001
activation-function	ReLu	optimizer	Adam
initial-learning-rate	0.01	LearnRateDropFactor	0.1
LearnRateDropPeriod	400	maxEpochs	525

115 Note: The model comprises 2 convolutional layers, each with a 3x1 kernel size and a total of 96 kernels. "num-
116 bilstm-layers" is set to 1 layer with 6 neurons, resulting in a unidirectional LSTM dimension of 12. The global
117 attention mechanism includes 3 layers with an attention dimension of 64. L2 regularization coefficient is 0.001.
118 ReLU is the chosen activation function, and Adam is the optimizer. The initial learning rate, "learning-rate," is 0.01.
119 Learning rate drop factor, "LearnRateDropFactor," is 0.1; learning rate drop period, "LearnRateDropPeriod," is 400;
120 and the maximum number of iterations, "maxEpochs," is 525.

121

122 **Table4** Hyperparameter optimization range setting for hybrid neural network models.

Model	Params	Search Scope
INFO-CNN-BiLSTM	Initial Learning Rate	$[10^{-4},10^{-1}]$
	L2Regularization	$[10^{-6},10^{-1}]$
	Neurons in hidden layer	$[6 ,100]$
NRBO-CNN-BiLSTM-Attention	Initial Learning Rate	$[10^{-3},10^{-2}]$
	L2Regularization	$[10^{-4},10^{-1}]$
	Neurons in hidden layer	$[10, 30]$

123

124 2.4. Performance evaluation metrics

125   In the predictive analysis of time series data using machine learning and deep learning approaches,

126 various loss functions are employed to evaluate the accuracy of the predictive models. This research

127 selects five globally recognized loss functions: Mean Absolute Error (MAE), Root Mean Squared Error

128 (RMSE), Mean Absolute Percentage Error (MAPE), Predictive Residual Error (PRD) and the Coefficient

129 of Determination (R²). The formulae for these functions are outlined below.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100\% \tag{3}$$

$$RPD = \frac{\sigma_{observed}}{RMSE} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{5}$$

Within this formula, Y_i refers to the actual observed value, $\hat{Y}_i$ to the value predicted by the model, and n is the number of samples. $\bar{Y}$ refers to the average of the true observations. In addition, $\sigma_{observed}$ is the standard deviation of observed values.

3. Empirical results

To enhance the accuracy and reliability of hybrid neural network models in financial time series forecasting, this study adopted two advanced optimization algorithms, INFO and NRBO, to tune the hyperparameters of the CNN-BiLSTM and CNN-BiLSTM-Attention models. To assess the quality of solutions during continuous iterations, an effective fitness function was employed to select solutions for the optimization objective function. For this time series forecasting problem, this study used the Root Mean Squared Error (RMSE) as the fitness function (f(s)) to evaluate the performance of solutions selected by the optimization algorithms throughout the iterative process.
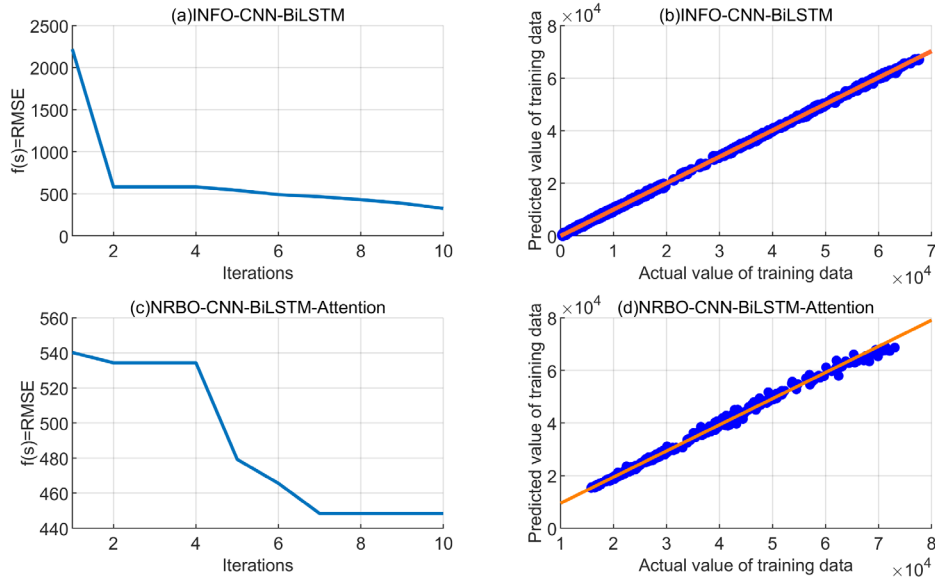
Fig. 1. Iterative curves of the fitness function and their performance in fitting in-sample linearity (5-day step).
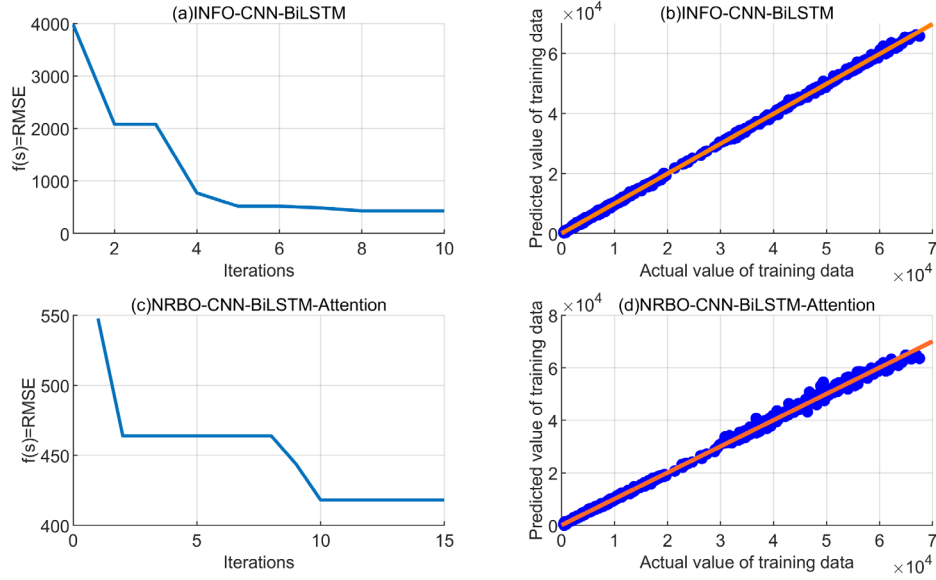
Fig. 2. Iterative curves of the fitness function and their performance in fitting in-sample linearity

(15-day step).

146

147   3.1. Determination of optimal parameter combination

148   Based on the optimal value ranges of three hyperparameters identified in Table 4, we employed an

149   optimization algorithm to determine the best hyperparameter configurations for the hybrid neural

150   network model. Fig. 1 and 2 illustrate the parameter optimization process for the 5-day and 15-day step

151   lengths, respectively. Each row presents the results for one model, showing that the fitting functions of

152   the three models gradually stabilize over the course of iterations. The predictive outputs of all models

153   align closely with the actual observations. Tables 5 and 6 summarize the optimal hyperparameter settings

154   for the two optimized hybrid neural network models under the 5-day and 15-day step length conditions,

155   respectively.

156   **Table 5**

157   The best value of 5-day step forecast parameters.

Model	Name of parameter	Best value
INFO-CNN-BiLSTM	Neurons in hidden layer	100
	L2Regularization	1.0000×10^{-6}
	Initial Learning Rate	3.6834×10^{-4}
NRBO-CNN-BiLSTM-Attention	Neurons in hidden layer	10
	L2Regularization	1.0000×10^{-4}
	Initial Learning Rate	0.01

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159

7

Table 6
The best value of 15-day step forecast parameters.

Model	Name of parameter	Best value
INFO-CNN-BiLSTM	Neurons in hidden layer	91
	L2Regularization	1.1056×10^{-5}
	Initial Learning Rate	3.4918×10^{-4}
NRBO-CNN-BiLSTM-Attention	Neurons in hidden layer	10
	L2Regularization	1.0000×10^{-4}
	Initial Learning Rate	0.0053

3.2. Forecast results analysis

3.2.1. In-sample forecasting

The predictive performance evaluation results of each model at 5-day and 15-day step lengths are presented in Tables 7 and 8, respectively. These results primarily reflect the models' ability to fit the known data in the training set. By comparing the prediction outcomes across different step lengths, we observed that both the CNN-BiLSTM model and the CNN-BiLSTM-Attention model significantly outperformed the basic LSTM model across all metrics. This finding aligns with the prevailing view in academia that, although artificial neural networks and their variants can enhance the ability to predict nonlinear features, single artificial intelligence methods may still risk falling into local optima (Movagharnejad et al., 2011; Huang and Wang, 2018). Furthermore, our analysis revealed that the hybrid neural network models exhibited superior in-sample fitting performance after optimizing the parameter combinations.

Further analysis of the data in Tables 7 and 8, comparing the effect of different step lengths on the models' in-sample prediction results, shows that each model fits the actual values more accurately when the prediction window is set to 15 days. In this setting, the INFO-CNN-BiLSTM model exhibits the best fitting capability. Specifically, this model achieves a MAE of 182.999, a RMSE of 249.128, and a MAPE of 0.039 on the training set, while also showing the highest RPD of 63.543 and a R^2 of 0.999. Following closely, the NRBO-CNN-BiLSTM-Attention model shows a MAE of 472.106, an RMSE of 641.286, and a MAPE of 0.109, with an RPD of 30.087 and an R^2 of 0.998. These results indicate that with a longer prediction window, these optimized hybrid neural network models provide a more precise fitting effect.

Table 7

Results of the in-sample forecast with a step size of 5 days. This table shows the fitting performance of LSTM, CNN-BiLSTM, CNN-BiLSTM-Attention, INFO-CNN-BiLSTM and NRBO-CNN-BiLSTM-Attention on the training set. The table includes MAE, RMSE, MAPE, PRD and R^2 on the training set.

Model	MAE	RMSE	MAPE	RPD	R^2
LSTM	1047.993	2433.358	0.180	6.398	0.975
CNN-BiLSTM	993.345	1524.866	0.176	10.222	0.990
CNN-BiLSTM-Attention	492.856	751.737	0.111	23.817	0.997
INFO-CNN-BiLSTM	182.999	249.128	0.039	63.543	0.999
NRBO-CNN-BiLSTM-Attention	472.106	641.286	0.109	30.087	0.998

Table 8

Results of the in-sample forecast with a step size of 15 days. This table shows the fitting performance of LSTM, CNN-BiLSTM, CNN-BiLSTM-Attention, INFO-CNN-BiLSTM, and NRBO-CNN-BiLSTM-Attention on the training set. The table includes MAE, RMSE, MAPE, PRD, and R^2 on the training set.

Model	MAE	RMSE	MAPE	RPD	R^2
LSTM	1051.091	2686.904	0.133	5.954	0.969
CNN-BiLSTM	1263.375	1852.818	0.096	8.602	0.986
CNN-BiLSTM-Attention	385.120	554.693	0.074	31.7418	0.998
INFO-CNN-BiLSTM	220.325	307.361	0.038	51.847	0.999
NRBO-CNN-BiLSTM-Attention	285.517	521.227	0.048	30.314	0.998

3.2.2. Out-of-sample results

Tables 9 and 10 present the out-of-sample prediction performance results for each model at 5-day and 15-day steps, respectively. Fig. 3 and 4 illustrate the prediction performance on the test set. These results enable us to evaluate whether the models can effectively apply patterns learned from the training data to unseen data, thus assessing their generalization capabilities. In both the 5-day and 15-day step length predictions, we find that the hybrid models significantly outperform the standalone LSTM model. Specifically, the NRBO-CNN-BiLSTM-Attention model exhibits the lowest MAE, RMSE, and MAPE on the test set, with 5-day step length results of 786.277, 995.032, and 0.025 respectively; and 15-day step length results of 524.576, 791.831, and 0.015. Additionally, this model also shows the highest RPD and R^2, with 5-day step length results of 16.507 and 0.993 respectively; and 15-day step length results of 16.038 and 0.996. Integrating these metrics, the NRBO-CNN-BiLSTM-Attention model demonstrates the strongest out-of-sample predictive capability, effectively addressing the limitations of time series.

9

208 Following closely are the CNN-BiLSTM-Attention model (MAPE=0.026) and the CNN-BiLSTM model

209 (MAPE=0.044). The INFO-CNN-BiLSTM model, while having a test set MAPE of 0.070, still performs

210 better than the CNN-BiLSTM, suggesting potential overfitting issues with the INFO algorithm.

211 Furthermore, a comprehensive assessment of out-of-sample prediction indicators shows that the 15-day

212 step length predictions generally outperform the 5-day step length predictions in terms of accuracy. This

213 suggests that a longer prediction window allows for better capture of the underlying patterns, leading to

214 more precise forecasts.

215 **Table 9**
216 Results of the out-of-sample forecast with a step size of 5 days. This table shows the prediction
217 performance of LSTM, CNN-BiLSTM, CNN-BiLSTM-Attention, INFO-CNN-BiLSTM, and NRBO-
218 CNN-BiLSTM-Attention on the testing set. The table includes MAE, RMSE, MAPE, PRD, and R^2 on
219 the testing set.

Model	MAE	RMSE	MAPE	RPD	R^2
LSTM	3815.341	4948.784	0.109	3.209	0.845
CNN-BiLSTM	2098.0857	2552.8682	0.065	5.903	0.958
CNN-BiLSTM-Attention	879.058	1137.193	0.026	13.742	0.991
INFO-CNN-BiLSTM	1987.536	2458.171	0.070	5.560	0.962
NRBO-CNN-BiLSTM-Attention	786.277	995.032	0.025	16.507	0.993

220

221 **Table 10**
222 Results of the out-of-sample forecast with a step size of 15 days. This table shows the prediction
223 performance of LSTM, CNN-BiLSTM, CNN-BiLSTM-Attention, INFO-CNN-BiLSTM, and NRBO-
224 CNN-BiLSTM-Attention on the testing set. The table includes MAE, RMSE, MAPE, PRD, and R^2 on
225 the testing set.

Model	MAE	RMSE	MAPE	RPD	R^2
LSTM	3816.414	5035.762	0.126	3.216	0.831
CNN-BiLSTM	1559.070	2433.800	0.044	5.191	0.960
CNN-BiLSTM-Attention	770.665	1014.012	0.026	13.183	0.993
INFO-CNN-BiLSTM	3154.474	3744.785	0.112	3.455	0.907
NRBO-CNN-BiLSTM-Attention	524.576	791.831	0.015	16.038	0.996

226

227 Furthermore, we employed the Model Confidence Set (MCS) test proposed by Hansen et al. (2005)

228 with a confidence level set at 0.05, as detailed in our Appendix D online. The MCS tests results reveal

229 that under the loss functions of MAE, MSE, and MAPE, the NRBO-CNN-BiLSTM-Attention model

exhibits the highest p-values, all equating to 1. This indicates that the NRBO-CNN-BiLSTM-Attention model achieves the highest accuracy in predicting Bitcoin prices. Beyond the deep architecture's proficient feature extraction capability, which captures long-term dependencies and global patterns (Chen et al., 2023), another contributing factor is the NRBO algorithm's utilization of the Newton-Raphson Search Rule (NRSR) and Trap Avoidance Operator (TAO). By integrating the concepts of gradient-based methods with the advantages of population-based optimization approaches, the NRBO algorithm overcomes the limitations of both gradient and non-gradient-based algorithms. This hybrid approach allows it to swiftly refine its search upon identifying promising regions, thereby optimizing model parameters more effectively and enhancing overall model performance.

To verify the robustness of our conclusions, we utilized 5-fold time series cross-validation to evaluate each model's performance on both training and test sets. By comparing the loss functions MAE, RMSE, and MAPE across these sets, we found consistent results with our empirical findings, thereby confirming their robustness. Detailed cross-validation results and a discussion on the causes of overfitting in the INFO-CNN-BiLSTM models are provided in the Appendix D online.

4. Conclusion

This paper employs hybrid deep learning models and their optimized versions to predict Bitcoin prices, comparing the results with the basic LSTM model and exploring the application of complex model architectures in Bitcoin price prediction. Empirical results demonstrate that, for both in-sample and out-of-sample prediction, the fitting and predictive abilities of the hybrid deep learning networks significantly surpass those of the standalone LSTM model. Notably, the NRBO-CNN-BiLSTM-Attention model exhibits a well-balanced performance across all evaluation metrics and shows exceptional predictive capabilities on the test sets for both 5-day and 15-day step lengths. Compared to the LSTM model, the MAPE value decreased by over 50%, markedly enhancing the prediction accuracy. However, despite the excellent fitting capability of the INFO-CNN-BiLSTM model, its performance on the test set was subpar, likely due to overfitting during the parameter optimization process. This raises questions the effectiveness of the INFO algorithm in optimizing deep learning parameters. Moreover, by comparing the prediction results between 5-day and 15-day step lengths, we suggest that restructuring the dataset by increasing the time step length could be an effective method to improve model prediction performance. In summary, our research finds that the hybrid deep learning model optimized with the NRBO algorithm,

11

260   NRBO-CNN-BiLSTM-Attention, demonstrates strong potential in Bitcoin price prediction, showing its

261   superiority across various model and parameter configurations.

262
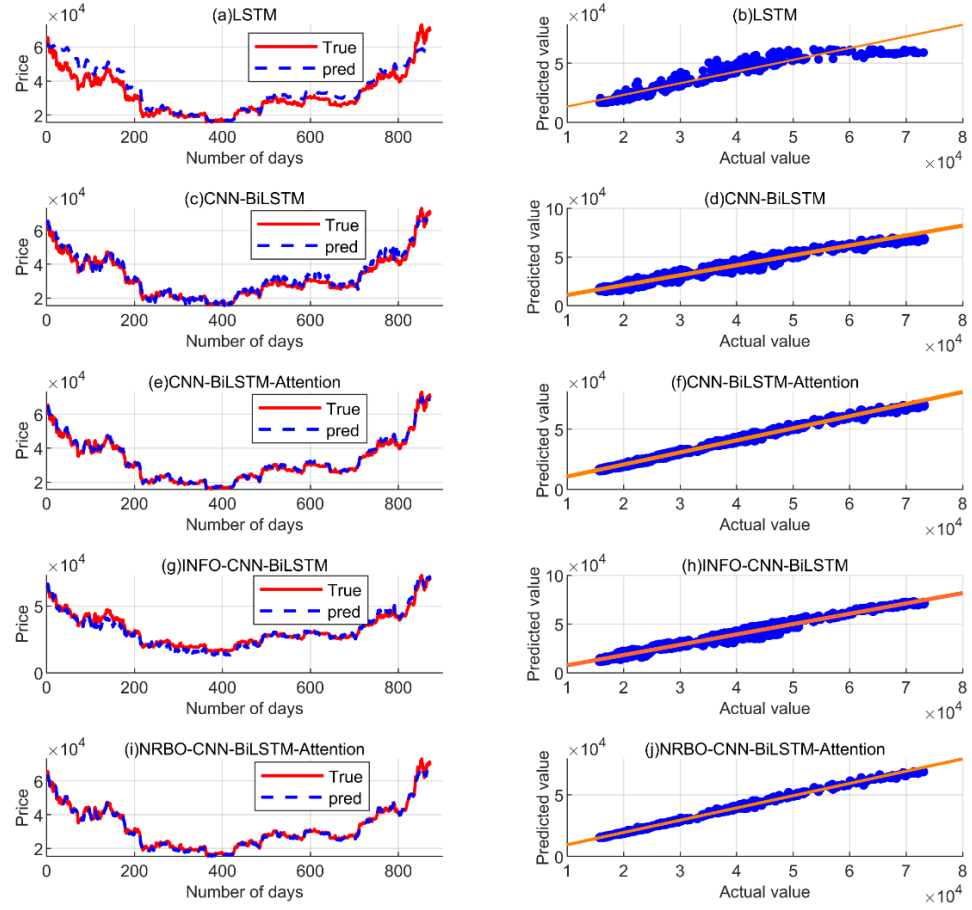
Fig. 3. Out-of-sample predicted performance (5-day step).
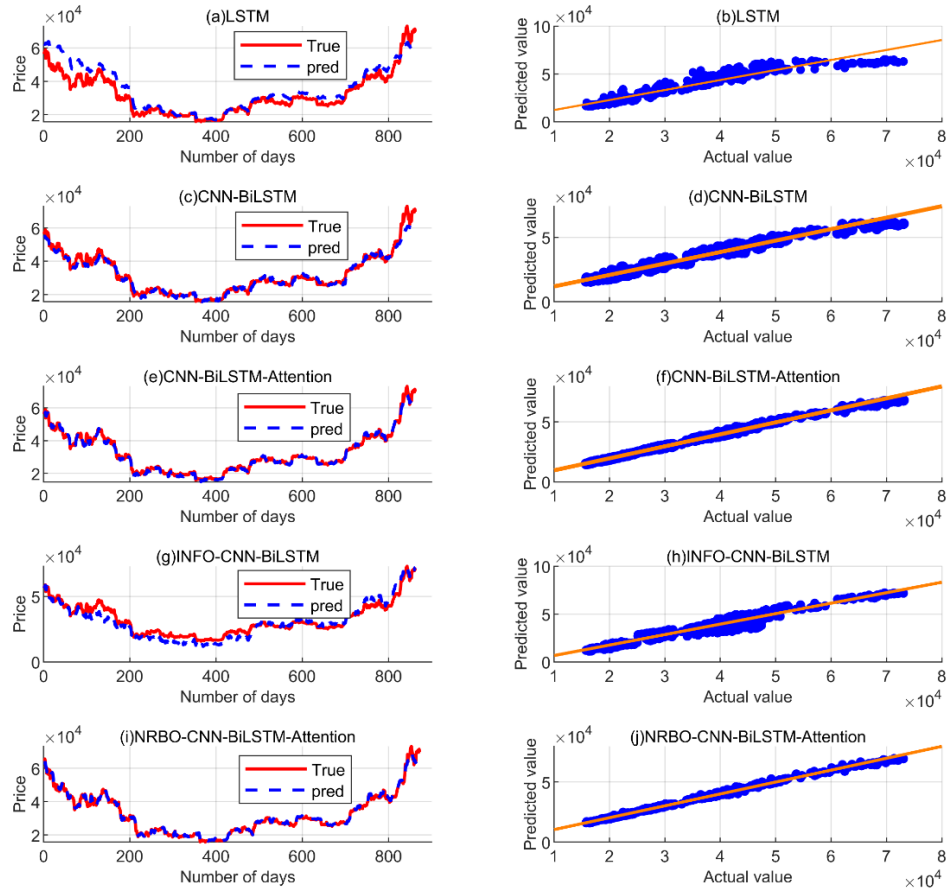
Fig.4. Out-of-sample predicted performance (15-day step).

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