SUGISAKA MASANORI

Journal of Robotics, Networking and Artificial Life
Vol. 11(1); May (2025), pp. 49–53
ISSN (Online): 2352-6386; ISSN (Print): 2405-9021
https://alife-robotics.org/jrnal.html

Research Article

A Comparative Study on Long-term Cryptocurrency Price Prediction Using LSTM, GRU, and Bi-LSTM

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ARTICLE INFO

Article History

Received 25 November 2023
Accepted 20 December 2024

Keywords

Price prediction
Cryptocurrency
LSTM
GRU
Bi-LSTM

ABSTRACT

Cryptocurrency price fluctuations, though widely studied, remain unpredictable, posing risks for investors. While many aspire to profit, the volatility makes accurate prediction challenging. Deep learning has recently gained traction as a promising approach for cryptocurrency price forecasting. This study focuses on long-term price prediction for Bitcoin, Ethereum, Litecoin, and Cardano using LSTM, GRU, and Bi-LSTM models. The performance of these models is evaluated and compared with findings from previous studies.

1. Introduction

Cryptocurrencies remain relatively unfamiliar in Japan, often perceived as a distant concept. However, they are expected to have a significant impact on our lives in the near future. Bitcoin, primarily used for investment and speculative trading, has transitioned from a niche product within by small online communities to a mainstream financial instrument, attracting both professionals and general investors. With a market capitalization in the billions of dollars, cryptocurrencies have become a new arena for speculators [1]. Despite their growing prominence, cryptocurrencies are highly volatile due to their lack of intrinsic value, absence of regulatory oversight, limited long-term investment options, thin order books, short-term trading strategies, and the influence of collective psychology [2]. This volatility presents both risks and opportunities, as skillful technical trading can yield substantial profits [3]. To address this, predicting cryptocurrency price movements using deep neural networks (DNNs) offers significant advantages. This study employs DNNs, including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (Bi-LSTM), to predict the prices of major cryptocurrencies such as Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Cardano (ADA), aiming to achieve greater accuracy than previous studies.

2. Method

2.1. *Cryptocurrency*

Cryptocurrency is a digital form of currency exchanged exclusively as electronic data, primarily used for online transactions. Unlike fiat currency, which is backed by government authority and has legal tender status, cryptocurrency operates independently of centralized institutions. Since the launch of Bitcoin in 2009, numerous derivative cryptocurrencies, known as altcoins, have been developed. The establishment of cryptocurrency exchanges, which facilitate conversions between fiat currencies and cryptocurrencies, has made owning cryptocurrency more accessible, driving its rapid adoption [4]. Today, a wide range of cryptocurrencies

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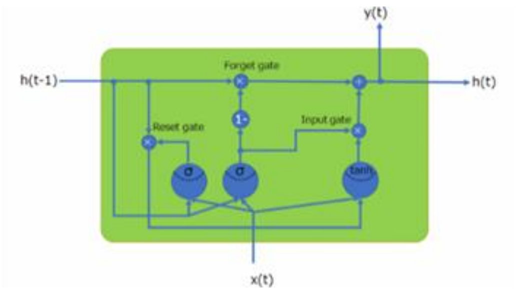

Fig. 2 The structure of GRU [6]

exist, including BTC (Bitcoin), ETH (Ethereum), LTC (Litecoin), NEM, Ethereum Classic, and LISK, with new cryptocurrencies continuously emerging. This research focuses on predicting the prices of four major cryptocurrencies: BTC (Bitcoin), ETH (Ethereum), LTC (Litecoin), and ADA (Cardano).

2.2. Algorithm

This section introduces the three algorithms employed in this research for cryptocurrency prediction: LSTM, GRU, and Bi-LSTM.

LSTM (Long Short-Term Memory)

Recurrent Neural Networks (RNNs) are designed to analyze time-series data by retaining information from past states. However, RNNs face challenges in processing long-term dependencies due to the vanishing gradient problem [5].

LSTM overcomes this limitation by maintaining long-term contextual relationships through memory cells managed by three gates: the forget gate, input gate, and output gate. Each gate uses a sigmoid function to control the flow of data. The architecture of LSTM is shown in Fig. 1.

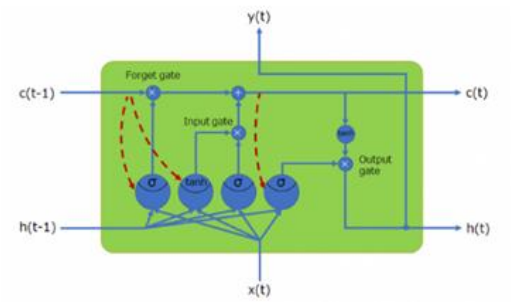

Fig. 1 The structure of LSTM [6]

GRU (Gated Recurrent Unit)

GRU achieves similar performance to LSTM but with reduced computational complexity, enabling faster training. While LSTM processes two states—cell state and hidden state—GRU combines these states into one. Additionally, GRU simplifies the architecture by merging the forget gate and input gate into a single update gate. These optimizations reduce the computational cost, making GRU more efficient. The structure of GRU is depicted in Fig. 2.

Bi-LSTM (Bidirectional LSTM)

Bi-LSTM enhances LSTM by incorporating both forward and backward layers, as illustrated Fig. 3. In standard LSTM, data flows only in the forward direction, processing information sequentially. Bi-LSTM, however, processes the input sequence in both directions: the forward layer analyzes data from x_0 to x_n, while the backward layer processes data from x_n to x_0. By combining information from both directions, Bi-LSTM can utilize more contextual information, improving its predictive accuracy. However, this bidirectional approach requires more computational resources and takes longer to process compared to standard LSTM [7].

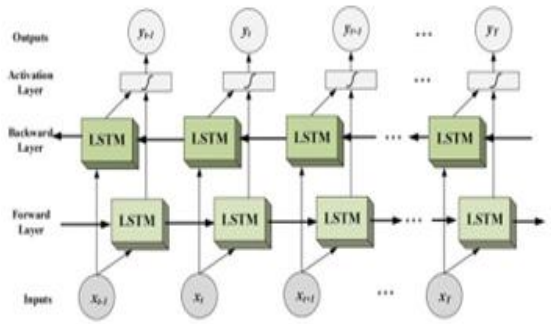

Fig. 3 The structure of Bi-LSTM [8]

3. Experiment Content

The experimental setup is described as follows:

- The algorithms tested in this study include LSTM, GRU, and Bi-LSTM.
- The cryptocurrencies targeted for prediction are Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Cardano (ADA).
- The evaluation metrics used are Root-Mean-Square Error (RMSE) and Mean-Absolute-Percentage Error (MAPE).

3.1. *Development environment*

The experiments were conducted on Google Colab, a platform offering free resources for machine learning. The hardware configuration typically includes 2 virtual CPU cores, 4 threads, up to 12.7GB of RAM, and approximately 225GB of storage. The deep learning models—LSTM, GRU, and Bi-LSTM were implemented in Python version 3.10.12. Libraries such as Sklearn and Keras were used for deep learning tasks, while numpy and pandas supported numerical computations and data manipulation.

3.2. *Data*

The dataset for this study was obtained from Yahoo Finance (https://finance.yahoo.com/). It includes daily price data for four cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Cardano (ADA).

Table 1 Data specifications

Attribute	Explanation	Type
Date	Date of transaction	Date
Open	First traded price	Continuous
High	Highest traded price	Continuous
Low	Lowest traded price	Continuous
Close	Last traded price	Continuous
Adj Close	The closing price before the split is the adjusted price after the split.	Continuous
Volume	Quantity of trades completed during the period	Continuous

Data was split into training and testing sets using an 80:20 ratio. Training data spans from January 1, 2018, to June 8, 2022, and testing data covers the period from June 9, 2022, to November 30, 2023. Detailed data attributes are listed in Table 1.

3.3. *Evaluation index*

Model performance was assessed using two standard metrics: Root-Mean-Square Error (RMSE): Measures the standard deviation of prediction errors. Lower values indicate better model performance. Mean-Absolute-Percentage Error (MAPE): Represents the average percentage error between actual and predicted values. Smaller percentages signify greater accuracy. The equations for these metrics are as follows:

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

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

Here, n is the total number of data points, y_i represents the actual value, and $\hat{y}_i$denotes the predicted value.

4. Experimental result

Table 2 presents the prediction results based on the conditions outlined in Chapter 3. Evaluation metrics are rounded to five decimal places. The lowest values (indicating the highest accuracy) are highlighted in bold. demonstrate that Bi-LSTM outperformed the other algorithms across all cryptocurrencies in terms of accuracy.

Table 2 Performance results of this research model

Currencies	Methods	RMSE	MAPE
BTC	LSTM	807.7135	0.0332
	GRU	873.7594	0.0362
	Bi-LSTM	**770.3047**	**0.0314**
ETH	LSTM	21.0737	0.0123
	GRU	33.0912	0.0192
	Bi-LSTM	**15.1817**	**0.0092**
LTC	LSTM	1.5991	0.0188
	GRU	1.7605	0.0207
	Bi-LSTM	**1.1928**	**0.0130**
ADA	LSTM	0.0203	0.0578
	GRU	0.0236	0.0695
	Bi-LSTM	**0.0172**	**0.0526**

5. Comparative verification

In the comparative analysis, the performance of the cryptocurrency price prediction model developed in this study is compared with models from previous studies [9], [10]. This evaluation aims to verify the effectiveness of the proposed model. For consistency, the experimental periods used in this study and the prior research are aligned during comparisons. Table 3 presents a comparison between this study's model and the model from the previous study [9], while Table 4 shows a comparison with the model from the previous study [10]. The results demonstrate that the Bi-LSTM model in this study consistently outperformed the others, confirming the effectiveness of the proposed approach.

Table 3 Comparison of Performance Between This Study and Previous Study [9]

Currencies	Studies	Methods	RMSE	MAPE
BTC	Our model	LSTM	1184.7059	0.0426
		GRU	1094.3126	0.0422
		Bi-LSTM	**647.2073**	**0.0221**
	[9]	LSTM	1447.648	0.03059
		ARIMA	1288.5	0.03479
		SARIMA	1802.31	0.04665

Table 4 Comparison of Performance Between This Study and Previous Study [10]

Currencies	Studies	Methods	RMSE	MAPE
BTC	Our model	LSTM	836.2219	0.0318
		GRU	901.6092	0.0312
		Bi-LSTM	**752.4224**	**0.0290**
	[10]	LSTM	1031.340	0.0397
		GRU	1274.171	0.057
		Bi-LSTM	1029.362	0.036
ETH	Our model	LSTM	59.4498	0.0339
		GRU	51.6724	0.0293
		Bi-LSTM	**45.7691**	**0.0253**
	[10]	LSTM	148.522	0.297
		GRU	98.314	0.148
		Bi-LSTM	83.953	0.124
LTC	Our model	LSTM	3.620	0.049
		GRU	5.453	0.078
		Bi-LSTM	**1.988**	**0.020**
	[10]	LSTM	9.668	0.064
		GRU	8.122	0.046
		Bi-LSTM	8.025	0.041

6. Conclusions

The superior performance of Bi-LSTM in this study highlights its ability to capture temporal dependencies in both forward and backward directions. This bidirectional approach, commonly effective in natural language processing tasks, appears to enhance the understanding of complex, non-linear relationships in cryptocurrency price movements [11] [12].

Additionally, the unique characteristics of cryptocurrency markets—being highly influenced by diverse factors such as news, investor sentiment, and trading volumes—may further explain the effectiveness of Bi-LSTM. By considering bidirectional dependencies, Bi-LSTM can more effectively model these intricate and dynamic interactions.

Future work could explore the integration of external data sources, such as news articles and social media data, to further leverage Bi-LSTM's capabilities. Such an approach holds promise for enhancing predictive accuracy, as it aligns with the algorithm's strength in handling sequential and context-rich data. This would provide deeper insights into how market-related events and collective investor behavior influence cryptocurrency price fluctuations.

Acknowledgements

This work was supported by JSPS KAKENHI Grant Numbers JP24K07929 and JP24K15516.

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