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Examining and Comparing the Efficiency of MLP and SimpleRNN Algorithms in Cryptocurrency Price Prediction

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Abstract

Cryptocurrencies have been widely identified and established as a new form of electronic currency exchange, carrying significant implications for emerging economies and the global economy. This research focused on the "examination and comparison of the efficiency of MLP and SimpleRNN algorithms in predicting cryptocurrency prices" using the Python programming language. Price predictions for Bitcoin, Ethereum, Binance Coin, Cardano, and Ripple were made using two deep learning algorithms (including the MLP algorithm and the SimpleRNN algorithm) over the period from 2017 to 2023. The results of cryptocurrency price prediction using deep learning algorithms were satisfactory; and the comparison of predictions across all cryptocurrencies indicated minimal differences between the algorithms studied, suggesting that they were efficient and had low error rates. Based on the obtained results regarding Bitcoin price prediction, the best algorithm was SimpleRNN; for Ethereum price prediction, the best algorithm was MLP; for Binance Coin price prediction, the best algorithm was SimpleRNN; for Cardano price prediction, the best algorithm was MLP; and for Ripple price prediction, the best algorithm was MLP.

Keywords: *MLP algorithm, SimpleRNN algorithm, cryptocurrency price*.

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1. Introduction

Cryptocurrency is a new type of digital currency that utilizes blockchain technology and cryptographic functions to achieve transparency, decentralization, and immutability. Bitcoin (BTC) is considered the first and most popular cryptocurrency, invented by an anonymous group or individual in 2009. Since then, 4,000 alternative digital currencies, such as Ethereum (ETH) and Ripple (XRP), have been created, demonstrating the emergence of the cryptocurrency market within the financial sector. BTC, ETH, and XRP are the most popular digital currencies, as they account for approximately 79.5% of the global cryptocurrency market value [1, 2].

The most significant issue concerning digital assets, particularly cryptocurrencies, is price volatility. Bitcoin's price exhibited substantial volatility from early April 2013 to December 31, 2019. Its price increased by 1,900% in 2017 and declined by 72% in 2018 [3-6]. Before 2013, interest in Bitcoin, its use in virtual transactions, and its price were low. Although Bitcoin has shown abnormal price fluctuations, it has proven resilient as a digital asset, regaining its value following numerous peaks and troughs, even when market uncertainty was high, particularly during the COVID-19 pandemic [7].

In recent years, deep learning methods have been used for time series forecasting, focusing on real-world applications such as the cryptocurrency market. Most of these models employ advanced machine learning techniques and architectures based on evolutionary and Long Short-Term Memory (LSTM) layers [8, 9]. These layers are used to filter noise in complex time series data while extracting valuable features, whereas LSTM layers are employed to efficiently capture sequence patterns and both short-term and long-term dependencies [10].

Despite the increasing importance of cryptocurrency prediction and research in this field, significant gaps remain. For example, one of the most important features to consider in cryptocurrency prediction could be economic or technical variables, yet previous research has shown that few studies on cryptocurrency prediction have focused on this aspect, often relying on endogenous variables or variables solely related to Bitcoin transactions. This is important as technical variables can impact cryptocurrency price prediction, making the lack of attention to this topic a research gap [10].

Another area that has received limited attention in research is the prediction of a large number of cryptocurrencies and the comparison of the most correlated cryptocurrencies among the existing options, which could also aid in decision-making and strategy development for cryptocurrency purchases. In other words, knowing that a particular cryptocurrency has a higher correlation with others can increase the probability of selecting it, directing strategies for buying or potentially selling cryptocurrencies [10, 11].

Iqbal et al. (2021) utilized machine learning techniques like XG BOOSTING, FBPROPHET, and ARIMA for time series analysis, evaluating their performance through parameters like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2. Despite testing all three models, ARIMA emerged as the best for Bitcoin price prediction in the cryptocurrency market, demonstrating RMSE and MAE scores of 322.4 and 227.3, respectively, making it potentially useful for cryptocurrency investors [12]. Ftiti et al. (2021) examine cryptocurrency volatility modeling and prediction using high-frequency data, focusing on four key markets (Bitcoin, Ethereum Classic, Ethereum, and Ripple) from April 2018 to June 2020 and considering the impact of the COVID-19 pandemic on volatility dynamics. Their findings highlight the generalized HAR model with positive and negative jumps as the best predictor during both crisis and non-crisis periods [13]. Akyildirim et al. (2021) analyzed the predictability of 12 cryptocurrencies on minute- and daily-frequency data using classification algorithms like SVM, logistic regression, artificial neural networks, and random forests, showing SVM's superior predictive accuracy [11]. This aligns with Koker and Kutmus (2020), who developed a machine learning-based reinforcement model for active cryptocurrency trading, demonstrating improved risk-adjusted returns over a simple buy-and-hold approach [14].

Apart from technical factors, global events such as war, terrorist attacks, and the COVID-19 pandemic can also affect cryptocurrency prices; however, this topic has received less attention in cryptocurrency prediction research. Therefore, alongside endogenous variables related to cryptocurrencies, technical variables and global factors should be considered in cryptocurrency prediction, as overlooking these factors can be seen as a research gap. Selecting the best feature or variable among the existing ones is also of great importance and has been less emphasized in previous research. One of the aims of the present study is to identify the most influential feature for prediction. By doing so, it can be determined which variable or feature is of greater importance and should receive more attention in future studies. Based on the above, this study aims to address existing research gaps by considering these factors. Specifically, this research utilizes a machine learning approach to predict cryptocurrency prices. Ultimately, the researcher seeks to answer the key question: What is the optimal machine learning model for predicting cryptocurrency prices?

2. Methodology

This study is a descriptive, quasi-experimental, ex-post-facto research, falling within the domain of positive research based on actual data. Additionally, it is classified as applied research, utilizing fundamental research results to improve behaviors, methods, tools, instruments, products, structures, and models used in human societies. Applied research aims to develop practical knowledge in a specific field. The data type is historical (ex-post-facto), and the research method is descriptive in execution, as there is no manipulation of the research variables. This research approach involves using appropriate statistical and machine learning methods to analyze and examine data collected to answer the study's questions effectively. Data analysis is a multi-stage process, where collected data are summarized, categorized, and processed to establish relationships between data points and enable scientific analyses. Both conceptual and empirical refinements are applied to the data, with statistical techniques and machine learning systems playing a crucial role in generalizing the findings. Analytical processes vary based on research type, theory development, and data collection tools used.

Data collection in this study is conducted in two parts: library-based and database-based. For the database section, data from active cryptocurrency exchange platforms are utilized. These data are processed through Python coding and Google Colab environments using deep learning algorithms to predict cryptocurrency prices. Given the large volume of data related to the research variables and the need for real-time data over very short time intervals, data are accessed via API. Data from cryptocurrency exchange sites, such as coinmarketcap.com, are used for this purpose.

2.1. MLP Algorithm

The Multilayer Perceptron (MLP) is a foundational type of Artificial Neural Network (ANN) crucial in developing deep learning. Its history dates back to the 1940s when the neural network concept was first introduced by Warren McCulloch and Walter Pitts. However, it gained prominence in the 1980s due to advancements in computing power and the development of backpropagation, a critical algorithm for training neural networks. An MLP comprises multiple layers of nodes/neurons organized into an input layer, one or more hidden layers, and an output layer. Each neuron connects to every neuron in the following layer, with weights indicating connection strength. Each neuron also has an associated activation function that processes the weighted sum of inputs to produce an output. During forward propagation, input data feed into the network, and computations proceed through weighted connections and activation functions across layers, producing an output. The network's performance is then evaluated against the expected outcome using a loss function like Mean Squared Error or Cross-Entropy. The backpropagation algorithm adjusts weights iteratively to minimize the discrepancy between predicted and actual outputs, using the chain rule of calculus to propagate errors backward through the network.

The backpropagation algorithm is used during the training phase to adjust weights iteratively, minimizing the difference between predicted and actual outputs. It calculates the gradient of the loss function with respect to the network weights, allowing for updates that reduce the error. This process includes the chain rule from calculus to propagate errors backward through the network, hence the term "backpropagation."

Schematically and mathematically, backpropagation in an MLP can be represented as follows:

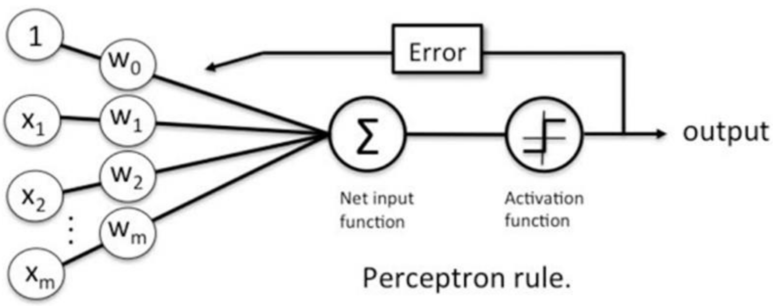

Figure 1. Backpropagation in a Multilayer Perceptron

- a(1) = δ (W(1) * x + b(2))
- a(2) = δ (W(2) * a(1) + b(2))
- ...
- y = δ (W(L) * x(L-1) + b(L))

Where:

- x is the input vector.
- W(i) represents the weights of the i-th layer.
- b(i) is the bias vector for the i-th layer.
- δ is the activation function, applied element-wise.
- a(i) denotes the output of the i-th layer.
- y is the final output vector.

2.2. SimpleRNN Algorithm

Simple Recurrent Neural Network (SimpleRNN) is a basic architecture within Recurrent Neural Networks (RNN), designed for processing sequential data by retaining memory or context from past inputs through recurrent connections. Though the RNN concept emerged in the 1980s, SimpleRNN in deep learning contexts has limitations, especially due to the "vanishing gradient" problem during training, which impedes the network's ability to capture long-range dependencies. SimpleRNN operates by processing sequential data step-by-step, maintaining an internal state (hidden state) that preserves relevant information from previous inputs. At each time step, an input and previous hidden state calculate the next hidden state using linear transformation and an activation function (typically tanh or sigmoid). The hidden state usually derives the output.

The equations are as follows:

ht = activation (Whx·xt + Whh·ht−1 + bh)
yt = Wyh·ht + by

where W_{hx} and W_{hh} are weight matrices, b_h is the hidden layer bias vector, W_{yh} is the output layer weight matrix, and b_{yb} is the output bias vector. The activation function is typically a nonlinear function, such as tanh or sigmoid. During training, the network's parameters (weights and biases) are updated using Backpropagation Through Time (BPTT) to minimize a chosen loss function, enabling the network to learn patterns in sequential data. Although SimpleRNN is intuitive and computationally simpler, it struggles with long-term dependencies due to the vanishing gradient problem. This limitation led to the development of advanced architectures like LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), which mitigate the vanishing gradient issue and are more effective in capturing long-range dependencies in sequential data.

3. Findings

The summary of descriptive statistics related to the variables is presented in Table 1. Indicators such as mean, standard deviation, maximum, minimum, and quartiles are studied to examine the descriptive statistics. Data from 2017 to December 2023 were analyzed for Bitcoin, Ethereum, Binance, Cardano, and Ripple.

The main variables studied include SMA (Simple Moving Average), EMA (Exponential Moving Average), high price, low price, opening price, closing price, trading volume, and turnover. For Bitcoin, the mean price over the study period was $22,324.5, with a maximum of $67,617.02 and a minimum of $3,216.63. For Ethereum, the mean price was $1,276.22, with a maximum of $4,815.01 and a minimum of $83.79. For Binance, the average price was $180.86, with a peak of $675.10 and a low of $4.47. Cardano's mean price was $0.4808, ranging from $2.967 to $0.0237. Ripple's mean price was $0.4831, with a maximum of $1.8377 and a minimum of $0.1378.

Table 1. Descriptive Statistics for Bitcoin-Related Variables

Variable	SMA	EMA	High	Low	Open	Close	Volume	Turnover
Mean	22332.75	22119.16	25250.51	19588.56	22316.75	22324.5	54821.45	1.22E+09
Std	16046.07	15946	18308.08	13936.74	16187.6	16187.27	26278.32	1.13E+09
Min	3534.69	3552.51	3674.59	3216.63	3216.63	3216.63	10055	34971330
25%	8433.28	8237.99	9502.02	7337.64	8310.29	8310.89	32677	3.85E+08
50%	19381.1	19219.71	21282.99	16950.86	19163.16	19173.28	54569	8.01E+08
75%	33396	32658.88	39699.02	29044.2	32954.42	32957.91	77642	1.76E+09
Max	62939.13	61980.42	67617.02	58641	67617.02	67617.02	99930	6.2E+09

Table 2. Descriptive Statistics for Ethereum-Related Variables

Variable	SMA	EMA	High	Low	Open	Close	Volume	Turnover
Mean	1265.92	1266.16	1480.48	1086.72	1275.81	1276.22	54821.45	70115575
Std	1150.49	1144.84	1338.26	990.45	1162.75	1162.61	26278.32	77860978
Min	102.96	111.62	124.15	83.79	83.79	83.79	10055	909929.7
25%	218.23	221.80	247.54	183.24	218.55	218.61	32677	11584571
50%	1229.76	1245.85	1387.81	1040.80	1212.58	1213.34	54569	37070534
75%	1860.85	1861.82	2046.65	1719.27	1875.11	1875.27	77642	1.1E+08
Max	4462.36	4360.62	4815.01	3993.85	4815.01	4815.01	99930	4.5E+08

Table 3. Descriptive Statistics for Binance-Related Variables

Variable	SMA	EMA	High	Low	Open	Close	Volume	Turnover
Mean	181.62	179.25	210.56	154.15	180.83	180.86	54821.45	9936257
Std	174.90	173.69	204.06	148.34	176.40	176.36	26278.32	11626310
Min	5.12	5.58	6.06	4.47	4.47	4.47	10055	49249.45
25%	17.46	16.98	21.32	15.14	17.39	17.39	32677	885749.6
50%	211.50	166.61	217.96	129.38	208.40	208.66	54569	3515971
75%	309.05	309.05	339.76	266.40	308.74	308.72	77642	17373163
Max	610.61	591.65	675.10	530.96	675.10	675.10	99930	60823218

Table 4. Descriptive Statistics for Cardano-Related Variables

Variable	SMA	EMA	High	Low	Open	Close	Volume	Turnover
Mean	0.48	0.48	0.59	0.40	0.48	0.48	54821.45	26452.69
Std	0.60	0.59	0.73	0.49	0.60	0.60	26278.32	38997.5
Min	0.03	0.03	0.04	0.02	0.02	0.02	10055	300.55
25%	0.07	0.07	0.09	0.05	0.07	0.07	32677	3371.33
50%	0.26	0.26	0.31	0.24	0.26	0.26	54569	10233.51
75%	0.53	0.52	0.64	0.45	0.52	0.52	77642	30124.73
Max	2.65	2.49	2.97	2.35	2.97	2.97	99930	272049.4

Table 5. Descriptive Statistics for Ripple-Related Variables

Variable	SMA	EMA	High	Low	Open	Close	Volume	Turnover
Mean	0.48	0.48	0.58	0.40	0.48	0.48	54821.45	26549.94
Std	0.27	0.26	0.35	0.20	0.28	0.28	26278.32	20839.99
Min	0.17	0.18	0.20	0.14	0.14	0.14	10055	2019.78
25%	0.31	0.31	0.33	0.25	0.30	0.30	32677	12318.16
50%	0.40	0.40	0.49	0.33	0.40	0.40	54569	21306.65
75%	0.54	0.55	0.69	0.47	0.57	0.57	77642	35056.24
Max	1.46	1.40	1.84	1.05	1.84	1.84	99930	147529.1

Ripple's average price during the study period was $0.48, with a maximum price of $1.84 and a minimum price of $0.14.

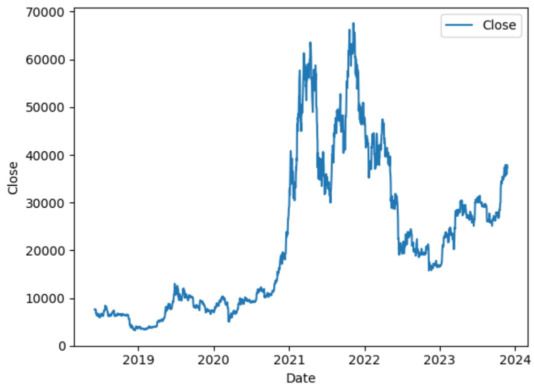

Figure 2. Daily Closing Price of Bitcoin During the Study Period

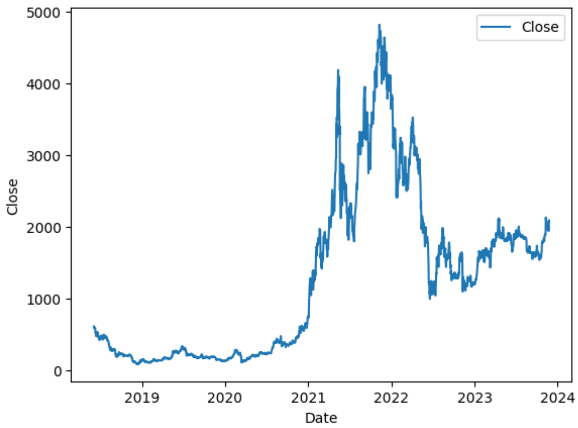

Figure 3. Daily Closing Price of Ethereum During the Study Period

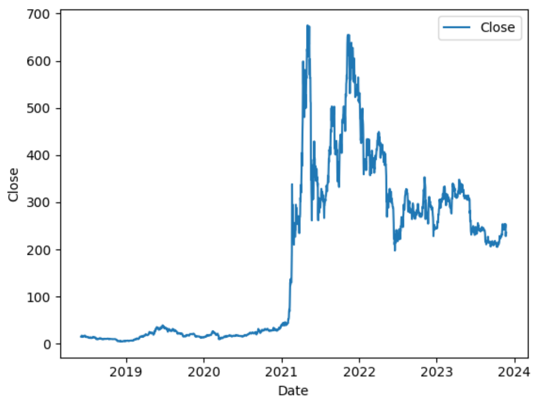

Figure 4. Daily Closing Price of Binance Coin During the Study Period

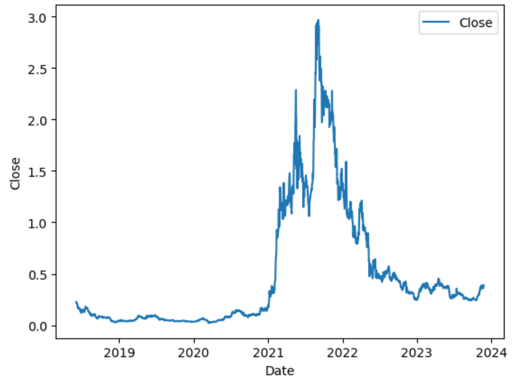

Figure 5. Daily Closing Price of Cardano During the Study Period

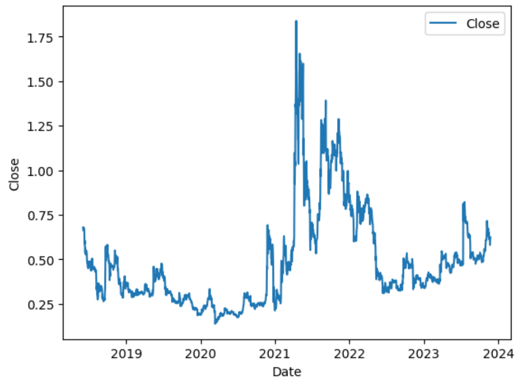

Figure 6. Daily Closing Price of Ripple During the Study Period

This section of the study involved forecasting cryptocurrency prices using two algorithms, MLP and SimpleRNN, with results compared across different cryptocurrencies.

3.1. Prediction of Bitcoin Price

The price prediction for Bitcoin was conducted using two algorithms: SimpleRNN and MLP.

- **SimpleRNN**: This algorithm was applied to the historical daily Bitcoin price data over the study years. The learning curve, model prediction assessment, and MSE error level were analyzed. Figure 7 shows the learning curve for the SimpleRNN algorithm for Bitcoin, demonstrating that training data closely fit the test data, with minimal error, reflecting a desirable result (MSE = 0.001619). Figure 8 presents the comparison between actual and predicted Bitcoin prices using SimpleRNN, showing that the predicted values closely followed the actual values, accurately capturing real trends.

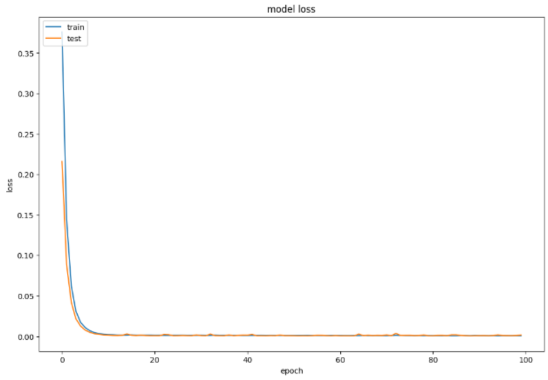

Figure 7. Learning Curve for SimpleRNN Algorithm on Bitcoin

Figure 8. Comparison of Predicted and Actual Bitcoin Prices Using SimpleRNN

- **MLP**: The MLP algorithm was also applied to Bitcoin's daily historical data. The learning curve in Figure 9 shows that the training data reasonably tracked the test data's fluctuations. Figure 10 presents a comparison of actual and predicted prices, indicating that the MLP algorithm captured the real value patterns effectively, with an acceptable MSE of 0.006794.

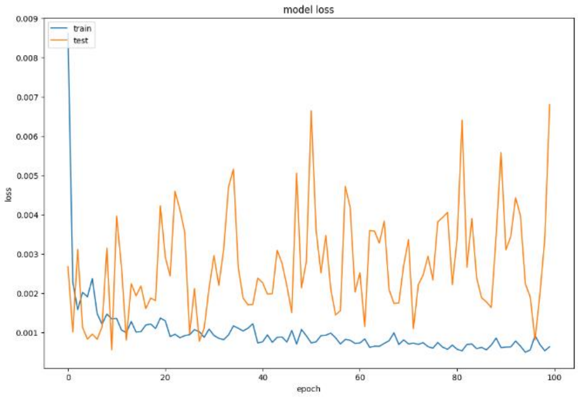

Figure 9. Learning Curve for MLP Algorithm on Bitcoin

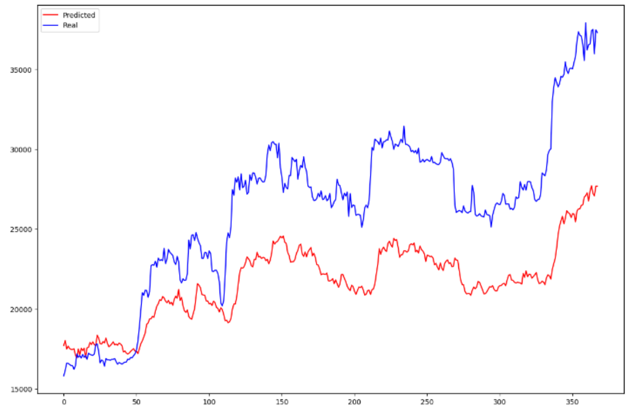

Figure 10. Comparison of Predicted and Actual Bitcoin Prices Using MLP

3.2. Ethereum Price Prediction

- **SimpleRNN**: The SimpleRNN algorithm was applied to the historical daily Ethereum price data over the study period. The learning curve, model prediction accuracy, and MSE error level were assessed. Figure 11 displays the learning curve for SimpleRNN on Ethereum, showing that training data matched well with the test data and resulted in a very low error. Figure 12 presents a comparison of actual and predicted Ethereum prices using SimpleRNN, showing that predicted values followed the actual values closely. The error for this algorithm is very low, with an MSE of 0.001043.

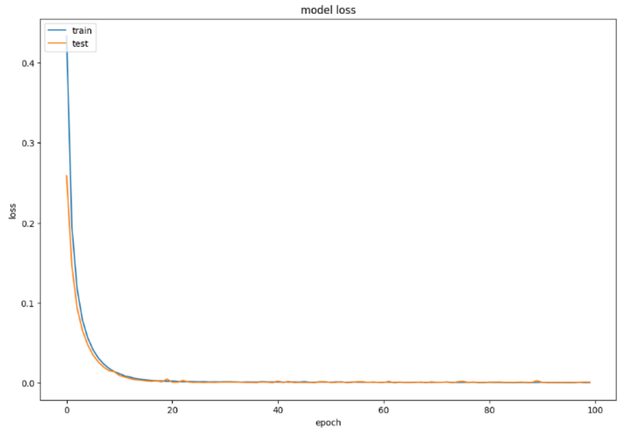

Figure 11. Learning Curve for SimpleRNN Algorithm on Ethereum

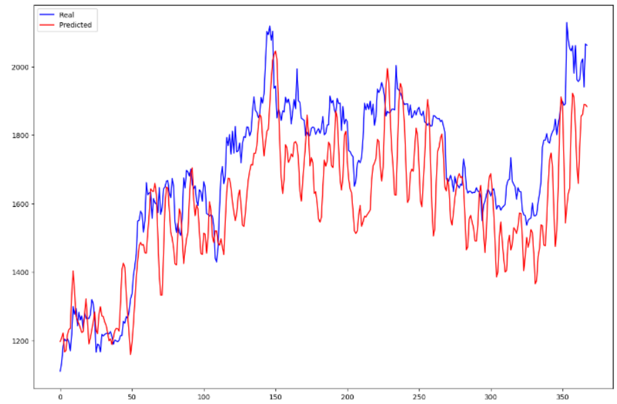

Figure 12. Comparison of Predicted and Actual Ethereum Prices Using SimpleRNN

- **MLP**: The MLP algorithm was also applied to Ethereum's daily historical data. The learning curve in Figure 13 shows that the training data tracked the fluctuations in the test data reasonably well. Figure 14 presents a comparison of actual and predicted prices, demonstrating accurate trend-following by the algorithm. The error rate is minimal, with an MSE of 0.0007923.

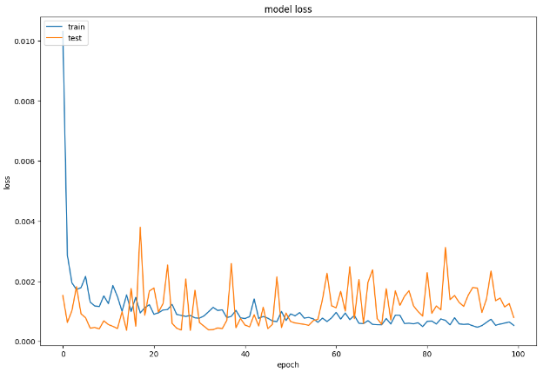

Figure 13. Learning Curve for MLP Algorithm on Ethereum

Figure 14. Comparison of Predicted and Actual Ethereum Prices Using MLP

3.3. Binance Price Prediction

- **SimpleRNN**: For Binance, SimpleRNN was implemented on daily historical price data. The learning curve, as seen in Figure 15, indicates a good fit between training and test data, yielding a very low MSE of 0.0003804. The comparison in Figure 16 shows that the predicted values closely matched the actual values.

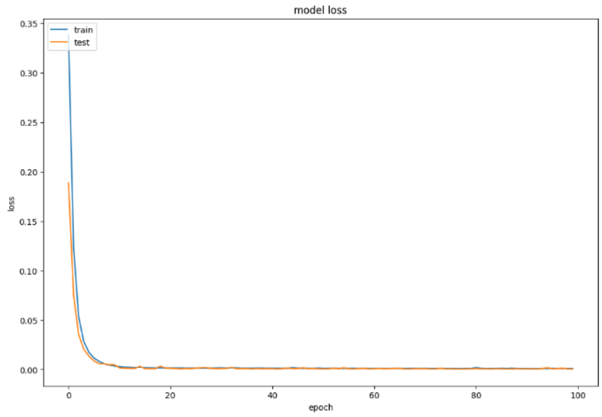

Figure 15. Learning Curve for SimpleRNN Algorithm on Binance

Figure 16. Comparison of Predicted and Actual Binance Prices Using SimpleRNN

- **MLP**: MLP was also applied to Binance's historical data. As shown in Figure 17, the learning curve demonstrates the algorithm's ability to follow the test data's fluctuations. The comparison in Figure 18 indicates a good alignment with actual values, with an MSE of 0.0006917.

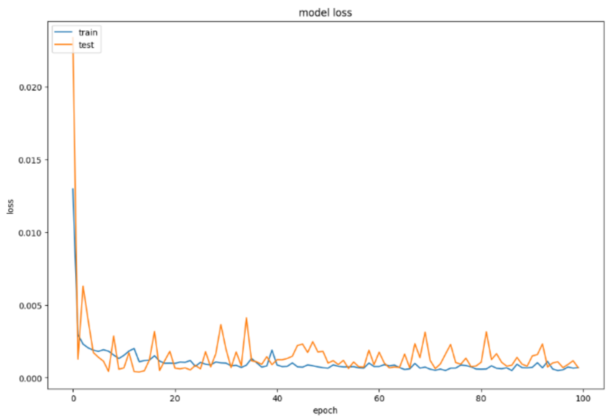

Figure 17. Learning Curve for MLP Algorithm on Binance

Figure 18. Comparison of Predicted and Actual Binance Prices Using MLP

3.4. Cardano Price Prediction

- **SimpleRNN**: SimpleRNN was applied to daily historical price data for Cardano. Figure 19 illustrates a learning curve with strong data alignment, achieving an MSE of 0.0007792. Figure 20 shows that predicted values closely followed the actual data patterns.

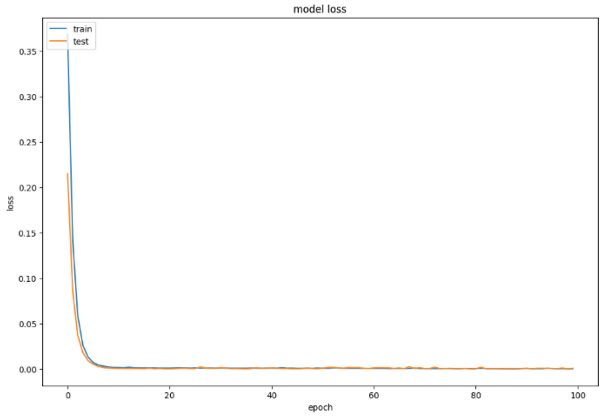

Figure 19. Learning Curve for SimpleRNN Algorithm on Cardano

Figure 20. Comparison of Predicted and Actual Cardano Prices Using SimpleRNN

- **MLP**: The MLP algorithm was also tested on Cardano's historical data. The learning curve in Figure 21 shows a close match with test data variations, and Figure 22 indicates good predictive alignment with actual values, with a very low MSE of 0.0002959.

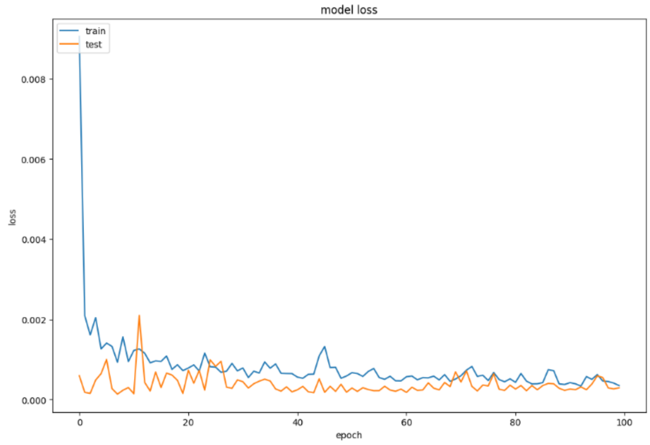

Figure 21. Learning Curve for MLP Algorithm on Cardano

Figure 22. Comparison of Predicted and Actual Cardano Prices Using MLP

3.5. Ripple Price Prediction

- **SimpleRNN**: SimpleRNN was run on Ripple's daily historical price data. The learning curve in Figure 23 shows good alignment with low error, and Figure 24 demonstrates accurate predictions. The MSE for SimpleRNN on Ripple is 0.002146.

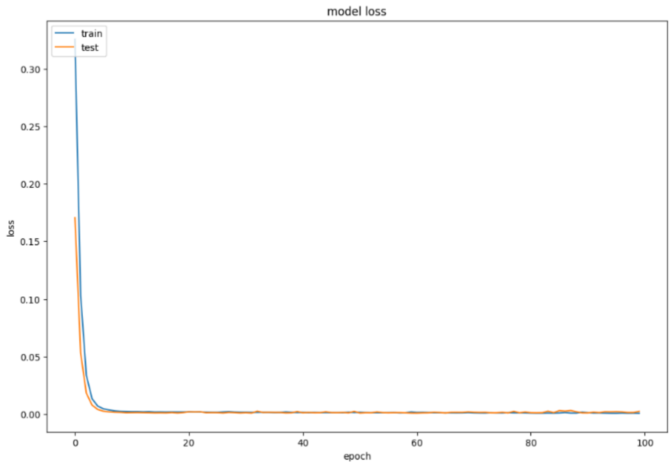

Figure 23. Learning Curve for SimpleRNN Algorithm on Ripple

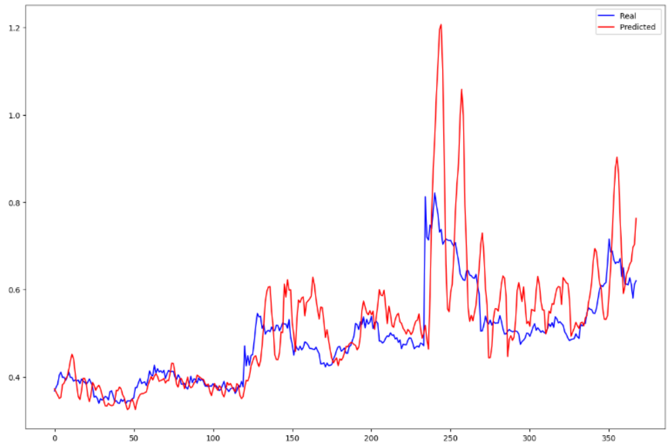

Figure 24. Comparison of Predicted and Actual Ripple Prices Using SimpleRNN

- **MLP**: MLP was also applied to Ripple's data, following test data well as shown in Figure 25. The comparison in Figure 26 reveals accurate predictions with a low MSE of 0.001036.

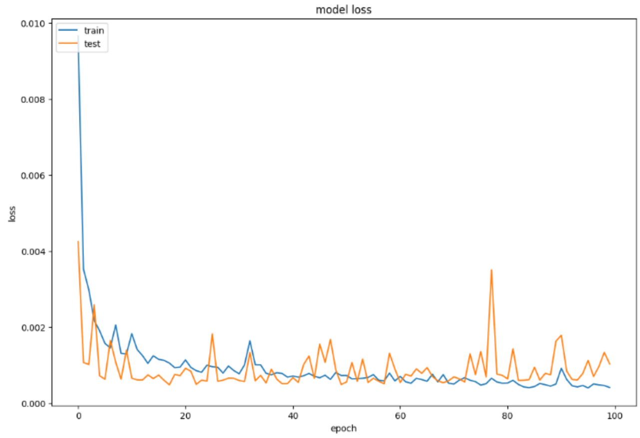

Figure 25. Learning Curve for MLP Algorithm on Ripple

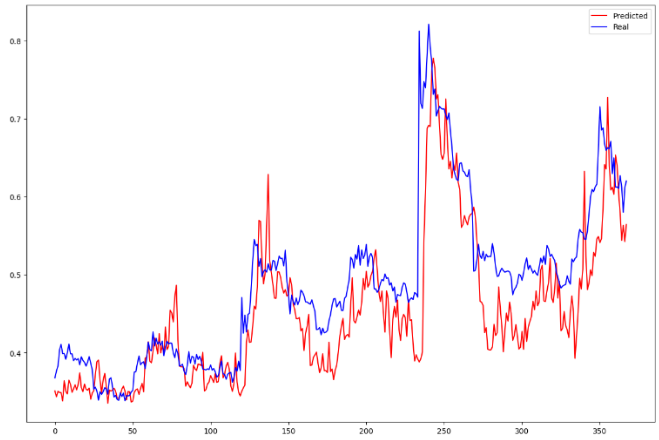

Figure 26. Comparison of Predicted and Actual Ripple Prices Using MLP

3.6. Comparison and Summary of Algorithm Performance Based on MSE Error Levels

Comparative MSE error levels across different algorithms for each cryptocurrency are summarized in tables below. For Bitcoin, MLP had an MSE of 0.006794, while SimpleRNN achieved 0.001619. In Ethereum, MLP performed better with an MSE of 0.000792 compared to SimpleRNN's 0.001043. For Binance, SimpleRNN outperformed MLP with an MSE of 0.000380 versus 0.000692. MLP performed best for Cardano with an MSE of 0.000296, while SimpleRNN had an MSE of 0.000779. Lastly, for Ripple, MLP was again more effective with an MSE of 0.001037 compared to SimpleRNN's 0.002146. Overall, MLP provided slightly lower error rates for Ethereum, Cardano, and Ripple, suggesting greater efficiency over SimpleRNN in these cases.

Table 6. Comparison of MSE for Bitcoin

Algorithm	MSE
MLP	0.006794
SimpleRNN	0.001619

Table 7. Comparison of MSE for Ethereum

Algorithm	MSE
MLP	0.000792
SimpleRNN	0.001043

Table 8. Comparison of MSE for Binance

Algorithm	MSE
MLP	0.000692
SimpleRNN	0.000380

Table 9. Comparison of MSE for Cardano

Algorithm	MSE
MLP	0.000296
SimpleRNN	0.000779

Table 10. Comparison of MSE for Ripple

Algorithm	MSE
MLP	0.001037
SimpleRNN	0.002146

4. Discussion and Conclusion

Research efforts have focused on developing deep machine learning models to forecast cryptocurrency market prices from 2017 to 2023. This study used five distinct deep learning algorithms to predict price fluctuations for major cryptocurrencies, including Bitcoin, Ethereum, Binance Coin, Cardano, and Ripple. While previous studies primarily relied on historical price data for cryptocurrencies, this study sought to incorporate broader cryptocurrency market data, rather than depending solely on the historical price data of each cryptocurrency.

The findings revealed that, overall, the algorithms employed demonstrated acceptable performance in forecasting cryptocurrency prices, with error levels converging toward zero across all algorithms for each cryptocurrency. The MLP algorithm emerged as a consistently robust performer, displaying superior predictive capabilities for most cryptocurrencies compared to other algorithms. According to the results, the best algorithm for Bitcoin price prediction was SimpleRNN; for Ethereum, it was MLP; for Binance Coin, it was SimpleRNN; for Cardano, it was MLP; and for Ripple, it was MLP.

Scientifically, these findings align with existing theories on the effectiveness of deep learning models in financial forecasting, particularly within the volatile and complex landscape of cryptocurrency markets. The success of these algorithms can be attributed to their inherent capacity to selectively retain and utilize historical information, enabling them to understand complex temporal dependencies within cryptocurrency data. Based on these findings, several recommendations for practical application are proposed as follows:

- Transitioning models from a research environment to real-world implementation allows continuous monitoring and evaluation of algorithm performance in actual cryptocurrency trading scenarios, facilitating ongoing adjustments and improvements.
- Given the inherent unpredictability of cryptocurrency markets, it is essential to develop risk management strategies. Despite the accuracy of the models, integrating risk assessment methods is crucial to mitigate potential losses arising from unexpected market behavior.
- Given the complexities of market behavior and behavioral finance factors driving significant market shifts, collaboration among financial experts, data scientists, and behavioral specialists should be strengthened. Combining expertise across these fields can lead to a more comprehensive understanding of cryptocurrency market dynamics, enriching model development and interpretation.
- Emphasis on ethical considerations in deploying machine learning models in financial markets is recommended. Transparently addressing the limitations and uncertainties associated with predictive models is essential to avoid undue reliance on automated trading systems.

Authors’ Contributions

Authors equally contributed to this article.

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Declaration of Interest

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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