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Article

Bitcoin Price Forecasting and Trading: Data Analytics Approaches

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Abstract: Currently, the most popular cryptocurrency is bitcoin. Predicting the future value of bitcoin can help investors to make more educated decisions and to provide authorities with a point of reference for evaluating cryptocurrency. The novelty of the proposed prediction models lies in the use of artificial intelligence to identify movement cryptocurrency prices, particularly bitcoin prices. A forecasting model that can accurately and reliably predict the market's volatility and price variations is necessary for portfolio management and optimization in this continually expanding financial market. In this paper, we investigate a time series analysis that makes use of deep learning to investigate volatility and provide an explanation for this behavior. Our findings have managerial ramifications, such as the potential for developing a product for investors. This can help to expand upon our model by adjusting various hyperparameters to produce a more accurate model for predicting the price of cryptocurrencies. Another possible managerial implication of our findings is the potential for developing a product for investors, as it can predict the price of cryptocurrencies more accurately. The proposed models were evaluated by collecting historical bitcoin prices from 1 January 2021 to 16 June 2022. The results analysis of the GRU and MLP models revealed that the MLP model achieved highly efficient regression, at R = 99.15% during the training phase and R = 98.90% during the testing phase. These findings have the potential to significantly influence the appropriateness of asset pricing, considering the uncertainties caused by digital currencies. In addition, these findings provide instruments that contribute to establishing stability in cryptocurrency markets. By assisting asset assessments of cryptocurrencies, such as bitcoin, our models deliver high and steady success outcomes over a future prediction horizon. In general, the models described in this article offer approximately accurate estimations of the real value of the bitcoin market. Because the models enable users to assess the timing of bitcoin sales and purchases more accurately, they have the potential to influence the economy significantly when put to use by investors and traders.

Keywords: deep learning; bitcoin; prediction models; cryptocurrency markets; statistical analysis

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1. Introduction

As a new alternative electronic currency exchange system, cryptocurrencies have been widely acknowledged as having significant consequences for developing markets and the global economy [1]. While impinging on most financial activities, the cryptocurrency trade has gained widespread recognition as one of the most popular and promisingly profitable investment options available today for investors. Although this financial sector is growing at a rapid pace, it is also marked by substantial volatility and significant price variations within a single year. Forecasting cryptocurrency prices is often regarded as one of the most challenging time-series predictions [2–4], mostly due to the substantial price volatility and enormous number of unpredictability-inducing elements involved. These challenges result from the complicated temporal dependencies inherent in the considerable number of unpredictable factors involved.

Blockchain (BC), the technology behind cryptocurrencies, is widely thought to be fundamental in providing the backbone of increased security and privacy in artificial intelligence (AI) across a wide range of sectors, including the Internet of Things (IoT) ecosystem. BC technology has several components spread throughout the entire global network of computer systems, particularly its digital recording of transactions [5,6]. A transaction and a block are two essential components of the BC, in that precise order. The authors [7] demonstrated that, with respect to exchange rates across cryptocurrencies over time, the impacts of networks on competition among the developing cryptocurrency market are dependent on two factors: (1) rivalries among the many different currencies and (2) competition among the numerous exchanges [8]. The authors [9] refer to the competition between cryptocurrencies as "a positive thing" and characterize it using the phrase "healthy competition." They also argue that technological and security innovations are important. According to the authors [10], bitcoin exhibits volatility shock transmissions, but the uncertainty of economic policies has no influence on the transmission of shocks. Bitcoin, sometimes referred to as cryptocurrency, is a form of digital or virtual currency used in several financial systems [11]. It is guarded by encryption, which prevents it from being copied or reused and ensures that it cannot be faked. The fact that it is not issued by a central authority or central bank. This is how it differs from traditional currencies. Instead, in contrast to traditional currencies, it is a decentralized virtual currency that can be exchanged using cryptographic protocols [12]. Other qualities include its production via BC technology [13], which is extraordinarily intricate, and attempts to store data in such a way that it is difficult—if not impossible—to update, cheat, or hack the system. Bitcoin has started to carve out a space for itself, which, depending on how it develops, may either aid other cryptocurrencies in their quest to achieve widespread recognition or play a significant role in the demise of cryptocurrencies as a whole. In their infancy, cryptocurrencies were impossible to forecast, particularly whether they would proceed toward widespread use across global markets in the near future [14].

The authors [15] investigated the ways in which big data and cryptocurrencies interact. Because the cryptocurrency market is one of the most alluring for financial speculation, deceptive business practices have become increasingly prevalent on social media platforms, including Facebook. Many people have made considerable amounts of money by speculating about digital markets, but every investment comes with a number of hidden risks, which is why some investors—particularly those with high risk tolerance—are interested in bitcoin and other cryptocurrencies. For this reason, traders and investors place their trust in forecasts [16,17].

Machine learning (ML) and AI algorithms are intriguing [18], even though their forecasting power varies depending on the coin, where low-volatility cryptocurrencies have a higher degree of predictability than the high-volatility varieties. Research has revealed that the usefulness of various information sets differs among ML algorithms when a group of algorithms is applied; as a result, prediction is likely substantially more challenging [19].

Thousands of different cryptocurrencies may be traded on digital exchanges, but bitcoin remains the most widely used. It is impacted by and interacts with external variables, including news, social media, and minor cryptocurrencies with a low market share, which are not often considered by investors and traders when they attempt to estimate the future of the cryptocurrency market. Bitcoin is also influenced by and interacts with internal influences, such as the bitcoin network. Due to the close links between cryptocurrencies, smaller ones have become sources of shocks that may have either a favorable or a negative impact on the performance of other cryptocurrencies. As shown by the authors [20], the independent currency of gold may be leveraged as an effective hedging strategy to reduce the risks associated with unexpected movements in the cryptocurrency market. However, due to the volatility and dynamism of cryptocurrency values, it is impossible to foresee their movement. There are hundreds of cryptocurrencies in circulation across the globe, and customers may choose from any of them.

One of the most controversial and puzzling trends in the world economy over the past 10 years has been the meteoric rise of cryptocurrencies like bitcoin. Investors are apprehensive about cryptocurrencies due to their frequent and unpredictable price swings, in addition to the fact that the majority of developing countries and users of this currency do not yet have the necessary infrastructure to adequately oversee cryptocurrency transactions. The goal of venture capitalists and other types of investors is to maximize their returns with the least amount of effort and in the shortest amount of time possible. Thus, they search for the most lucrative and secure enterprises they can find. Therefore, it is absolutely necessary for academics, financial experts, investors, and traders to collaborate and to determine how to reliably forecast the future value of cryptographic products.

In this research, we take on the challenge of predicting cryptocurrency prices by employing an innovative deep-learning model. The gated recurrent unit (GRU) and multilayer perceptron (MLP) methods are used in the proposed model to generate accurate price forecasts. In the reported findings of the simulation of the proposed method, the values for mean square error (MSE), root mean square error (RMSE), Pearson correlation (R), and R-squared (R2) are presented and compared with those of other similar approaches. Finally, evidence is provided to demonstrate that the recommended approach is superior to the alternatives being considered . This article uses data from bitcoin, the most popular cryptocurrency, to predict future prices using various AI algorithms and techniques to achieve the following results:

- Adopting AI algorithms, such as the GRU and MLP models, to predict bitcoin prices reliably.
- These models have significant repercussions for investors, who can use them to perform trustworthy, precise, and potentially correct predictions of bitcoin prices.
- Improving novel approaches to increase the accuracy of our forecasts in comparison to what was found in earlier research.
- Providing a reliable technique for forecasting future bitcoin prices using data from cryptocurrency history

This paper addresses the following research questions: "In what ways might AI algorithms aid investors and decision makers in anticipating bitcoin prices?" and "What is the best model for prediction future bitcoin values?"

2. Background Study

Concerning time-series analysis, bitcoin price analysis and forecasting are highly intricate as well as highly demanding tools. Due to substantial variations in the volatility of bitcoin time series, which are significantly impacted by an immense number of variables, understanding and manipulating bitcoin is a complicated process. As documented in the literature, several recent research attempts have embraced and applied deep learning approaches to predict bitcoin prices and their directional movement to increase forecasting accuracy. Some fascinating discoveries and practical implications are succinctly given below.

By using various advanced prediction models, Derbentsev et al. [20] sought to estimate the short-term dynamics of the three cryptocurrencies that were the most capitalized on at the time of their creation: bitcoin (BTC), Ether (ETC or Ethereum), and XRC (Ripple). Furthermore, they assessed the prognostic accuracy of several models, including artificial neural networks (ANNs), random forests (RFs), the binary autoregressive tree model (BART), and their combinations. From 1 August 2015 to 1 December 2019, 1583 daily bitcoin prices were gathered using this data. The researchers' test findings revealed that the ANN and BART models had an average accuracy of 63% when predicting directional movement, which was much greater than the "naïve" model's accuracy of 58%.

On the other hand, Chowdhury et al. [21] applied advanced ML prediction models for the index and components of cryptocurrencies to forecast the future prices of the index and its constituents. To aid cryptocurrency traders, they sought to forecast the CCi30 index's final value, as well as that of nine major cryptocurrencies. They used several diverse types of ML models in their investigation, including gradient-boosted trees, ANNs, k-nearest neighbor models, robust ensemble learning models, and others. Closing prices from 1 January 2017 to 31 January 2019 were used as data. Among these state-of-the-art models, ensemble models and gradient-boosted trees provide the most accurate predictions, with performances comparable to or even better than those of several previously presented models.

Pintelas et al. [22] conducted a fascinating study evaluating advanced deep learning models to forecast cryptocurrency prices and price movements. Their investigation indicated that deep learning algorithms have substantial limits when it comes to accurate predictions. Based on their experimental findings, the authors concluded that more sophisticated algorithmic techniques are required for the construction of efficient and dependable cryptocurrency models to achieve greater reliability. Similar work was conducted by Livieris et al. [23], who looked at whether the three commonly used ensemble processes of averaging, bagging, and stacking could improve the forecasting performance and reliability of deep learning models. From the beginning of 2018 through the end of 2019, the authors analyzed hourly BTC, ETH, and XRC prices. In addition, they conducted a comprehensive performance evaluation of many ensemble models using different Conv- and long short-term memory (LSTM)-based learners as their foundation. Despite a significant increase in processing complexity, their investigation showed that deep and ensemble learning might be useful for creating robust and reliable bitcoin prediction models.

According to Patel et al. [24], a hybrid cryptocurrency prediction approach has been developed, with particular emphasis on Litecoin and Monero cryptocurrencies. The proposed model is constructed with a recurrent neural network (RNN) architecture, and to accomplish the model goals, it uses both the LSTM and GRU layers. Daily Litecoin data from 24 August 2016 to 23 February 2020, as well as daily Monero data from 30 January 2015 to 23 February 2020, were used in the analysis. The data included information on the average price, opening and closing prices, high and low prices, transaction volumes, and other factors for both Litecoin and Monero.

AI has spawned several subfields, one of which is ML, which can predict the future by looking at data from both the present and the past. Model-based forecasting models have numerous advantages over other forecasting models, as previous research has demonstrated that they not only produce results that are near or exactly the same as the actual results but also improve precision and accuracy. As a result of these benefits, model-based forecasting has a variety of advantages over other types of forecasting techniques. Neural networks (NNs), support vector machines (SVMs), and deep learning are a few examples of several types of ML approaches, all of which are viable options. The authors demonstrated that including cryptocurrencies in a portfolio increases its efficiency in two separate ways. The first is by lowering the standard deviation, and the second is by giving alternatives to investors with a greater variety of asset allocation. It has been recommended that the optimal allocation for cryptocurrencies should lie anywhere between 5% and 20%, depending on the risk tolerance of the investor. Two ML techniques—RFs and stochastic gradient-boosting machines (SGBMs)—were employed for time-series data forecasting, according to the authors [25,26]. Based on their findings, it appears that the ML ensemble approach may be used to forecast bitcoin prices. Making the appropriate decision at the appropriate time, achieved through careful planning, is critical for decreasing the risks associated with the investment process.

Furthermore, McNally et al. [27] investigated how reliably one could anticipate the direction of bitcoin prices measured in US dollars (USD). Multiple NN techniques were used in the research, including RNNs, LSTM networks, and the autoregressive integrated moving average (ARIMA) technique. The LSTM network outperformed the other evaluated networks in terms of classification accuracy (52%) and root mean square error (RMSE; 8%). It was expected that nonlinear deep learning algorithms would outperform the ARIMA approach in predicting a system's behavior in the future. Bitcoin price predictions were made using the convolutional neural networks (CNNs) and RNNs introduced by

Yogeshwaran et al. [28], who used data collected at intervals ranging from five minutes to two hours. CNNs showed a reduced degree of inaccuracy of about 5% in predicting bitcoin prices, but about 15% more errors were seen when using RNNs. To predict bitcoin prices, Demir et al. [29] used several techniques, including LSTM networks, naive Bayes, and the nearest neighbor approach; the accuracy of these techniques varied from 81.2% to 97.2%. By including RNNs and LSTM in their body of work, Rizwan, Narejo, and Javed [30] expanded the scope of their investigation to incorporate deep learning methodologies. Their research discovered that LSTM had a prediction accuracy of 52% and an RMSE of 8%, while the results of eXtreme Gradient Boosting (XGBoost) and LSTM were the same for Linardatos and Kotsiantis [31], except that the latter determined that the second method had a lower RMSE of 0.999. When comparing ARIMA to other approaches, including RFs, SVM, LSTM, and WaveNet, for predicting future bitcoin prices, Felizardo et al. [32] discovered that ARIMA had a lower error rate. Computational methods are often held in higher esteem.

Finally, Dutta, Kumar, and Basu [33] demonstrated novel deep learning methods by combining the LSTM and GRU models, where the latter achieved the best error result with an RMSE of 0.019. Furthermore, Ji et al. [34] successfully predicted bitcoin prices using a variety of methods, including deep neural networks (DNNs), LSTM, and CNNs. They were able to obtain 60% accuracy, suggesting room for improvement via the use of deep learning techniques and the provision of detailed descriptions of key factors. These authors stressed the necessity for reliable prediction models, not only when predicting future results but also when working with data from within and outside the sample.

While attempting to forecast bitcoin values, Wu et al. [35] used not one but two different LSTM models, one of which was a basic LSTM model and the other an LSTM model that incorporates an autoregression (AR) model. Another study [36] used LSTM to predict bitcoin prices. When projecting bitcoin values, the data indicated that the LSTM model performed much better than traditional ML models. Nonetheless, much of the research simply employed normal ML algorithms used in stock price prediction and applied them to bitcoin. The problem with this approach is that the use of standard algorithms fails to capture the unique qualities of cryptocurrency successfully. In addition, another study presented bitcoin price projections based on the distinctive characteristics of the cryptocurrency that set it apart from equities and stocks, including the following elements: the bitcoin transaction graph was used by other academics [37] to predict bitcoin prices, but because every bitcoin transaction is stored in a public ledger that anyone with internet access can view, developers have been able to create software that can accurately forecast bitcoin prices by analyzing the transaction identifier, sender, receiver, value, and timestamp, which are included in every bitcoin transaction. The authors of [38] developed a sophisticated method for predicting future bitcoin prices using the edges that appear most often in the transaction network. Katsiampa, P [39] compared GRACH models to predict the bitcoin price and it is observed that the AR-CGARCH model is appropriate model for predicting price of bitcoin

3. Methodology

Currently, many people are interested in bitcoin, ever since it and other cryptocurrencies emerged as popular investment vehicles. As a result, a growing number of new platforms are being developed to accommodate these assets. The relevance of research articles on bitcoin price prediction is shown by the profitability of the cryptocurrency and the ongoing support for its platform. However, the great bulk of cryptocurrency research is focused entirely on attempting to anticipate cryptocurrency values. Consumers are frustrated as a direct consequence of the need to make tough judgements rapidly concerning activities that promote profit maximization. This causes customers to feel as if their time is being wasted—they must liquidate their Bitcoin holdings if the price of the cryptocurrency increases, and they must purchase bitcoin whenever it decreases. In addition, the performance of these deep learning models is still low, and little research has studied how these models might be used to provide recommendations for the aforementioned kinds of activities. As a solution to these problems, the herein study presents a deep learning model with some innovative input features.

As can be seen in Figure 1, the approach that has been recommended takes the shape of an overarching plan. The outcome of the recommended approach is calculated utilizing historical data on bitcoin prices.

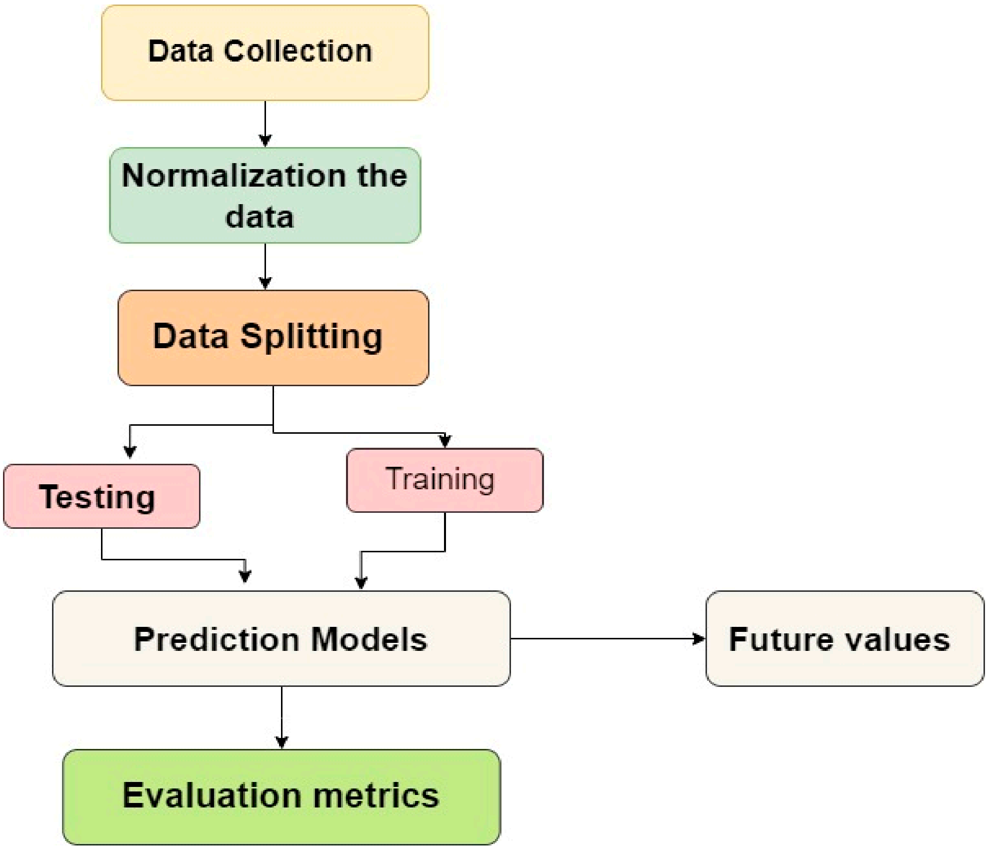

Figure 1. Framework of the proposed system.

3.1. Dataset

The data generated between 1 January 2021 and 16 June 2022 were collected as a sample from Market Watch (https://www.marketwatch.com (accessed on 20 July 2022)). In this study, the dependent variable is the bitcoin price, which is calculated in terms of the USD value of a bitcoin.

3.2. Normalization

Min–max normalization is one of the most frequently used methods for normalizing data. The lowest value is converted to 0, the greatest value is transformed to 1, and all other values are changed to a decimal between 0 and 1 for each characteristic:

$$z_n = \frac{x - x_{min}}{x_{max} - x_{min}}(New_{max_x} - New_{min_x}) + New_{min_x} \tag{1}$$

where x_{max} is the maximum value 1 and x_{min} is the minimum value 0, and where the highest value is 1, the lowest value is 0, and x_{max} and x_{min} are the maximum and minimum values, respectively. The lowest number is denoted by New_{min_x} and the biggest number by New_{max_x}. Figure 2 shows the performance of the *min–max* normalization method for data normalization.

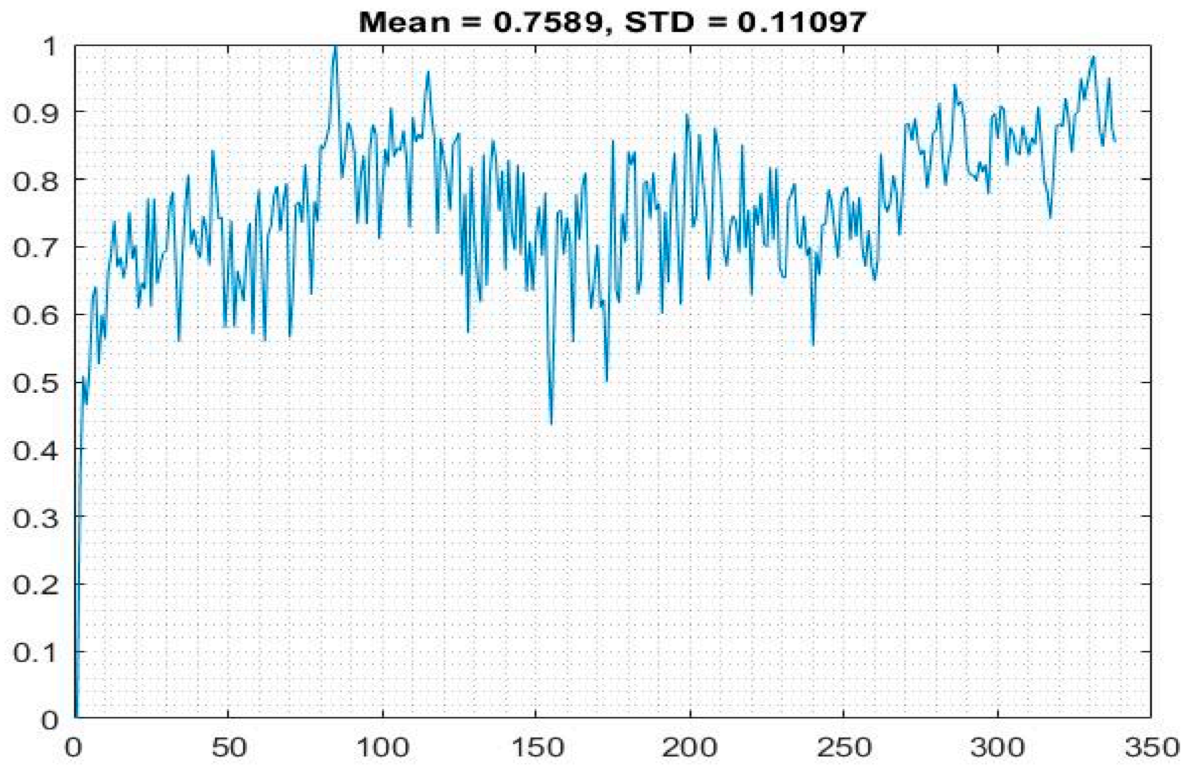

Figure 2. Data normalization.

3.3. Prediction Models

This section explains the mathematical model of the GRU and MLP models, which are used to conduct the investigation.

3.3.1. Gated Recurrent Unit (GRU)

Another kind of RNN that can resolve the issue of vanishing gradients is called the GRU. Figure 3 demonstrates that the GRU, first described by [40–43], is analogous to LSTM but with fewer gates: one referred to as an update gate and another as a reset gate. The movement of data and information throughout the network is under the combined control of these two gates. The update gate is responsible for determining the quantity of data from the past that must be transmitted to proceed, while the quantity of information that will be forgotten is determined by the reset gate. The following equations provide a summary of the GRU:

$$\mu_t = \sigma\left(V_\mu x_t + W_\mu o_{t-1} + b_\mu\right) \tag{2}$$

$$r_t = \sigma\left(V_r x_t + W_r o_{t-1} + b_\mu\right) \tag{3}$$

$$i_t = tanh(V_o x_t + W_o(r_t \odot\ o_{t-1}) + b_0) \tag{4}$$

$$o_t = \sigma(\mu_t \odot\ o_{t-1}\ (1 - \mu_t)\ \odot\ i_t) \tag{5}$$

where x_t represents the input; o_t the output; μ_t the update gate output; r_t the reset gate output; $\odot$ the Hadamard product; and V, W, and b the parameters or weight matrices.

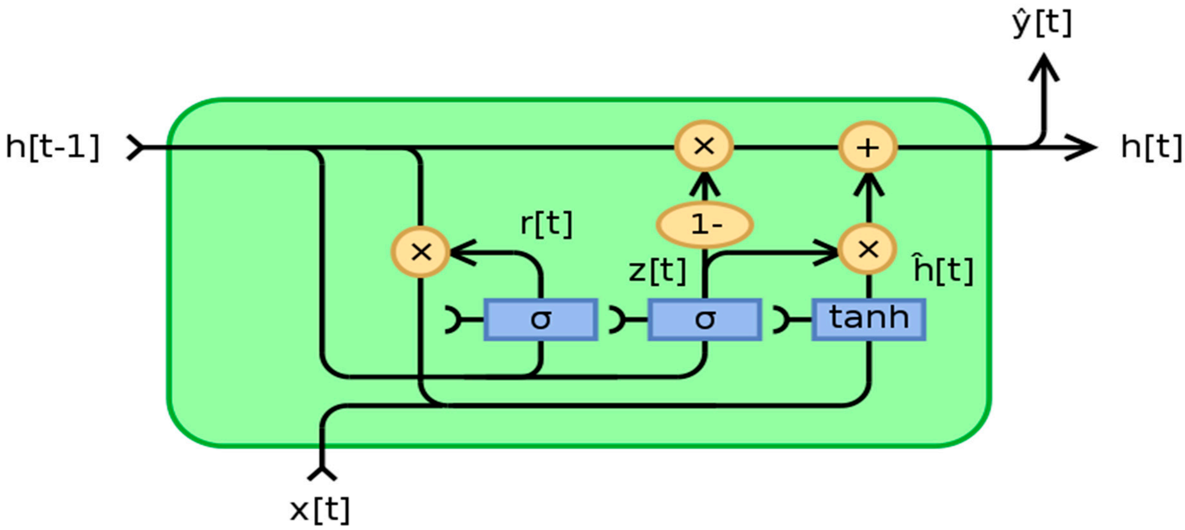

Figure 3. GRU model.

3.3.2. Multilayer Perceptron (MLP)

The first step in using NNs for predictive modeling is identifying the type of NN to employ and type of network design to use. MLPs are the most resilient and unique form of NN considered in this research, and a backward propagation approach is used to train the MLP NN; thereafter, errors travel through the network and are adapted to its hidden layers. Thus, the ANN is trained using error correction learning (for which real system responses must be known). The weights are changed using the average update of the weights (batch learning), which is determined by including all the patterns in the input file (an epoch) and aggregating all weight modifications. In addition, a criterion for stopping is required. Even if there are additional alternatives, such as a maximum number of repetitions or a threshold for the mean square error (MSE), cross-validation is the most utilized method. With this strategy, it is advisable to terminate training once the best generalization has been made. To evaluate the trained network, only a tiny portion of the training data is used [44–48]. In other words, if the network performance, measured by the MSE, begins to decline or to stagnate, training should be halted.

$$\xi = \sum_{i=1}^{n} w_i x_i - b = w^T x - b \tag{6}$$

$$y = \sigma(\xi) \tag{7}$$

$$\sigma(\xi) = \frac{1}{1 + e^{-(\xi)}} \tag{8}$$

where x_i is the number of the ith input, w_i is the link weight from the ith input, w = $(w_1 \ \ldots \ w_n)T$ is the total weight, and x_i is the number of the ith input $(x_1 \ \ldots \ x_n)$. A threshold or bias is denoted by the letter b, while the letter n indicates the total number of inputs. The job of the activation function s(x) is typically to transfer real numbers into the interval, and this can be performed by a continuous or discontinuous function. It is also possible to utilize the sigmoidal activation function and express it using Equation (8). Figure 4 shows the architecture of the MLP model and Table 1 shows its parameters.

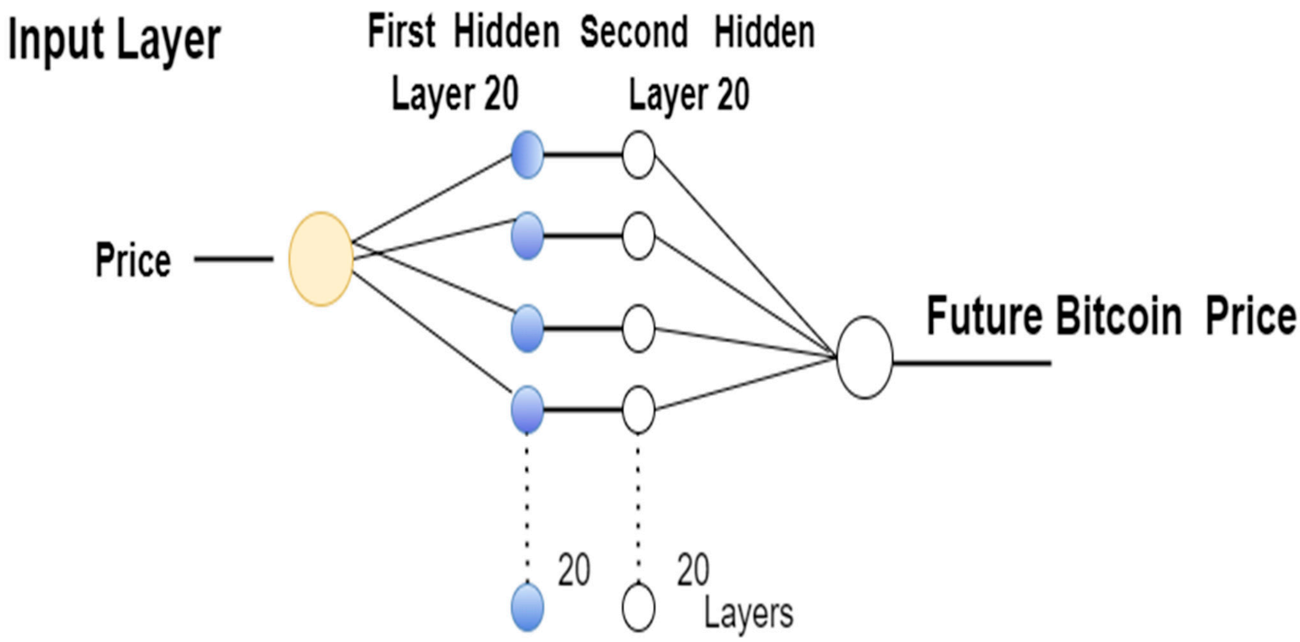

Figure 4. Structure of the MLP for predicting bitcoin prices.

Table 1. Parameters of the developed MLP model.

First hidden layer	15
Second hidden layer	15
Input layer	4
Maximum number of iterations	100
Maximum number of epochs	70
Delays	[1 2 5 7]
Gradient	1.26
Validation check	6

It is essential that data ought to be normalized before it is fed into a model. The min-max normalization is used for scaling the data before obtaining prediction values. The MLP classifier models require at least two layers. The bitcoin data is in a decent state to be put into some kind of MLP model. For the purpose of simplicity, we will be using two layers, with 20 nodes hidden in each of the first and second layers. The only output will be a forecast of the price of bitcoin, and the maximum number of iterations will be 100, while the maximum number of epochs will be 70. When evaluating the model with the MSE metric, if the forecast is not accurate, these parameters can be modified.

Pseudocode MLP

1. Initialization variable delay number, number of feedforwardleyars max-iteration
2. Load data set X
3. Normalization dataset (X)
4. Split the dataset 70% training and 30% as testing
5. -building and ANN architecture
6. for d = Delays
7. X = [X; x(:,Range-d)];
8. end
9. make prediction
10. calculate prediction by using evaluation metrics

3.4. Evaluation Metrics

The *MSE*, *RMSE*, Pearson correlation, and coefficient of determination (R^2) metrics were utilized to evaluate the GRU and MLP models for bitcoin price prediction.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(y_{i,exp} - y_{i,\ pred} \right)^2 \tag{9}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(y_{i,exp} - y_{i,pred} \right)^2}{n}} \tag{10}$$

$$R\% = \frac{n\left(\sum_{i=1}^{n} y_{i,exp} \ \times y_{i,\ pred}\right) - \left(\sum_{i=1}^{n} y_{i,exp}\right)\left(\sum_{i=1}^{n} y_{i,\ pred}\right)}{\sqrt{\left[n\left(\sum_{i=1}^{n} y_{i,exp}\right)^2 - \left(\sum_{i=1}^{n} y_{i,exp}\right)^2\right]\left[n\left(\sum_{i=1}^{n} y_{i,pred}\right)^2 - \left(\sum_{i=1}^{n} y_{i,pred}\right)^2\right]}} \times 100 \tag{11}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \ \left(y_{i,\ exp} - y_{i,\ pred}\right)^2}{\sum_{i=1}^{n} \ \left(y_{i,\ exp} - y_{avg,\ exp}\right)^2} \tag{12}$$

where y (*i,exp*) and y (*i,pred*) are the experimental value and predicted value of data point I, respectively. In this instance, the experimental data are represented by y (*avg,exp*), whereas training values are represented by n.

4. Experiments

In this section, we present the results of a comprehensive evaluation of the suggested AI algorithms' performance in predicting bitcoin price movements. We used the GRU and MLP to predict bitcoin prices, and all experiments were carried out on a computer equipped with a 2.27 GHz Intel Core i5 processor, 8.0 gigabytes of RAM, and a MATLAB 2020 environment for creating computer programs. The dataset was collected between 1 January 2021 and 16 June 2022.

4.1. Results

In this section, the results of the proposed GRU and MLP models, which were used to predict bitcoin prices, are presented. The datasets were divided into training and testing categories for the evaluation and performance of the presented models. The results of the GRU and MLP models are as follows.

4.1.1. Results from the Training Phase

Model training is a fundamental AI process resulting in a functioning model that may subsequently be verified, tested, and deployed. The model's performance during training will eventually decide how well it operates when it is finally incorporated into an application for an end user. To elaborate, 80% of the dataset was considered for training for both models. Table 2 presents the findings obtained from applying the GRU and MLP models during the training process in the period from 1 January 2021 to 16 June 2022. During this time, the performances of all models were satisfactory, with the MLP model reporting the lowest MSE of 8.444×10^{-5} and the GRU model showing the highest MSE of 0.016518.

Table 2. Results of the GRU and MLP models during the training process.

Models	**MSE**	**RMSE**	**R %**	**R^2 %**
GRU	0.016518	0.12852	98.70	95.51
MLP	8.444×10^{-5}	8.444×10^{-5}	99.15	98.21

As shown in Figure 5, there was complete agreement in the GRU model (R = 98.70 %) and in the MLP model (R = 99.15%) between the values predicted by both (y-axis) and the values obtained from historical bitcoin prices (x-axis). In addition, as seen in Table 2, the MSE and RMSE were much lower than expected in the MLP model, which demonstrates the validity of the created model and its ability to predict bitcoin price movements accurately.

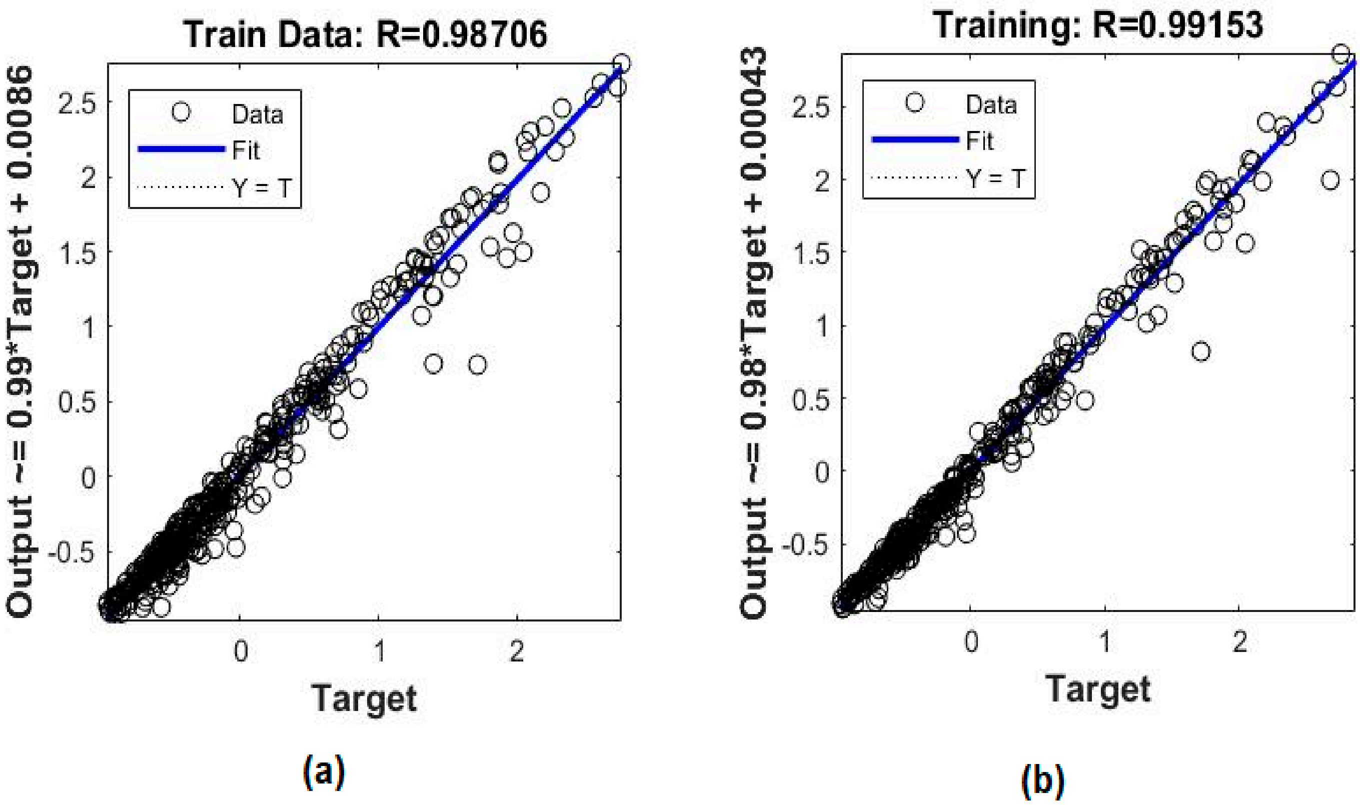

Figure 5. Regression plot for predicting bitcoin prices: (**a**) GRU model and (**b**) MLP model.

4.1.2. Results of the Proposed Model in the Testing Phase

To examine the proposed model, 20% of the dataset was considered for testing. The testing phase involves assessing the constructed model and determining its ability to predict future bitcoin prices. The proportion of instances that were properly categorized represents the precision of the findings, while the RMSE quantifies the number of errors committed. The degree of regression, as well as the MSE and RMSE are displayed in Table 3. In every model, the degree of regression for the testing data is consistent, and the prediction errors of the MLP model during testing are exceptionally low (MSE = 0.000109). Both the MSE and RMSE values are independently satisfactory. The model that used the GRU approach achieved an MSE of 0.03354. When taken as a whole, these findings produce a degree of regression that is far higher than that of earlier investigations with different existing models.

Table 3. Results of the GRU and MLP models from the testing process.

Models	**MSE**	**RMSE**	**R %**	**R^2%**
GRU	0.03354	0.18314	96.35	91.09
MLP	0.000109	0.01044	98.90	95.9

Determining whether there is a statistically significant correlation between the prediction and observation values is crucial. In Figure 6, the correlation between the prediction values and the bitcoin price is shown. The MPL model achieved the highest regression (R = 98.90%), whereas the deep learning GRU model achieved (R = 96.35%).

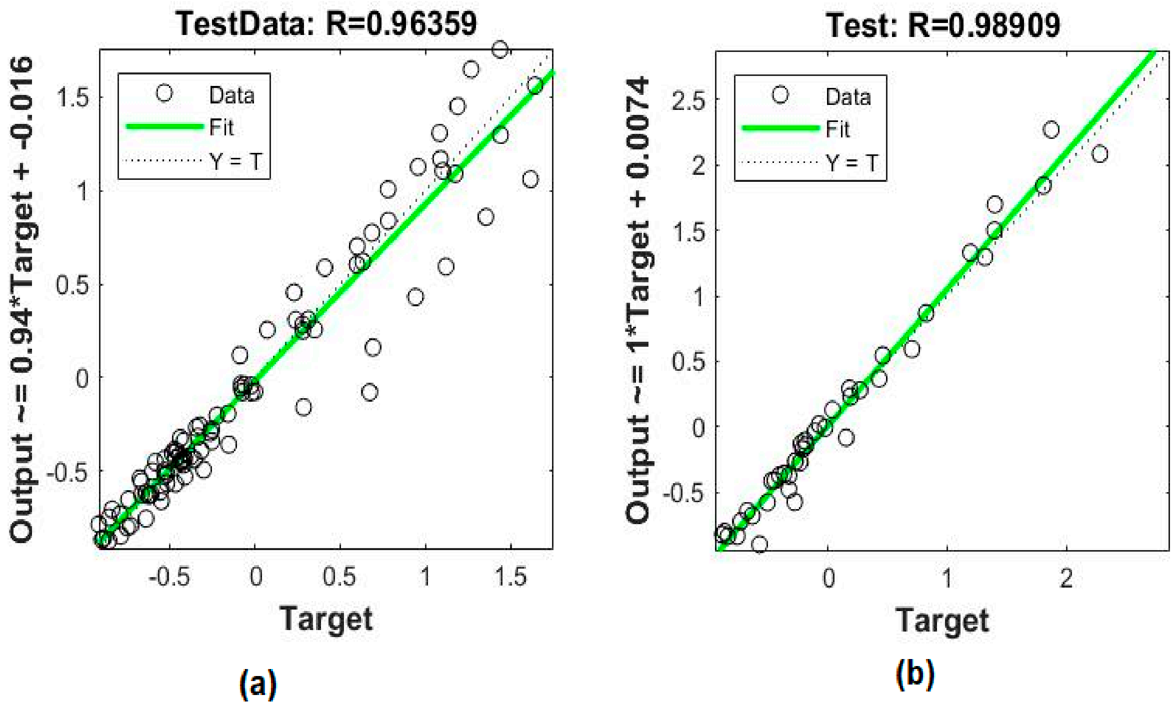

Figure 6. Regression plot for predicting bitcoin price: (**a**) GRU model and (**b**) MLP model.

Figure 6 is a correlation matrix that represents the inter-variable correlation (closing price). According to the matrix, there is strong support for bitcoin. For this reason, if the value of the monitored currency changes, the value of the other coins will change accordingly. Figure 7 shows the performance of the GRU and MLP models for predicting bitcoin cryptocurrency values over a period of 60 days from 16 June 2022 to 16 March 2022. It is observed that the bitcoin price has been going down.

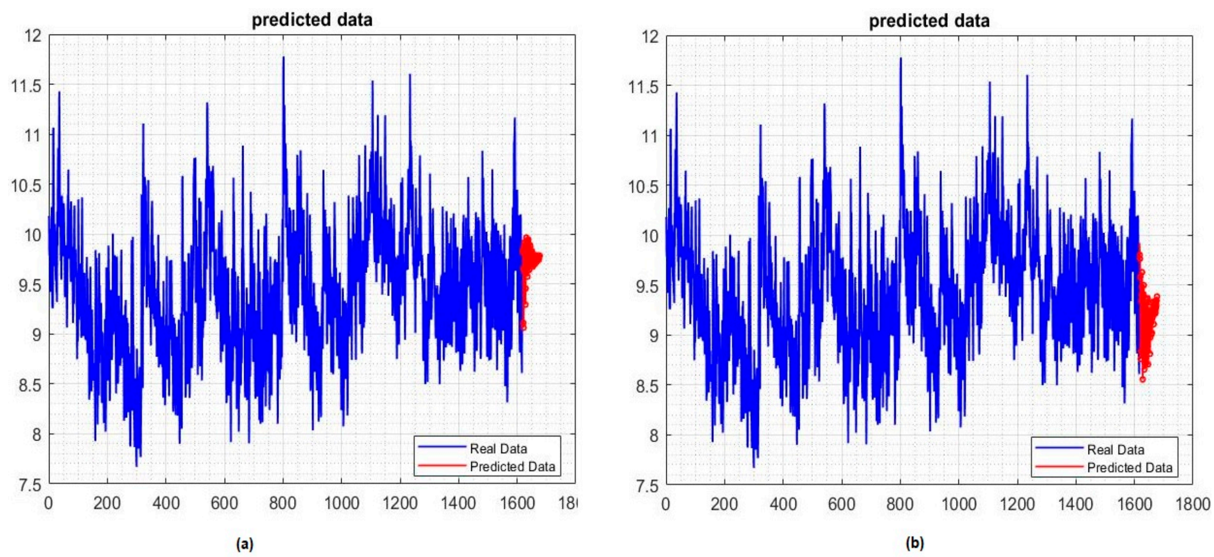

Figure 7. Forecasting future values in time-period of 60 days. (**a**) GRU model and (**b**) MLP model.

There are five important characteristics contained inside the bitcoin data. The correlation strategy was put into action so that correlations could be discovered between these traits. The relationships between the attributes of bitcoin cryptocurrency are illustrated in Figure 8.

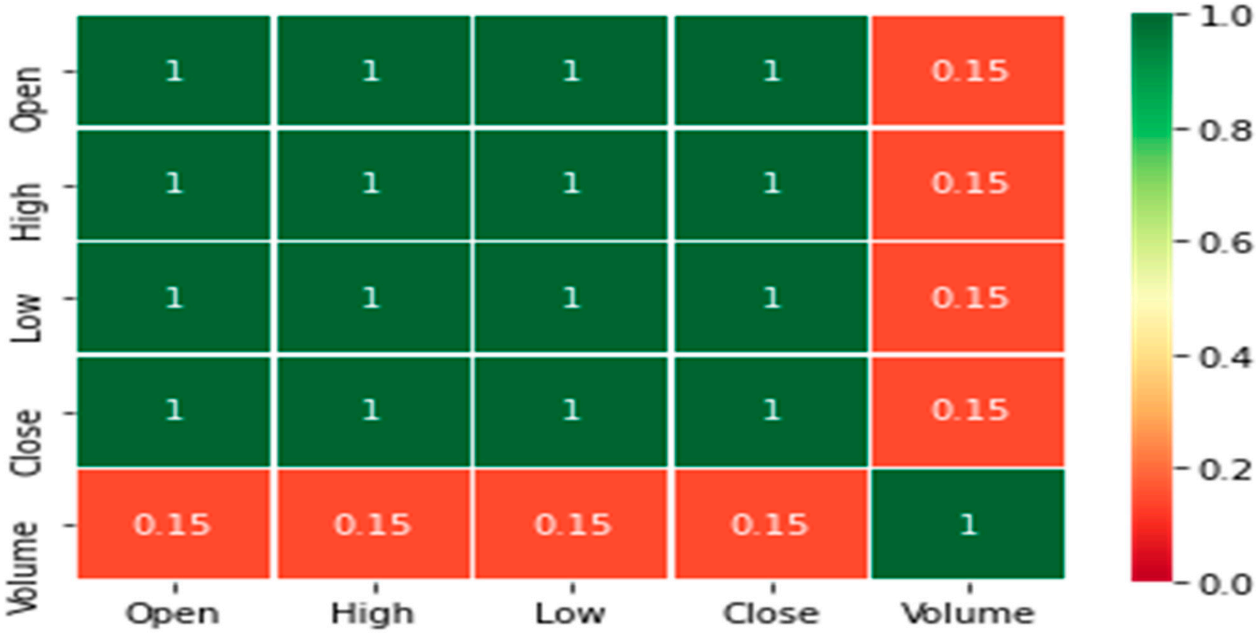

Figure 8. Correlation between the features of bitcoin.

5. Discussion

To model bitcoin prices, both the price change over time and the current value of one bitcoin must be considered, and this can be done with an exceptionally low error rate, as demonstrated in this work. In contrast, the former remains an open question for all scholars. Researchers have utilized both internal and external criteria to classify the rise and fall of BTC prices, as documented in the literature. Because bitcoin prices are stochastic, it is impossible to predict their movement. Regardless, academics have been able to predict bitcoin values using a variety of feature sets to varying degrees of success.

Furthermore, the models constructed by the GRU and MLP approaches demonstrate great levels of accuracy, although the former yielded values lower than those produced by the latter. Based on our prior research, we can say that the MLP model benefits most from the inclusion of bitcoin transactions in its training and testing data. Although the R^2 metric shows that all models fit the training and testing data equally and can accurately predict bitcoin prices, the MSE and RMSE metrics reveal that the utilization of all series in the training and testing data provided models with better performance in terms of the directional movement problem.

Therefore, while these models may estimate a value within a small percentage of the following day's value, they are unable to tell us whether the cryptocurrency's price will rise or fall that day. In addition, the GRU and MLP models' architectures were built to utilize data effectively from the training and testing sets, and they are capable of accurately and reliably predicting price movements without compromising regression performance. Figure 9 shows the results of the GRU model with respect to R^2 during the training and testing phases. It shows that the GRU model has achieved (R^2 = 95.51%) during the training phase and (R^2 = 91.09%) during the testing phase. Figure 10 shows the R^2 results of the MLP model: it is found that the MLP has superior regression (R^2 = 98.21%) during training and (R^2 = 95.09%) during testing. A comparison between the presented GRU and MPL models and existing systems is presented in Table 4, proving that the proposed systems have achieved much fewer prediction errors.

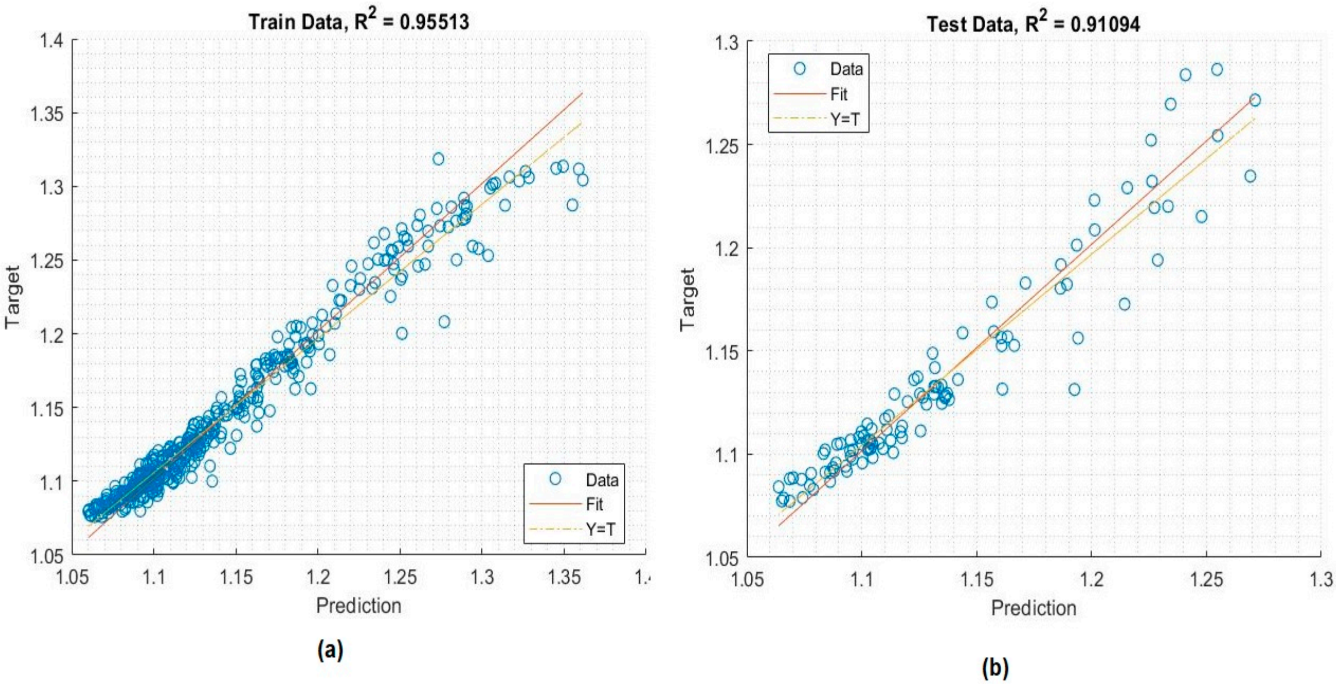

Figure 9. Performance of the GRU model for predicting bitcoin price: (**a**) training phase and (**b**) testing phase.

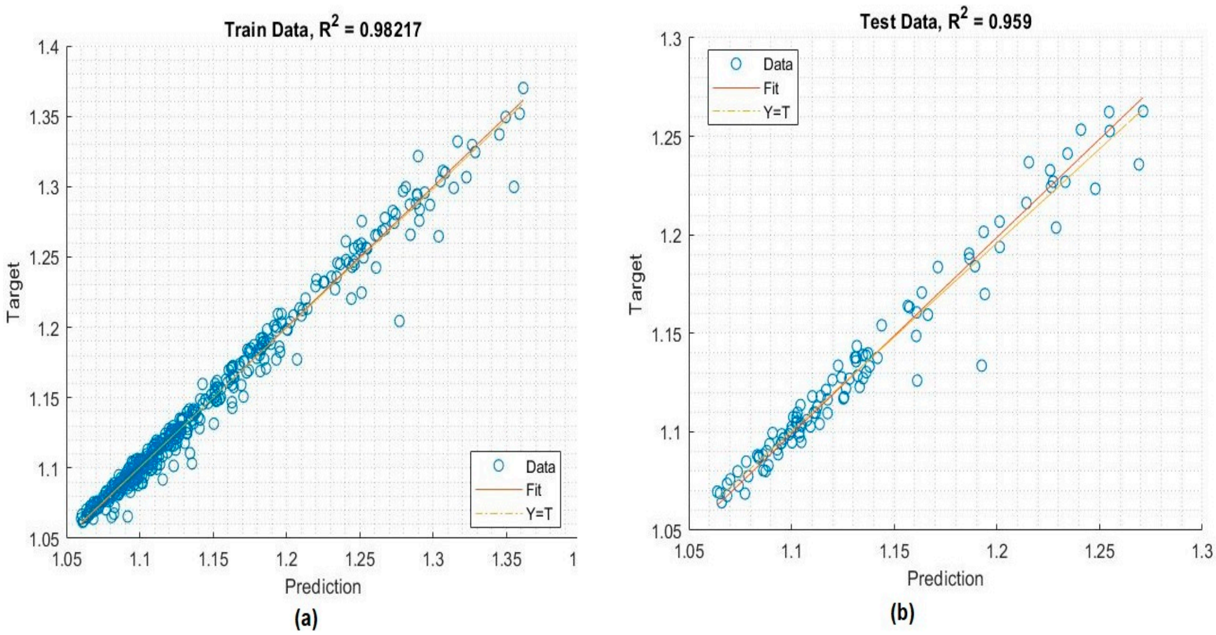

Figure 10. Performance of the MLP model for predicting bitcoin price: (**a**) training phase and (**b**) testing phase.

The deep learning LSTM model was suggested as a means of forecasting the prices of bitcoin within the scope of this research. The bitcoin data sets were compiled using information gathered from a variety of periods, and the technique that was suggested used to predict bitcoin prices over a variety of time intervals.

Table 4. Comparison results between the proposed system and the existing models.

Reference	Existing Models	Study Currency	Obtaining Results
[49]	Logistic regression and linear discriminant analysis	BTC and LTC	R2 score LR: 66% LDA: 65.3%
[50]	ARIMA, LSTM, and GRU	BTC	RMSE ARIMA: 302.53, LSTM: 603.68 GRU: 381.34
[51]	LSTM	BTC	RMSE = 0.092
[52]	LSSVM BP SPAE-B	BTC	RMSE = 272.155 RMSE = 540.087 RMSE = 131.643
[53]	MLP LSTM	BTC	RMSE = 20.09 RMSE = 19.250
[54]	ARIM	BTC	MSE = 167
[55]	Multiplicative error	BTC	MSE = 93.27
[56]	RIMA PROPHET	BTC	R = 94 R = 68
[57]	LSTM	BTC	RMSE = 31.60
[58]	GRACH	BTC	R = 72.22
[59]	neuro-fuzzy	BTC	R = 71.21
	Proposed system (GRU)	BTC	MSE = 0.016518 RMSE = 0.12 $R^2(\%)$ = 95.51
	Proposed system (MPL)	BTC	MSE = 8.444×10^{-5} RMSE = 0.0091 $R^2(\%)$ = 98.21

6. Conclusions

The process of modeling and predicting bitcoin prices was developed as a result of this study's comparison of approaches. The period was chosen to be from 1 January 2021 to 16 June 2022, and the GRU and MLP models were used in the design of the bitcoin price prediction model for robustness, with the highest performance levels having been achieved using the MLP model. The favorable outcomes of this study allow us to draw the following conclusions:

- Advanced AI models that can predict bitcoin prices and price movements were proposed in this study.
- Central bankers, investors, asset managers, private forecasters, and other cryptocurrency market experts will find these results useful in determining which indicators produce the most accurate and dependable price change projections. New and substantial explanatory factors are suggested in our analysis to allow these agents to forecast the bitcoin price phenomena.
- The MLP model attained slightly better results than the GRU model for predicting future bitcoin prices.
- The MLP model had a training phase score of R = 99.15%, which is excellent for a newly constructed model. In general, the results are good and demonstrate the potential for additional applications in several sectors, such as financial technology, BC, and AI development. There is a high degree of accuracy in predicting the current bitcoin value, but it is far more difficult to estimate price growths and declines.
- It is safe to say the study findings have important consequences for asset managers' decision-making going forward, allowing them to avoid substantial price changes and

their related potential expenses. These agents can also use it to alert financial markets and prevent catastrophic losses from price volatility.

- Consequently, we are interested in conducting further research with the objective of improving the accuracy of interval prediction methods. These methods are used to make price predictions for periods up to 60 days into the future. In addition, we anticipate advancing the state of the art with a deep learning model that can advise cryptocurrency clients on what they should do to maximize their profit over the long term by combining the findings of the current work with those of the existing literature on interval prediction research.

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References

1. Nasir, M.A.; Huynh, T.L.D.; Nguyen, S.P.; Duong, D. Forecasting cryptocurrency returns and volume using search engines. *Financ. Innov.* **2019**, *5*, 2. [CrossRef]
2. Livieris, I.E.; Stavroyiannis, S.; Pintelas, E.; Pintelas, P. A novel validation framework to enhance deep learning models in time-series forecasting. *Neural Comput. Appl.* **2020**, *32*, 17149–17167. [CrossRef]
3. Kang, C.Y.; Lee, C.P.; Lim, K.M. Cryptocurrency Price Prediction with Convolutional Neural Network and Stacked Gated Recurrent Unit. *Data* **2022**, *7*, 149. [CrossRef]
4. Ye, Z.; Wu, Y.; Chen, H.; Pan, Y.; Jiang, Q. A Stacking Ensemble Deep Learning Model for Bitcoin Price Prediction Using Twitter Comments on Bitcoin. *Mathematics* **2022**, *10*, 1307. [CrossRef]
5. Gautam, K.; Sharma, N.; Kumar, P. Empirical Analysis of Current Cryptocurrencies in Different Aspects. In Proceedings of the ICRITO 2020—IEEE 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions), Noida, India, 4–5 June 2020; pp. 344–348.
6. Adams, R.; Kewell, B.; Parry, G. Blockchain for Good? Digital Ledger Technology and Sustainable Development Goals. In *Handbook of Sustainability and Social Science Research*; Filho, W.L., Marans, R., Callewaert, J., Eds.; World Sustainability Series; Springer: Cham, Switzerland, 2018.
7. Killer, C.; Rodrigues, B.; Stiller, B. Security Management and Visualization in a Blockchain-based Collaborative Defense. In Proceedings of the ICBC 2019—IEEE International Conference on Blockchain and Cryptocurrency, Seoul, Republic of Korea, 14–17 May 2019; pp. 108–111.
8. Gandal, N.; Halaburda, H. Competition in the Cryptocurrency Market (29 September 2014). CESifo Working Paper Series No. 4980. Available online: https://ssrn.com/abstract=2506577 (accessed on 25 July 2021).
9. Iwamura, M.; Kitamura, Y.; Matsumoto, T. Is Bitcoin the Only Cryptocurrency in the Town? Economics of Cryptocurrency and Friedrich A. Hayek (28 February 2014). Available online: https://ssrn.com/abstract=2405790 (accessed on 16 June 2022).
10. Kyriazis, N.A. A Survey on Empirical Findings about Spillovers in Cryptocurrency Markets. *J. Risk Financ. Manag.* **2019**, *12*, 170. [CrossRef]
11. Hassani, H.; Huang, X.; Silva, E. Big-Crypto: Big Data, Blockchain and Cryptocurrency. *Big Data Cogn. Comput.* **2018**, *2*, 34. [CrossRef]

12. Nizzoli, L.; Tardelli, S.; Avvenuti, M.; Cresci, S.; Tesconi, M.; Ferrara, E. Charting the Landscape of Online Cryptocurrency Manipulation. *IEEE Access* **2020**, *8*, 113230–113245. [CrossRef]
13. Rebane, J.; Karlsson, I.; Papapetrou, P.; Denic, S. Seq2Seq RNNs and ARIMA models for Cryptocurrency Prediction: A Comparative Study. In Proceedings of the SIGKDD Workshop on Fintech (SIGKDD Fintech'18), London, UK, 19–23 August 2018.
14. Rehman, M.U.; Apergis, N. Determining the predictive power between cryptocurrencies and real time commodity futures: Evidence from quantile causality tests. *Resour. Policy* **2019**, *61*, 603–616. [CrossRef]
15. Liew, J.; Li, R.Z.; Budavári, T.; Sharma, A. Cryptocurrency Investing Examined. *J. Br. Blockchain Assoc.* **2019**, *2*, 8720. [CrossRef]
16. Kristoufek, L. What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. *PLoS ONE* **2015**, *10*, e0123923. [CrossRef]
17. Wamba, S.F.; Kamdjoug, J.R.K.; Bawack, R.E.; Keogh, J.G. Bitcoin, Blockchain and Fintech: A systematic review and case studies in the supply chain. *Prod. Plan. Control Manag. Oper.* **2019**, *31*, 115–142. [CrossRef]
18. Chen, W.; Zheng, Z.; Ma, M.; Wu, J.; Zhou, Y.; Yao, J. Dependence structure between bitcoin price and its influence factors. *Int. J. Comput. Sci. Eng.* **2020**, *21*, 334–345. [CrossRef]
19. Balcilar, M.; Bouri, E.; Gupta, R.; Roubaud, D. Can volume predict bitcoin returns and volatility? A quantiles-based approach. *Econ. Model.* **2017**, *64*, 74–81. [CrossRef]
20. Derbentsev, V.; Matviychuk, A.; Soloviev, V.N. Forecasting of Cryptocurrency Prices Using Machine Learning. In *Advanced Studies of Financial Technologies and Cryptocurrency Markets*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 211–231.
21. Chowdhury, R.; Rahman, M.A.; Rahman, M.S.; Mahdy, M. Predicting and Forecasting the Price of Constituents and Index of Cryptocurrency Using Machine Learning. *arXiv* **2019**, arXiv:1905.08444.
22. Pintelas, E.; Livieris, I.E.; Stavroyiannis, S.; Kotsilieris, T.; Pintelas, P. Investigating the Problem of Cryptocurrency Price Prediction: A Deep Learning Approach. In *IFIP International Conference on Artificial Intelligence Applications and Innovations*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 99–110.
23. Livieris, I.E.; Pintelas, E.; Stavroyiannis, S.; Pintelas, P. Ensemble Deep Learning Models for Forecasting Cryptocurrency Time-Series. *Algorithms* **2020**, *13*, 121. [CrossRef]
24. Patel, M.M.; Tanwar, S.; Gupta, R.; Kumar, N. A Deep Learning-Based Cryptocurrency Price Prediction Scheme for Financial Institutions. *J. Inf. Secur. Appl.* **2020**, *55*, 102583. [CrossRef]
25. Andrianto, Y. The Effect of Cryptocurrency on Investment Portfolio Effectiveness. *J. Financ. Account.* **2017**, *5*, 229. [CrossRef]
26. Derbentsev, V.; Babenko, V.; Khrustalev, K.; Obruch, H.; Khrustalova, S. Comparative Performance of Machine Learning Ensemble Algorithms for Forecasting Cryptocurrency Prices. *Int. J. Eng. Trans. A Basics* **2021**, *34*, 140–148.
27. McNally, S.; Roche, J.; Caton, S. Predicting the Price of Bitcoin Using Machine Learning. In Proceedings of the 26th Euromicro International Conference on Parallel, Distributed, and Network-Based Processing, Cambridge, UK, 21–23 March 2018.
28. Yogeshwaran, S.; Kaur, M.J.; Maheshwari, P. Project Based Learning: Predicting Bitcoin Prices using Deep Learning. In Proceedings of the 2019 IEEE Global Engineering Education Conference (EDUCON), Dubai, United Arab Emirates, 9–11 April 2019.
29. Demir, A.; Akılotu, B.N.; Kadiroğlu, Z.; Şengür, A. Bitcoin Price Prediction Using Machine Learning Methods. In Proceedings of the 2019 1st International Informatics and Software Engineering Conference (UBMYK), Ankara, Turkey, 6–7 November 2019.
30. Rizwan, M.; Narejo, S.; Javed, M. Bitcoin price prediction using Deep Learning Algorithm. In Proceedings of the 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS), Karachi, Pakistan, 14–15 December 2019.
31. Linardatos, P.; Kotsiantis, S. Bitcoin Price Prediction Combining Data and Text Mining. In *Advances in Integrations of Intelligent Methods. Smart Innovation, Systems and Technologies*; Hatzilygeroudis, I., Perikos, I., Grivokostopoulou, F., Eds.; Springer: Singapore, 2020.
32. Felizardo, L.; Oliveira, R.; Del-Moral-Hernández, E.; Cozman, F. Comparative study of Bitcoin price prediction using WaveNets, Recurrent Neural Networks and other Machine Learning Methods. In Proceedings of the 6th International Conference on Behavioral, Economic and Socio-Cultural Computing (BESC), Beijing, China, 28–30 October 2019.
33. Dutta, A.; Kumar, S.; Basu, M. A Gated Recurrent Unit Approach to Bitcoin Price Prediction. *J. Risk Financ. Manag.* **2020**, *13*, 23. [CrossRef]
34. Ji, S.; Kim, J.; Im, H. A Comparative Study of Bitcoin Price Prediction Using Deep Learning. *Mathematics* **2019**, *7*, 898. [CrossRef]
35. Wu, C.H.; Lu, C.C.; Ma, Y.F.; Lu, R.S. A new forecasting framework for bitcoin price with LSTM. In Proceedings of the 2018 IEEE International Conference on Data Mining Workshops (ICDMW), Singapore, 17–20 November 2018; pp. 168–175.
36. Ammer, M.A.; Aldhyani, T.H.H. Deep Learning Algorithm to Predict Cryptocurrency Fluctuation Prices: Increasing Investment Awareness. *Electronics* **2022**, *11*, 2349. [CrossRef]
37. Greaves, A.; Au, B. *Using the Bitcoin Transaction Graph to Predict the Price of Bitcoin*; Stanford University: Stanford, CA, USA, 2015.
38. Yu, K.; Tan, L.; Aloqaily, M.; Yang, H.; Jararweh, Y. Blockchain-Enhanced Data Sharing With Traceable and Direct Revocation in IIoT. *IEEE Trans. Ind. Inform.* **2021**, *17*, 7669–7678. [CrossRef]
39. Katsiampa, P. Volatility estimation for bitcoin: A comparison of garch models. *Econ. Lett.* **2017**, *158*, 3–6. [CrossRef]
40. Banupriya, S.; Kottilingam, L. An Analysis of Privacy Issues and Solutions in Public Blockchain (Bitcoin). In *2021 2nd International Conference for Emerging Technology (INCET)*; IEEE: Piscataway, NJ, USA, 2021; pp. 1–7. [CrossRef]
41. Banupriya, S.; Kottilingam, K. A Blockchain-Based Framework for Transparent, Secure, and Verifiable Online Examination System. *J. Uncertain Syst.* **2022**, *15*, 2241002. [CrossRef]

42. Gulcehre, C.; Cho, K.; Pascanu, R.; Bengio, Y. Learned-norm pooling for deep feedforward and recurrent neural networks. In *Machine Learning and Knowledge Discovery in Databases*; Springer: Berlin/Heidelberg, Germany, 2014; pp. 530–546.
43. Yamak, P.T.; Yujian, L.; Gadosey, P.K. A Comparison between ARIMA, LSTM, and GRU for Time Series Forecasting. In Proceedings of the 2nd International Conference on Algorithms, Computing and Artificial Intelligence, Sanya, China, 20–22 December 2019; pp. 49–55.
44. Al-Adhaileh, M.H.; Aldhyani, T.H.H. Artificial intelligence framework for modeling and predicting crop yield to enhance food security in Saudi Arabia. *PeerJ Comput. Sci.* **2022**, *2022*, e1104. [CrossRef] [PubMed]
45. Al-Nefaie, A.H.; Aldhyani, T.H.H. Predicting Close Price in Emerging Saudi Stock Exchange: Time Series Models. *Electronics* **2022**, *11*, 3443. [CrossRef]
46. Aldhyani, T.H.H.; Alzahrani, A. Framework for Predicting and Modeling Stock Market Prices Based on Deep Learning Algorithms. *Electronics* **2022**, *11*, 3149. [CrossRef]
47. Alzain, E.; Alshebami, A.S.; Aldhyani, T.H.H.; Alsubari, S.N. Application of Artificial Intelligence for Predicting Real Estate Prices: The Case of Saudi Arabia. *Electronics* **2022**, *11*, 3448. [CrossRef]
48. Kim, J.-H.; Sung, H. Understanding Bitcoin Price Prediction Trends under Various Hyperparameter Configurations. *Computers* **2022**, *11*, 167. [CrossRef]
49. Sebastião, H.; Godinho, P. Forecasting and trading cryptocurrencies with machine learning under changing market conditions. *Financ. Innov.* **2021**, *7*, 3. [CrossRef]
50. Awoke, T.; Rout, M.; Mohanty, L.; Satapathy, S.C. Bitcoin Price Prediction and Analysis Using Deep Learning Models. In *Communication Software and Networks*; Lecture Notes in Networks and Systems; Springer: Singapore, 2021; Volume 134. [CrossRef]
51. Mahendra, E.; Madan, H.; Gupta, S.; Singh, S.V. Bitcoin Price Prediction Using Deep Learning and Real Time Deployment. In Proceedings of the 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), Greater Noida, India, 18–19 December 2020; pp. 264–268. [CrossRef]
52. Shengao, Z.; Mengze, L.; Chunxiao, Y. The Empirical Analysis of Bitcoin Price Prediction Based on Deep Learning Integration Method. *Comput. Intell. Neurosci.* **2022**, *2022*, 1265837. [CrossRef]
53. Jiang, X. Bitcoin Price Prediction Based on Deep Learning Methods. *J. Math. Financ.* **2022**, *10*, 132–139. [CrossRef]
54. Azari, A. Bitcoin Price Prediction: An ARIMA Approach. *arXiv* **2019**, arXiv:1904.05315.
55. Sebastian, T.; Werner, K. Framework based on multiplicative error and residual analysis to forecast bitcoin intraday-volatility. *Phys. A Stat. Mech. Its Appl.* **2022**, *589*, 126613. [CrossRef]
56. Yenidoğan, I.; Çayir, A.; Kozan, O.; Dağ, T.; Arslan, C. Bitcoin Forecasting Using ARIMA and PROPHET. In *2018 3rd International Conference on Computer Science and Engineering (UBMK)*; IEEE: Piscataway, NJ, USA, 2018; pp. 621–624. [CrossRef]
57. Shin, M.; Mohaisen, D.; Kim, J. Bitcoin price forecasting via ensemble-based LSTM deep learning networks. In Proceedings of the 2021 International Conference on Information Networking (ICOIN), Jeju Island, Republic of Korea, 13–16 January 2021; Volume 1, pp. 603–608.
58. Ampountolas, A. Cryptocurrencies Intraday High-Frequency Volatility Spillover Effects Using Univariate and Multivariate GARCH Models. *Int. J. Financ. Stud.* **2022**, *10*, 51. [CrossRef]
59. Atsalakis, G.S.; Atsalaki, I.G.; Pasiouras, F.; Zopounidis, C. Bitcoin price forecasting with neuro-fuzzy techniques. *Eur. J. Oper. Res.* **2019**, *276*, 770–780. [CrossRef]