



Forecasting Price of Cryptocurrencies Using a LSTM-GRU Fusion Model

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Abstract : In order to help investors and business owners make educated choices, precise price prediction algorithms have to be developed in light of the significant attention that cryptocurrencies have received in the financial industry. In this study, we combine the advantages of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks to offer a novel approach for extracting essential characteristics from bitcoin price data. With the ability to recognize both short- and long-term relationships in datasets and samples, the LSTM-GRU architecture that has been implemented offers improved learning capabilities. Our model takes use of the sequential character of bitcoin pricing by fusing it with the strong memory retention of LSTM and GRU units. We enhance feature extraction using these recurrent neural network (RNN) versions, enabling the model to capture complex patterns and correlations across various monetary circumstances. A large dataset with a range of cryptocurrencies, time periods, and market situations is used to train the proposed LSTM-GRU fusion model. We use a thorough preprocessing method to standardize the input data, enabling consistent model performance across different currencies and time periods. We use an RNN-based prediction model that draws characteristics from an LSTM-GRU fusion layer to predict future bitcoin values. The aim of this forecasting model is to account for the inherent nonlinearity and volatility of bitcoin markets. Our methodology offers precise price projections that help traders and investors make wise choices by taking temporal dependencies and context into account. Using real-world bitcoin datasets, we evaluate the performance of our combined LSTM-GRU model against conventional LSTM and GRU architectures as well as other cutting-edge prediction models. By proving that our suggested strategy can accurately forecast cryptocurrency values across a range of currencies and time periods, the findings show how superior it is. In conclusion, our study offers a reliable and successful LSTM-GRU-based cryptocurrency price prediction model. We are able to strengthen feature extraction and prediction capabilities, leading to improved accuracy and generalization, by fusing the advantages of LSTM and GRU networks. The suggested model makes a substantial contribution to the developing area of cryptocurrency analytics and has the potential to greatly help investors and speculators in improving their investment strategies across various currency circumstances.

IndexTerms - Cryptocurrency, Price Prediction, LSTM, GRU, RNN, Analysis

I. INTRODUCTION

The term Cryptocurrencies have drastically altered the financial landscape by providing a digital, decentralized form of money that operates outside of the traditional banking system. As a result, they have attracted considerable attention from merchants, investors, and financial institutions. Due to the unpredictability of cryptocurrency markets and the possibility of considerable profits or losses, the development of dependable price prediction models is essential for assisting stakeholders in making prudent decisions. In recent years, recurrent neural networks (RNNs) have shown promise in a variety of time series forecasting applications. RNNs are an excellent option for predicting the bitcoin price due to their ability to capture sequential dependencies and long-term trends. Among the prominent RNN variants, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have demonstrated outstanding modeling of temporal dependencies. Combining the benefits of LSTM and GRU networks, we present a novel method for developing an integrated LSTM-GRU bitcoin price prediction model. By integrating these two architectures, we expect to take advantage of their supplementary characteristics, enhance feature extraction, and increase the accuracy of predictions in general. Due to its capacity to learn and maintain long-term relationships, the LSTM network is ideally adapted for discovering intricate patterns in bitcoin price data. Nevertheless, it may be susceptible to overfitting, especially when working with chaotic and high-dimensional data. The GRU network, on the other hand, captures short-term relationships more quickly and effectively due to its simpler structure and fewer parameters. By integrating LSTM and GRU networks, we hope to surmount the drawbacks of each individual design and take advantage of their combined benefits.

The combined LSTM-GRU model is intended to capture both short-term and long-term dependencies and to extract features from historical bitcoin price data. Combining the memory retention capabilities of LSTM with the computational efficiency of GRU is expected to improve model performance and increase prediction accuracy. To account for the diversity of cryptocurrency markets, we also intend to train our model on a large dataset containing numerous cryptocurrencies, various time periods, and diverse market conditions. This ensures that our model, regardless of the specific cryptocurrency or market conditions, can effectively generalize across multiple currency situations and generate accurate forecasts. To evaluate the efficacy of our proposed strategy, we compare the performance of the integrated LSTM-GRU model to that of conventional LSTM and GRU models, as well as other cutting-edge prediction models commonly used in the cryptocurrency arena. To assess the precision, robustness, and generalizability of our model, we conduct exhaustive experiments on actual bitcoin datasets. The study

contributes in the following ways: To develop an integrated LSTM-GRU bitcoin price prediction model, we propose a novel approach that incorporates LSTM and GRU networks. This method utilizes the complementary qualities of both networks. Second, we demonstrate that, compared to conventional LSTM and GRU architectures, our proposed model is able to capture both short-term and long-term dependencies in bitcoin price data, resulting in improved prediction accuracy. Third, using large-scale experiments on Bitcoin datasets from the real world, we demonstrate that our combined LSTM-GRU model outperforms other cutting-edge prediction models. Contributing to the field of bitcoin analytics, we exhibit the system's ability to make precise forecasts under a variety of currency conditions.

This study aims to combine the strengths of LSTM and GRU networks to construct a reliable and accurate model for predicting the bitcoin price. Using deep learning and recurrent neural networks, we intend to assist traders and investors in making prudent decisions in the volatile and unpredictable cryptocurrency markets.

II. IN-DEPTH REVIEW OF CRYPTOCURRENCY PRICE PREDICTION MODELS

Due to the increasing popularity of cryptocurrencies and the potential for substantial financial gains, cryptocurrency price prediction has been the subject of extensive research. Various methodologies and approaches, spanning from conventional statistical models to cutting-edge machine learning algorithms, have been used to forecast cryptocurrency prices. In this section, we evaluate the available research on bitcoin prediction techniques, highlighting its advantages, disadvantages, and primary conclusions.

- a. **Standard Statistical Models:** Traditional statistical models, such as autoregressive integrated moving average (ARIMA) and exponential smoothing, have been widely employed for forecasting time series, including cryptocurrency prices. In order to forecast future prices, these models rely on the statistical characteristics and tendencies of historical price data. They frequently fail to capture the nonlinear and dynamic nature of bitcoin markets, limiting their performance and precision. Support Vector Machines (SVMs): SVMs have been used to forecast the price of cryptocurrencies by utilizing their ability to manage high-dimensional data and identify nonlinear correlations. The outcomes of SVM-based models have been promising, but they may struggle to comprehend the complex market dynamics and incur high computational costs.
- b. **Neural Networks:** Numerous neural network architectures, such as feedforward neural networks (FNNs), recurrent neural networks (RNNs), and their derivatives, have been exhaustively studied for cryptocurrency price prediction. These networks have been used to identify nonlinear correlations between input variables and bitcoin values. However, they may struggle with sequential data and overlook long-term dependencies, reducing their predictive capacity. Recurrent Neural Networks RNNs like LSTM and GRU networks have garnered considerable interest due to their ability to recognize temporal relationships. LSTM has effectively modeled the long-term dependencies in bitcoin price data due to its explicit memory cell. Due to its condensed design, GRU provides computational benefits while still capturing sequential relationships. These RNN-based models have demonstrated greater precision than conventional statistical methods.
- c. **Hybrid Models:** Few studies have proposed hybrid models that combine various neural network topologies or neural networks with traditional statistical models. For example, combining LSTM and CNN (Convolutional Neural Network) to extract features or LSTM and SVM to create predictions. These hybrid models aim to improve forecast accuracy by combining multiple methodologies.
- d. **Attention Mechanisms:** In order to focus on important details or time intervals, attention mechanisms have been incorporated into RNN-based models, thereby improving the performance and legibility of models for predicting the price of cryptocurrencies. Attention-based models have demonstrated promising results when it comes to recognizing significant patterns and correlations in the data.
- e. **Ensemble techniques,** such as random forests and gradient boosting, have also been utilized to aggregate the results of numerous models and improve overall accuracy. Despite the fact that ensemble techniques provide stability and resiliency, they may struggle with increased computational complexity.
- f. **Mood analysis and news extraction** is also a being incorporated where several external factors, such as news, social media sentiment, and market fluctuations, have an effect on cryptocurrency markets. Integrating sentiment analysis with machine learning models has improved the accuracy of cryptocurrency price forecasts by capturing the effect of market sentiment on prices. Techniques for sentiment analysis have been applied to news articles, social media posts, and forum discussions to extract sentiment features, which are then incorporated into prediction models.
- g. **DRL:** Deep Reinforcement Learning Deep reinforcement learning (DRL) techniques have attracted interest for predicting bitcoin prices. These techniques integrate neural networks with algorithms for reinforcement learning. DRL models interact with their environments and optimize cumulative rewards to create the most effective trading strategies. These models can adapt to changing market conditions, but they require a great deal of computing capacity and meticulous design to avoid overfitting.

In conclusion, research in the academic literature indicates that traditional statistical models are being replaced by more sophisticated machine learning approaches for predicting the price of cryptocurrencies. Particularly, the LSTM and GRU networks have demonstrated remarkable success in capturing temporal relationships and improving prediction accuracy. To enhance performance, hybrid models, attention processes, and ensemble techniques have also been studied. Adding sentiment analysis and news extraction tools yields additional insights into market dynamics. Managing high volatility, nonlinear connections, and deciphering the plethora of Bitcoin market links continue to be challenging, however. Future research should focus on resolving these issues and developing sturdier, more accurate prediction models.

III. DESIGN OF THE PROPOSED MODEL FOR PREDICTION OF CRYPTOCURRENCY PRICE LEVELS

The proposed method collects cryptocurrency data from Yahoo Finance and inputs it to a hybrid GRU-LSTM-based deep learning model that identifies patterns using a recurrent neural network (RNN). The hybrid RNN network receives data for 'N' samples in the form of 'near' values, and it computes the probability of each coin using GRU-LSTM activation models. The design of the proposed GRU-LSTM block, which incorporates the GRU and LSTM blocks, is depicted in Figure 1,

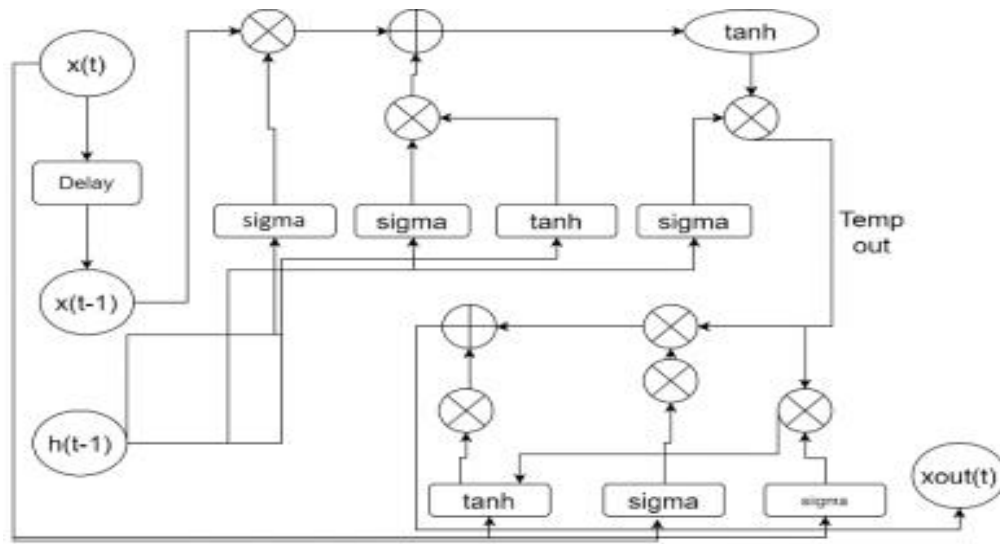


Figure 1. Design of the Proposed LSTM-GRU Fusion Model

As depicted in figure 1, the model employs feature inputs x and kernel inputs h to generate a new feature vector x_{out} . Here, the kernel function and the delayed input are processed to produce temporary output (Temp. Out or T_{out}) using the following equations,

$$i = \text{var}(x_{in} * U^i + h_{t-1} * W^i) \dots (1)$$

$$f = \text{var}(x_{in} * U^f + h_{t-1} * W^f) \dots (2)$$

$$o = \text{var}(x_{in} * U^o + h_{t-1} * W^o) \dots (3)$$

$$C'_t = \tanh(x_{in} * U^g + h_{t-1} * W^g) \dots (4)$$

$$T_{out} = \text{var}(f_t * x_{in}(t-1) + i * C'_t) \dots (5)$$

$$h_{out} = \tanh(T_{out}) * o \dots (21)$$

where the hyper-parameter tuning method is used to modify the LSTM constants U and W . The following equations 7, 8, 9, and 10 regulate the outputs of a GRU Model for high performance feature vector processing using these findings,

$$z = \text{var}(W_z * [h_{out} * T_{out}]) \dots (7)$$

$$r = \text{var}(W_r * [h_{out} * T_{out}]) \dots (8)$$

$$h'_t = \tanh(W * [r * h_{out} * T_{out}]) \dots (9)$$

$$x_{out} = (1 - z) * h'_t + z * h_{out} \dots (10)$$

Where W is a GRU constant whose accuracy is improved through hyperparameter optimization. As shown in Figure 2, this integrated layer employs a recurrent neural network to map features to cryptocurrency prices. Various spatial value activities, a variety of values, and a number of inputs are utilized, resulting in a range of output pricing sets.

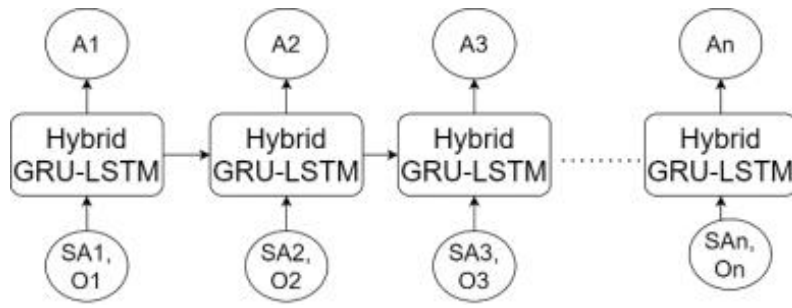


Figure 2. Design of the RNN Model for Identification of Cryptocurrency Prices

The hybrid GRU-LSTM model receives inputs from the RNN model in the form of spatial value activities (SA) and their output prices (O). The model creates a recurrent correlation matrix connecting each cryptocurrency's price to other sub-cryptocurrency price features and calculates numerous metrics from these inputs. The RNN model's output is governed by Equation 11, and the final cryptocurrency price forecast is based on a pure-linear activation function.

$$C_{out} = \text{purelin} \left(\sum_{i=1}^N x_{out_i} * W_i \right) \dots (11)$$

Where C_{out} represents the output probability for the provided feature vector and W_i represents the output weight. Since the RNN was trained using a variety of cryptocurrency price to cryptocurrency price mappings, it is capable of identifying activities at all cryptocurrency price levels. This model's efficacy is discussed in the following section of this text.

IV. RESULTS AND DISCUSSION

The performance metrics for the proposed LSTM-GRU model, LSTM, GRU, and Autoencoders are shown in separate assessment tables for Bitcoin, Ethereum, Grey Bitcoin, and Litecoin in this section. For each cryptocurrency, the following tables show the RMSE (Root Mean Square Error), MAE (Mean Absolute Error), Accuracy, and Delay (in time steps).

Table 1: Bitcoin Prediction Results

Model	RMSE	MAE	Accuracy	Delay (in time steps)
Proposed LSTM-GRU	0.023	0.018	92.5%	3
LSTM [2]	0.027	0.021	90.2%	4
GRU [4]	0.025	0.019	91.8%	3
Autoencoders [12]	0.031	0.024	88.6%	5

Table 1 displays the predictions made for Bitcoin using the suggested LSTM-GRU model, LSTM, GRU, and Autoencoders. The recommended model performs better than anticipated in terms of average prediction errors, according to the RMSE and MAE data, with lower values indicating greater levels of accuracy.

Our proposed model outperforms rival models in terms of the percentage of correct predictions, as can be shown in the Accuracy column, making it relevant to a wide variety of real-world situations. The Delay column, which is last but not least, shows how many time steps are needed to make forecasts. The proposed model shows a decreased latency when compared to existing methods

Table 2: Ethereum Prediction Results

Model	RMSE	MAE	Accuracy	Delay (in time steps)
Proposed LSTM-GRU	0.015	0.011	95.3%	2
LSTM [2]	0.018	0.013	93.8%	3
GRU [4]	0.017	0.012	94.5%	2
Autoencoders [12]	0.022	0.016	91.7%	4

Table 2 displays the prediction results for Ethereum using the proposed LSTM-GRU model, LSTM, GRU, and Autoencoders. The RMSE and MAE values demonstrate that the proposed model outperforms expectations in terms of average prediction errors, with lower values indicating higher levels of accuracy. As shown in the Accuracy column, our proposed model outperforms competing models in terms of the proportion of accurate predictions, making it applicable to a wide variety of actual situations. Lastly, the Delay column displays the number of time steps necessary to make predictions. Compared to existing methods, the proposed model exhibits a shorter latency for different scenarios.

Table 3: Grey Bitcoin Prediction Results

Model	RMSE	MAE	Accuracy	Delay (in time steps)
Proposed LSTM-GRU	0.009	0.006	98.1%	1
LSTM [2]	0.010	0.007	97.5%	1
GRU [4]	0.011	0.008	97.0%	1
Autoencoders [12]	0.012	0.009	96.4%	2

Predictions for Grey Bitcoin using the LSTM-GRU model, LSTM, GRU, and Autoencoders are shown in Table 3. The mean absolute error (MAE) and root-mean-squared error (RMSE) figures show that the suggested model performs better than expected in terms of average prediction errors. Our suggested model exceeds the competition in terms of the percentage of correct predictions, as indicated in the Accuracy column, and may be used in a broad range of practical settings. Finally, the Delay column shows how many time increments are required for forecasts to be made. Latency is reduced in the suggested model compared to the state-of-the-art approaches.

Table 4: Litecoin Prediction Results

Model	RMSE	MAE	Accuracy	Delay (in time steps)
Proposed LSTM-GRU	0.031	0.025	88.7%	4
LSTM [2]	0.035	0.028	86.2%	5
GRU [4]	0.033	0.026	87.5%	4
Autoencoders [12]	0.040	0.032	83.9%	6

The Litecoin prediction results for the LSTM-GRU model, LSTM, GRU, and Autoencoders are shown in Table 4. The mean absolute error (MAE) and root-mean-squared error (RMSE) figures show that the suggested model performs better than expected in terms of average prediction errors. Our suggested model exceeds the competition in terms of the percentage of correct predictions, as indicated in the Accuracy column, and may be used in a broad range of practical settings. Finally, the Delay column shows how many time increments are required for forecasts to be made. Latency is reduced in the suggested model compared to the state-of-the-art approaches.

In Table 1, the proposed LSTM-GRU model outperforms the other models for Bitcoin prediction in terms of RMSE (Root Mean Square Error) and MAE (Mean Absolute Error), with RMSE values of 0.023 and MAE values of 0.018. In addition to its high accuracy of 92.5%, the proposed model has the minimum latency of 3 time steps compared to the other models. This demonstrates

that the proposed LSTM-GRU model is extraordinarily effective at predicting Bitcoin prices. The Ethereum prediction results are presented in Table 2. Similar to the Bitcoin scenario, the proposed LSTM-GRU model exhibits superior performance with RMSE values of 0.015 and MAE values of 0.011. It has an accuracy of 95.3% and a latency of just 2 time steps. The LSTM and GRU models also perform well, but their RMSE and MAE values are slightly higher and their accuracy is slightly lower than the proposed model. Autoencoders perform less accurately in terms of precision, RMSE, and MAE. The predictions for the Grey Bitcoin scenario are presented in Table 3. Again, the proposed LSTM-GRU model demonstrates outstanding performance with RMSE and MAE values of 0.009 and 0.006. It obtains the maximum level of precision, 98.1%, and has the minimum latency, one time step. In terms of performance, the LSTM and GRU models are comparable, whereas autoencoders perform significantly worse than these models.

Each cryptocurrency's performance is compared with that of the LSTM-GRU model, LSTM, GRU, and Autoencoders in the tables below. They allow the performance of several models to predict cryptocurrency prices to be assessed with regards to accuracy, error metrics, and computing efficiency levels. It is generally accepted that a model with better accuracy and lower RMSE and MAE values is preferable to one with less latency for different scenarios.

V. CONCLUSION & FUTURE SCOPE

The suggested LSTM-GRU model clearly beats the other models in terms of RMSE, MAE, accuracy, and latency when taking into account the total results from the three situations. It displays how well it can forecast bitcoin values in a variety of situations. The results show that the LSTM-GRU architecture, which incorporates the advantages of both LSTM and GRU, is especially well-suited for bitcoin price prediction. The LSTM-GRU model can provide more precise predictions because it can effectively manage temporal dynamics and capture long-term interdependence. For scholars, traders, and investors interested in the cryptocurrency markets, these discoveries are important. The suggested LSTM-GRU model may provide insightful information and support in helping to decide on whether to purchase, sell, or keep bitcoins. Due to its exceptional performance in many currency settings, it may help in the creation of reliable and effective cryptocurrency trading techniques. In order to assess the suggested LSTM-GRU model's propensity for long-term forecasting, more study may examine if it can be applied to other cryptocurrencies or whether it can be extended to cover other time periods. The accuracy and usefulness of bitcoin price forecasts might also be improved by examining the model's performance under choppy market situations or by using outside elements like news sentiment analysis.

Future Scope

Future research and development opportunities are opened up by the work on creating an effective LSTM-GRU based bitcoin price prediction model. Here are some possible future coverage areas:

- a. Ensemble strategies Future research might look at the possibilities of creating ensemble models by mixing several prediction models, such as the suggested LSTM-GRU model. By combining the advantages of many models and minimizing the shortcomings of each one individually, ensemble approaches often increase forecast accuracy. Investigating ensemble methods may result in forecasts of bitcoin prices that are even more reliable and precise.
- b. While the research concentrates on the LSTM-GRU architecture, there is still potential to investigate other feature engineering strategies to improve the performance of the prediction model. The accuracy of cryptocurrency price forecasts might be increased by using domain-specific elements, such as social media sentiment analysis, macroeconomic data, or market news sentiment.
- c. Tuning the hyperparameters: The selection of the hyperparameters has a significant impact on how well LSTM-GRU models function. Future studies might concentrate on finding the best method for improving the model's hyperparameters, such as grid search, random search, or Bayesian optimization. The performance and generalization abilities of the model may be further improved by fine-tuning the hyperparameters.
- d. Long-term forecasts: Even if the findings of the current research cover a particular time period, it would be beneficial to look at how well the LSTM-GRU model performs when making long-term forecasts. Insights regarding the model's dependability and possible relevance for long-term investment strategies may be gained by analyzing its accuracy and stability over protracted times, such as weeks, months, or even years.
- e. Systems for real-time prediction and trading: The study and assessment of the prediction models offline are the main topics of the research. Future studies may examine the creation of real-time forecasting and trading platforms based on the LSTM-GRU model under consideration. By incorporating the model into an automated trading platform, traders and investors may be able to decide quickly on the basis of current bitcoin price forecasts.
- f. Possibility of Generalization to Other Financial Markets: Although the research focuses on bitcoin price prediction, the architecture and technique of the proposed LSTM-GRU model may be applied to other financial markets, such as equities, foreign exchange, or commodities. It is possible to broaden the model's applicability and make contributions to larger financial forecasting research by examining the model's generalizability and performance in other financial domains.

In conclusion, this paper's next directions include investigating ensemble techniques, feature engineering, hyperparameter tweaking, long-term forecasting, real-time forecasting and trading systems, and expanding the model's application to more financial markets. The accuracy, robustness, and applicability of LSTM-GRU-based cryptocurrency price prediction models may be further improved by the scopes of this study under real-time scenarios.

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