Cryptocurrency Price Prediction Model Using GRU, LSTM and Bi-LSTM Machine Learning Algorithms

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Abstract: The rapid rise of cryptocurrencies has indeed created both investment opportunities and forecasting challenges. Accurate predictions of cryptocurrency prices are crucial for traders and financial planners to make informed decisions. Recent studies have employed deep learning techniques, specifically Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Bidirectional LSTMs (Bi-LSTM), to analyze the price movements of popular cryptocurrencies. In a comparative analysis, the GRU model consistently outperformed both LSTM and Bi-LSTM models across various cryptocurrencies, demonstrating its effectiveness in modeling financial data. The performance of these models was evaluated using the Mean Absolute Percentage Error (MAPE) after preprocessing, normalizing, training, and evaluating the data. The results indicated that GRU provided the most accurate predictions, with lower MAPE values compared to its counterparts. For instance, a study focusing on Bitcoin, Ethereum, and Litecoin found that the GRU model achieved superior performance metrics, confirming its suitability for cryptocurrency price forecasting. This suggests that traders and investors can rely on GRU-based models for more accurate predictions, ultimately aiding in better investment strategies in the volatile cryptocurrency market.

1 INTRODUCTION

A fiat currency is a currency that is divisible, transferable, durable, and scarce [1]. This system has some drawbacks, including no tangible backing for currencies and no ability to control the money supply, which may contribute to hyperinflation and income inequality [2]. Financial institutions and credit card companies facilitate many transactions, which increase costs, lengthen transfer times, and expose ledgers to manipulation. As a result, individuals cannot control or own data. As a result of government regulations and legal agreements, the current financial system still enjoys public trust regardless of these limitations. A breach of trust has resulted in significant financial losses in the past, such as during the dot-com bubble and the housing bubble of 2008 [3]. It has been proven that trust breaches can result in significant financial losses in the past, such as during the dot-com bubble and the 2008 real estate bubble. In October 2008, a group operating under the pseudonym [4] created the first digital currency, Bitcoin, using blockchain technology. International financial institutions are becoming increasingly interested in P2P transactions, which can be carried out over the internet without intermediaries [5]. There is currently research being conducted by academia, government agencies, and media outlets as well as citizens.

Since its inception, the cryptocurrency market has been the subject of controversy and debate, but it has gradually expanded into one of the largest alternative investment venues [6]. Bitcoin [5] pioneered the use of cryptocurrencies as a means of investing, according to CoinMarketCap.com [7], [8]. In response to this remarkable growth, big data and virtual assets are enabling us to move into a new era of financial. Investors have faced new risks as a result of the new markets, but they have also been provided with more tools to manage them.

During the crypto boom of 2017, governments worldwide began standardizing and regulating digital currencies. More people now use Bitcoin more comfortably thanks to blockchain technology's safety [9]. In addition to using blockchain technology for security, it is also important to consider cryptocurrencies' legality when considering illegal users [10]. Consequently, there are ongoing discussions and examinations about cryptocurrency law. In addition to technological innovation and legal frameworks, digital currencies also incorporate moral considerations. The authors examine cryptocurrency viewpoints, characteristics, and legal and economic issues in regard to monetary elements [11]. As a currency, Bitcoin does not meet the economic requirements in accordance with traditional views and features. Among the many cryptocurrencies available on the digital market, BTC is well known. Considering cryptocurrencies' interconnectedness, small cryptocurrencies can have a negative impact on larger cryptocurrencies. According to research [12], gold acts as a stand-alone currency, making it an appropriate asset to hedge cryptocurrency price fluctuations. With virtual currencies evolving and becoming more volatile, conventional assets, such as gold, may serve as stabilizing elements, reducing risk and diversifying portfolios [13].

Cryptocurrencies are inherently volatile and dynamic, making price forecasting difficult. Researchers in this field explore and study the complexities of cryptocurrencies to provide a better understanding of what drives price fluctuations in this market. We will use machine learning and deep learning algorithms to identify latent patterns in data to improve prediction accuracy. An analysis of deep learning models is presented in this article for predicting Bitcoin, Ethereum, and Litecoin prices. In order to forecast cryptocurrency prices, LSTMs and gated recurrent units (GRUs) are both types of recurrent neural networks. It is demonstrated that DL algorithms are capable of increasing prediction accuracy and handling the inherent nonlinearities of time series data in this study.

2 LITERATURE REVIEW

In artificial intelligence, machine learning predicts the future based on past data. The use of historical cryptocurrency price data to train machine-learning models may allow us to predict the price movement of cryptocurrencies in the future. In contrast with traditional forecasting models, machine learning-based forecasting is able to provide results that are close to or identical to the actual outcome while also improving accuracy [14]. There has been an increase in the use of neural networks (NNs), decision trees (DTs), and support vector machines (SVMs) for this purpose. Cryptocurrencies improve multiasset portfolio performance in various ways [15]. The portfolio's minimal variance is enhanced, and the efficient frontier is moved forward. Cryptocurrencies also reduce standard deviations and boost Sharpe ratios when added to portfolios.

BTC price forecasts can be made using machine learning algorithms, according to the literature. A machine learning algorithm predicted the price of Bitcoin, Ethereum, LTC, XRP, and Stellar [14]. As compared to Artificial Neural Networks (ANNs) and Deep Learning, SVMs produced the highest accuracy. Using correlation analysis, [16] selected the most reliable predictors of BTC and ETH prices based on several factors. Based on the selected features, linear regression performed better than SVM, linear regression, and random forest (RF). LSTM, which is a type of deep learning, was also tested for predicting Bitcoin and Ethereum prices, and LSTM achieved the best result for Bitcoin. An ensemble model based on machine learning has been used to forecast nine different cryptocurrency prices using ANNs, KNNs, gradient-boosted trees, and ensemble models [17], [18].

The ensemble learning model produced the lowest prediction errors, according to the findings. Prediction errors were the lowest for the ensemble learning model. RF and Gradient Boosting Machines (GBM) were incorporated into an ensemble model to predict three cryptocurrencies - BTC, ETH, and XRP - in [19]. These predictions were then calculated using MAPE, and the results indicated a range of MAPE values between 0.92% and 2.61%. A lot of DL models have been developed recently that focus on predicting financial time series. During deep learning, artificial neural networks are trained on large datasets. This type of network can learn and make intelligent decisions, unlike traditional neural networks. RNNs, including LSTMs and GRUs, are frequently used to predict time series. As described in [20], an LSTM model using selected features is used in conjunction with an ANN and RF to predict BTC prices. Based on the results, an LSTM model outperformed both ARIMA and SVM. A hybrid model combining LSTMs and GRUs was used to predict Monero's (XMR) and LTC's prices [21].

The gold price has been predicted using various models developed by researchers. A new algorithm for artificial bee colonies was developed by the Author [22] in combination with a wavelet neural network method. Blockchain technology and cryptographic functions are used in cryptocurrency to achieve transparency, decentralization, and immutability [23], [24]. An anonymous person or group invented Bitcoin (BTC) in 2009, making it the first and most popular cryptocurrency. ETH and Ripple (XRP) are among the alternative cryptocurrencies created since then, proving that cryptocurrency has emerged as a financial asset. Most cryptocurrencies are dominated by BTC, ETH, and

XRP, which account for almost 79.5% of all cryptocurrency market capitalization. In addition to helping cryptocurrency investors make prudent investment decisions, cryptocurrency price predictions can help financial researchers study cryptocurrency market behaviour. The same methods can be used to predict cryptocurrency prices as for stock price predictions. AutoRegression Integrated Moving Averages (ARIMAs) have been used to predict cryptocurrency prices and movements [25]. Although these models are more accurate at predicting time series than Deep Learning algorithms, they cannot recognize non-linear patterns in very complex prediction problems [26], [27].

3 PROPOSED METHODOLOGY

In this section, we describe how the study was processed and modelled. After that, a selection of cryptocurrency prediction plots is demonstrated. Lastly, we evaluate the performance and analysis of the study. Through the use of LSTMs, GRUs, and Bi-LSTMs, we use deep learning techniques to make predictions about Bitcoin, Ethereum, and Litecoin prices. As part of the evaluation process for Bitcoin, Ethereum, and LTC, historical data is collected, exploratory data visualization is performed, each dataset is divided into training and testing datasets, and three different types of machines are trained, tested, and compared.

3.1 Dataset

Each deep learning model is composed of three layers (LSTM, Bi-LSTM, and GRU), each with 100 neural connections. Figure 1 shows how the dataset was preprocessed. As part of the deep learning process, we conducted a variety of preprocessing techniques on the cryptocurrency data. Following data imputation, we reshaped the data so that it can be applied to LSTMs, Bi-LSTMs, and GRUs. Upon examining the dataset, we found that there were missing values, which were then replaced using the previously recorded observations using a straightforward imputation technique. A normalized model ensures accuracy, avoids bias and is fundamental to model fitting. For the purpose of reducing the potential issue of unequal treatment, we used MinMax Scaling to normalize variables with different scales prior to fitting the model. Studies have shown that these methods can enhance the performance of models [28]. As a result, we scaled the data using MinMax Scalar in this study. As a way of maintaining continuity between cryptocurrencies, we divided training into 80:20 tests. Testing datasets have been collected since 1 January 2022; training datasets have been collected since 1 January 2018, and training datasets have been collected since 1 January 2018. These studies utilized a number of Python 3 libraries, including NumPy, Pandas, Matplotlib, Keras, and scikit-learn.

3.2 Machine Learning Algorithms

3.2.1 Long Short-Term Memory – LSTM

LSTMs are an update to RNNs. Thus, long-term dependence problems can be avoided, while vanishing gradient problems are solved through an additional mechanism that regulates information and allows it to persist over time [29]. There is a recurrent network of interconnected memory blocks in the LSTM architecture. Memory blocks are also responsible for maintaining the network's state throughout its existence as well as regulating data flow between individual cells. According to Figure 1, an LSTM has input. x_t, output h_t, and an activation function h_t. Input gate calculations determine what information should remain in a cell's state, while output gate calculations compute what information should be sent out.

These (1) – (5) describe how LSTM networks forward train:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \tag{1}$$

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_t\right), \tag{2}$$

$$c_t = f_t * c_{t-1} + i_t * \tanh(W_c[h_{t-1}, x_t] + b_c), \tag{3}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o), \tag{4}$$

$$h_t = o_t * \tanh(c_t). \tag{5}$$

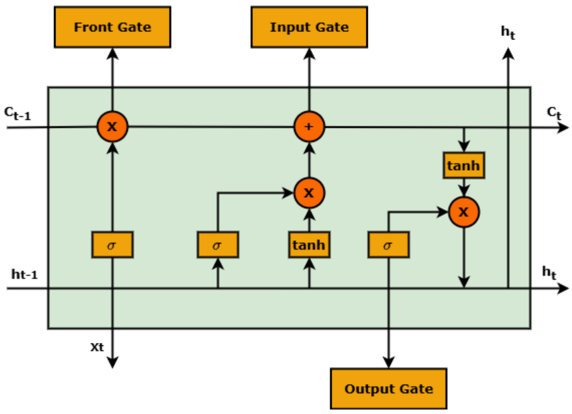

Figure 1: An LSTM algorithm's structure.

In the case of x_t, h_t, and c_t, it is the input gate, forget gate, and output gate, respectively, at time step t.

This matrix is represented by and is composed of two weight matrices and one bias vector. Sigmoid functions (tanh) are also used to limit the output along with hyperbolic tangent functions (sig).

3.2.2 Gated Recurrent Unit (GRU)

A new extension of RNN, GRU, was developed using the architecture of LSTM networks [30]. In addition to handling arbitrary input sequences, GRUs store information about past inputs in a state that is continually updated. GRUs perform different operations inside than LSTMs, so they are also different in their inner workings. As opposed to LSTMs, GRUs have simpler control of information flow, and they need fewer gates. Reset gates and update gates determine what should be forgotten by GRUs. Their training may be easier than LSTMs. Although GRUs have a simple architecture, they are capable of performing as well as LSTMs in a broad range of applications [31].

GRUs have been proven to be more efficient at modelling language than LSTMs in the Penn Treebank dataset. GRUs are superior to non-GRUs for noisy language models, as shown by this result. According to a comparison of natural language processing models, GRUs are as good as LSTMs and CNNs when used across benchmarks [30]. GRUs are well suited to a variety of NLP tasks, demonstrating their adaptability and strength. One of the advantages of GRUs is that they can catch long-range connections more effectively than standard RNNs. Due to the current information and the organization's express, GRUs can recall or dispose of verified information based on their current plan's update and reset entryways. For activities requiring memory retention and application of long sequences of information, selective retention is imperative. It is because GRUs are capable of managing long-term dependencies that they excel at translating lengthy text sequences. Therefore, GRUs excel at handling multiple consecutive information tasks and can even outperform RNNs and LSTMs under certain circumstances [31].

One hundred neurons make up the GRU network, allowing it to capture complex sequences and temporal patterns in data. This training process will use 32 batches to span twenty epochs while balancing resource use and effectiveness. For overfitting to be avoided, 20% of neurons should be turned off during training according to the Dropout of 0.2. With Adam, sparse gradients can be easily handled, and the learning rate is adaptive. Since it incorporates linear activation as part of its other methods, the GRU design is particularly suitable for tasks such as forecasting time series or predicting continuous values. Reset and update gates are present in the GRU. A gate that updates the hidden state with a new input determines the amount of hidden state to be forgotten by a gate that resets the state with a new input. GRUs contain reset gates (r_t), update gates (z_t), hidden states (h_t), and candidate hidden states (h_{tt}) following (6) – (9):

$$r_t = \sigma(W_r[h_{t-1}, x_t]), \tag{6}$$

$$z_t = \sigma(W_z[h_{t-1}, x_t] + b_t), \tag{7}$$

$$h_t = (1 - z_t) * (h_{t-1}] + z_t * h_{tt}), \tag{8}$$

Anywhere

$$h_{tt} - \tanh(W_h[r_t + h_{t-1}, x_t]) \tag{9}$$

weight matrices $W_r. W_2, W_h$

As shown in the figure, σ represents the sigmoid activation function. Function for activating tangents $tanh$. Weight matrices W.

3.2.3 Bi-Directional Long Short-Term Memory

In RNNs, long-term gradients explode and disappear over time due to LSTMs. Due to back-propagation through time (BPTT), it is hard for standard RNNs to prepare long successions, which can result in exploding or disappearing gradients. Bi-LSTM cells are used in place of RNN cells to resolve this issue.

In a cell case, data is entered through three entryways. In the first entryway, sigmoid layers choose which data to discard, as illustrated by the following (10).

$$C_t = f_t. C_{t-1} + i_t. C_t. \tag{10}$$

Equations (1) - (3) are then used to update the state of the cells.

Our paper uses a Bi-LSTM that we developed. Essentially, it is a deep learning algorithm that feeds the input sequence into two different networks, one of which follows normal time and the other follows reverse time. There is a sequential output from each network at each time step. The stacked layer Bi-LSTM architecture allows for both forward and backward information to be obtained at each time step, leading to high classification accuracy.

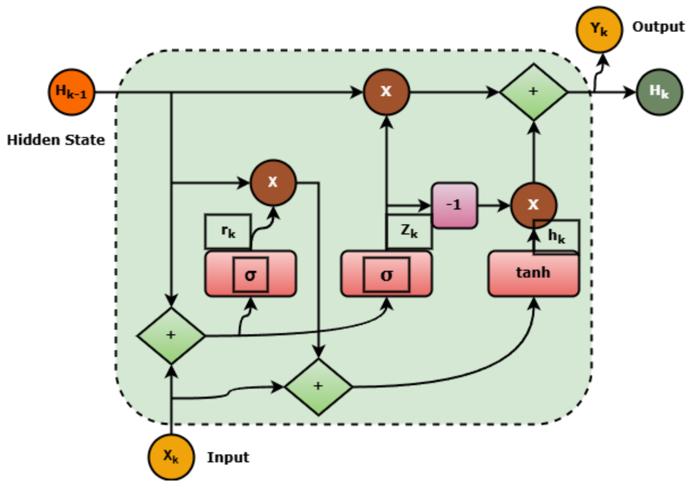

Figure 2: Block diagram of a GRU cell.

According to (11)-(13), bi-LSTM classifiers can handle data both forward and backwards.

$$h_t = f(w_1 x_t + w_2 h_{t-1}), \quad (11)$$

$$h_t = f(w_3 x_t + w_5 h_{t+1}), \quad (12)$$

$$O_t = g(w_4 h_t + w_6 h_t), \quad (13)$$

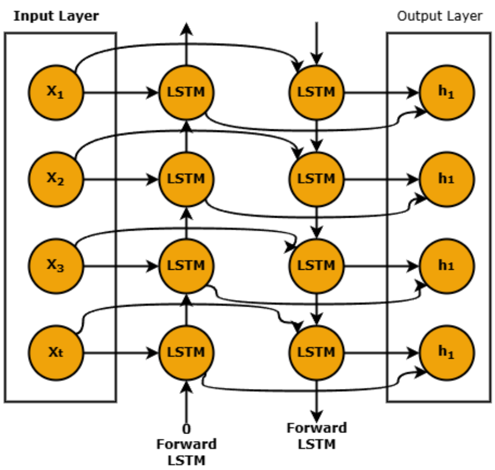

Figure 3: A block model of bidirectional LSTM algorithm (Bi-LSTM).

3.3 Performance Metrics

Our evaluation of the proposed DL algorithms used both RMSE and MAPE. A prediction model that has a smaller RMSE and MAPE value will perform better:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - P_t)^2}{n}}, \quad (14)$$

$$MAPE = \frac{100}{N} * \sum_{I=1}^{n} \frac{|A_t - P_t|}{A_t}. \quad (15)$$

A forecast is represented by P_t, an actual value by A_t, and a time step by n is represented by n.

4 RESULT ANALYSIS AND DISCUSSION

A comparison of RMSE values for three deep learning models is presented in Figure 4 based on prices predicted for Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). Performance metrics such as RMSE are used as a measure of predictive accuracy, with lower values indicating a better prediction. According to the results, LSTM produces the lowest accurate predictions for BTC compared to other models. While Bi-LSTM is an improvement over LSTM, it still exhibits relatively high error rates for BTC and ETH. A GRU model, however, demonstrates superior prediction accuracy across all three cryptocurrencies with the lowest RMSE. The GRU model, as well as all other models, predicts Litecoin prices accurately with very low errors. Among all three models evaluated, the GRU model proves to be the most accurate for predicting cryptocurrency prices.

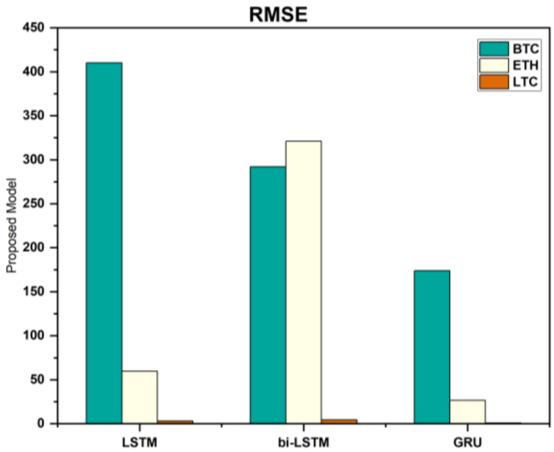

Figure 4: RMSE comparison of LSTM, Bi-LSTM, and GRU models for cryptocurrency price prediction.

Figure 5 illustrates the MAPE model using LSTM, Bi-LSTM, and GRU to predict Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). MAPE measures predictive accuracy, with lower values indicating better accuracy. All three cryptocurrencies maintain moderate error levels, with Ethereum showing slightly higher error levels than Bitcoin and Ethereum Classic. A comparison of the MAPE values between the Bi-LSTM model and the Bi-LSTM shows that the Bi-LSTM model is less efficient, especially for Bitcoin and Ethereum. Among all cryptocurrencies, GRU exhibits the lowest MAPE, demonstrating superior predictive abilities. In this study, it is confirmed that GRU consistently outperforms both LSTMs and Bi-LSTMs in forecasting cryptocurrency prices.

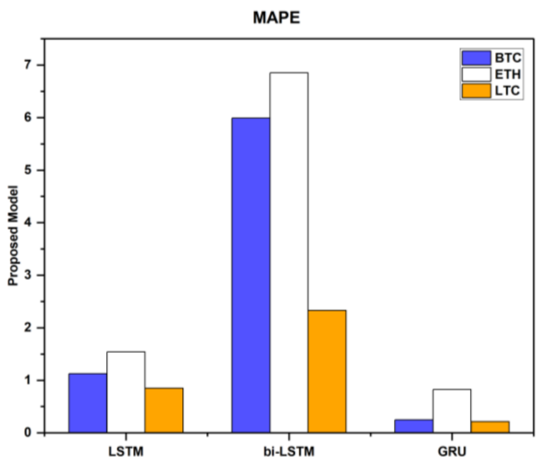

Figure 5: MAPE comparison of LSTM, Bi-LSTM, and GRU models for cryptocurrency price prediction.

From early 2018 to mid-2021, Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC) closed at their respective closing prices in Figure 6. The x-axis represents timelines, and closing prices are represented by the y-axis. During the period between late 2020 and early 2021, Bitcoin's price spiked to almost $60,000 before rapidly dropping. As opposed to Ethereum, Litecoin's price ranges remain relatively stable throughout the same period. Compared to Bitcoin, Ethereum and Litecoin show more consistent price movements, but their volatility is lower.

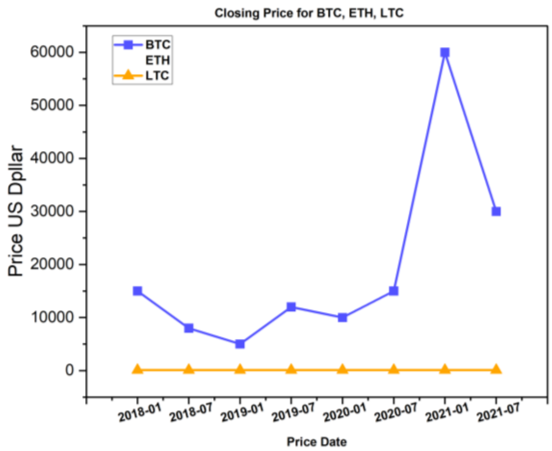

Figure 6: Closing price trends of BTC, ETH, and LTC from 2018 to 2021.

5 CONCLUSIONS

For the purpose of predicting cryptocurrency prices, the researchers employed three prominent deep learning algorithms: Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Bidirectional LSTM (Bi-LSTM). Historical data from Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC) were systematically used to train and validate the models, enabling a thorough evaluation of their respective predictive capabilities. Among these algorithms, GRU consistently demonstrated superior performance, achieving notably lower Root Mean Square Errors (RMSEs) and Mean Absolute Percentage Errors (MAPEs) across all three cryptocurrencies. In contrast, LSTM and Bi-LSTM models yielded consistently higher prediction errors compared to GRU, particularly noticeable for BTC and ETH, indicating a relative disadvantage in accurately modeling complex market fluctuations. The study highlights GRU's simpler architectural design, fewer training parameters, and enhanced ability to efficiently capture temporal dependencies, positioning it as an optimal choice for modeling highly volatile and dynamically evolving financial time series data like cryptocurrency prices. These findings provide valuable insights for investors, traders, financial analysts, and researchers, assisting them in developing informed strategies, managing risks effectively, and enhancing research methodologies within the rapidly evolving landscape of digital finance.

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