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Predicting Prices of Different Cryptocurrencies Based on LSTM Models

Haoyue Li[1,a,*]

[1]Zhongnan University of Economics and Law, Wuhan, 430073, China
a. lhy66900@163.com
**corresponding author*

Abstract: For more than a decade, as the number and value of cryptocurrencies exploded, more and more investors flocked to the cryptocurrency market with the expectation of positive returns. The price of cryptocurrencies, on the other hand, is extremely volatile. As a result, there is a great need to develop an accurate price prediction model to assist investors in making decisions and profit. This paper focuses on developing an LSTM-based prediction model for Bitcoin, Ethereum, EOS, and Solana cryptocurrency price prediction and calculating their RMSE and MAPE. Furthermore, four models are compared using this calculated MAPE. Based on the comparison results, the impact of cryptocurrency volatility, liquidity, and technology level on the accuracy of the LSTM prediction model is also examined. The paper concludes that the LSTM model can predict the price of Bitcoin more accurately because Bitcoin has the least volatility, the most liquidity and uses the oldest but most secure consensus mechanism.

Keywords: Bitcoin, Ethereum, EOS, Solana, LSTM

1. Introduction

In 2007, due to repeated theft and misuse of government information and loopholes in the regulation of financial institutions, a man who goes by the name Satoshi Nakamoto on the Internet argued that a monetary system consisting of institutional credit would pose a systemic problem. He proposed an innovative and even revolutionary idea: creating a credit-independent currency. The global subprime crisis that erupted a year later in 2008 proved his fears that a monetary system based on large financial institutions and national credit was unstable. A new digital currency called Bitcoin was developed by Satoshi Nakamoto a year later. Blockchain technology, on which Bitcoin was based, completely transformed the financial industry. Online peer-to-peer payments are made possible by this digital currency. The currency initially had a problem with double spending. A consensus mechanism was used later to resolve the issue. The cryptocurrency will be cryptographically secure as a result of using a consensus mechanism. All blockchain-based cryptocurrencies require a consensus mechanism because of the aforementioned factors.

This paper selects four popular cryptocurrencies that use different consensus mechanisms, and these consensus mechanisms can represent four stages of development of cryptocurrency consensus mechanism technology. As consensus mechanism technology evolves, transaction processing speed is getting faster, but security is getting less and less guaranteed.

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This paper focuses on preparing an LSTM-based prediction model for price prediction of Bitcoin, Ethereum, EOS, and Solana cryptocurrencies and calculating their RMSE and MAPE. In addition, four models are compared based on this calculated MAPE, and a more accurate LSTM price prediction model is derived for investors' reference. Several factors that may affect the accuracy of the LSTM model, namely the volatility, liquidity, and technology level of cryptocurrencies, are also proposed to provide ideas for improving the model's accuracy in the future.

2. Literature Review

Among many predictive modeling tools, deep learning stands out for its powerful learning and performance, and it has become the tool of choice for time series forecasting in finance. As early as the end of the 20th century, Donaldson used artificial neural networks (ANNs) to indicate S&P500 stock prices and cross-validated the advantages of neural networks over traditional methods such as weighted least squares methods [1]. LSTM gained importance and has been widely used in the financial field since 2014, when the LSTM algorithm was very successful in machine translation. Sutskever et al. used a multilayer long and short-term memory network for English-French translation of the WMTG14 dataset, and the final BLEU score of the entire test set was 34.8, which outperformed the phrase-based SMT system and was more advantageous for long sentence translation [2]. Subsequently, LSTM models were also applied to deal with financial time series. Murtaza used a 2-layer LSTM network to predict the NIFTY50 stock price and obtained a test set result with RMSE of 0. 00859, which was significantly more accurate than the econometric model [3].

In the study of cryptocurrency price prediction, deep learning and LSTM-related models are also becoming mainstream. In the early days when bitcoin was in the public eye, Shah et al. applied the potential source model in Bayesian regression to the bitcoin prediction and achieved good results by binary classification. The binary classification method yielded a good bitcoin investment return [4]. By researching the sophistication metrics of the cryptocurrency flow network and employing one of the unique complexity variables, the residual diversity variable of bitcoin network traffic, to enhance the predictability of cryptocurrency volatility, Yang et al. established a dynamic strong partnership between these complexity metrics and bitcoin returns and volatility [5]. Later, McNally et al. attempted to foretell the BPI using a Bayesian recurrent neural networks and a both long- and short-term memory network. ARIMA, a standard technique for making predictions, was utilized to evaluate the accuracy of their predictions. Results showed that deep nonlinear learning outperformed linear learning by a large margin [6]. In conclusion, the use of LSTM models for predicting the prices of multiple cryptocurrencies is relatively lacking and needs further research.

3. LSTM Neural Network

The Long Short-Term Memory (LSTM) recurrent neural network was proposed by Hochreiter et al. [7]. LSTM is a special kind of recurrent neural network. A recurrent Neural Network (RNN) ensures continuous data transmission through an internal multi-loop loop and adjusts the weights continuously by backpropagation. When propagation to the activation function, the slope will become extremely large or small, and the gradient explosion or gradient disappearance problem will occur. LSTM is to solve this problem. LSTM structure has an external RNN loop and an internal self-loop, in which input gates, output gates, and forget gates are added to control the cell state. This structure also allows LSTM to control the information flow better.

Figure 1 depicts a simplified representation of the LSTM architecture, which consists of memory cells, input gates, output gates, and forget gates and uses a control gate mechanism [8]. Data from

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the past can be stored in a memory cell, data from the present can be regulated by the input gate, data from the previous moment can be regulated by the forget gate, and the output data from the present moment can be regulated by the output gate. This framework can be used to store only the relevant information while discarding all other data. The input is denoted by Xt in the structure diagram at time t, likewise, the current state of the cell, denoted by ht. Feedforward network layers are represented by the little boxes with inside each cell in the diagram [9]. The σ and tanh both represent the activation functions [10]. Next, the prediction accuracy of each model is compared, and then the feedforward network layer's number of hidden neurons is gradually increased through training and debugging until an optimal value is reached. Each control gate's computation method is outlined below.

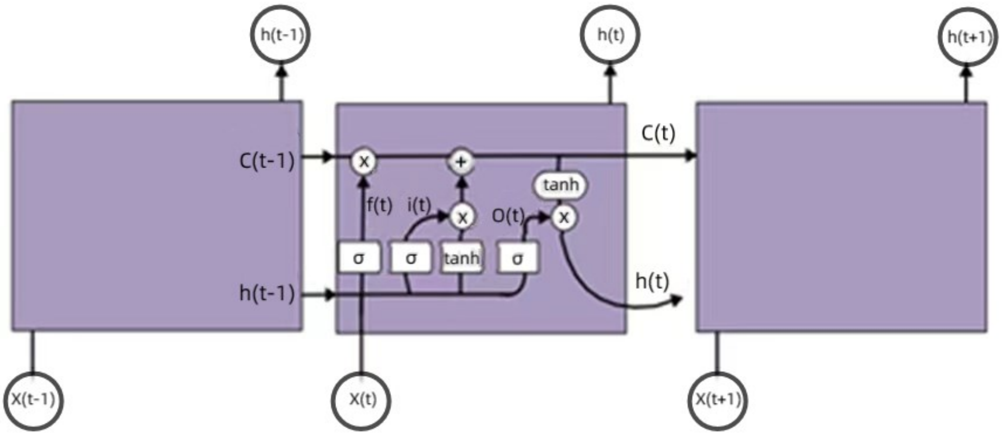

Figure 1: LSTM network structure [11].

Initially, we determine the candidate state value $\tilde{C}_t$ of the input cell at time t and the value of the input gate i_t.

$$i_t = \sigma(W_i * (X_t, h_{t-1}) + b_i) \quad (1)\ [11]$$

$$\tilde{C}_t = tanh(W_c * (X_t, h_{t-1}) + b_c) \quad (2)\ [11]$$

Next, the activation value f_t of the forget gate at time t is calculated with the following equation.

$$f_t = \sigma\left(W_f * (X_t, h_{t-1}) + b_f\right) \quad (3)\ [11]$$

From the above two steps, it is possible to calculate the cell state update value C_t at time t.

$$C_t = i_t * \tilde{C}_t + f_t * C_{t-1} \quad (4)\ [11]$$

After computing the cell state update value, the output gate value can finally be calculated.

$$O_t = \sigma(W_o * (X_t, h_{t-1}) + b_o) \quad (5)\ [11]$$

$$h_t = O_t * tanh(C_t) \quad (6)\ [11]$$

The LSTM can then use the input to create a long-term memory function with the help of the aforementioned calculation.

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4. Data Processing and Modeling

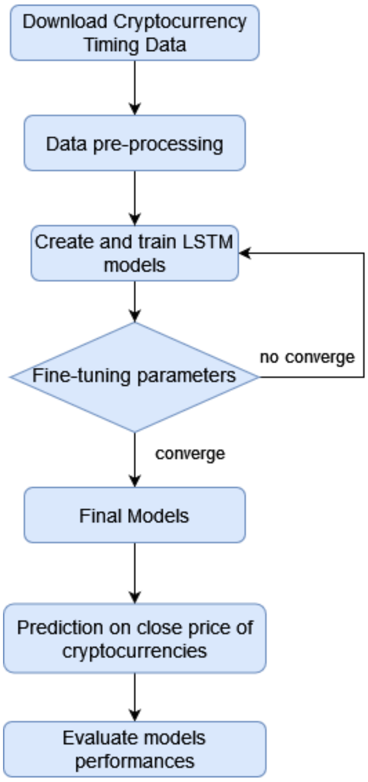

Figure 2: Experimental flow chart.

Using learning samples, the LSTM model creates a nonlinear mapping relationship between the input data and the output data in order to predict the close price of cryptocurrencies. New data is inputted based on this relationship, and the output data is the outcome of the prediction. The LSTM model is used in this study to forecast the close prices of the cryptocurrencies BTC, ETH, EOS, and SOL. The samples are drawn from cryptocurrency time series data.

As shown in Figure 2, the training process of the experiment is completed in several steps, including data download, data pre-processing, creating models, fine-tuning parameters, price prediction, and model evaluation.

1. Data download. The CryptoCompare API was used to obtain 944 time series data from January 1, 2020, to August 1, 2022, including time, open, high, low, volume, adjusted close, and close price.

2. Data pre-processing. Due to the different order of magnitude of the indicators in the time series data, the sample characteristics need to be normalized to eliminate the disparity in the magnitude of the data. Minmaxscaler() is used to normalize the data, scaling all data to values between 0 and 1. The samples are then separated into three groups: training, validation, and test. The LSTM model is trained on the training set, fine-tuned on the validation set, and evaluated on the test set to determine how well it predicts future data. Training set and validation set contain 661 data points, with 90% used for training models and 10% for checking their accuracy. The test set includes 283 unique pieces of information.

3. Creating models. A single-layer multivariate LSTM model was trained. The choice of the optimizer in the model is essential. In this paper, referring to the study of scholars SANGC et al. [10], the Adam optimizer performs better in terms of training time and entropy loss when the

amount of data is equal. Therefore, Adam is chosen as the optimization algorithm. The rest of the parameters are shown in Table 1.

Table 1: Model parameters.

Parameter name	Parameter value	Parameter name	Parameter value
Number of network layers	1	Optimization algorithm	Adam
Loss function	MSE	Batch size	8
Time step list	[10, 20, 30, 40]	Num units list	[16, 32, 64, 128]

4. Fine-tuning parameters. There is a hidden layer in the LSTM neural network, and underfitting and overfitting are both possible when the number of neurons there is too small or too large. The model's capacity for prediction is correlated with the number of neurons. Therefore, the number of neurons in the hidden layer is selected by adjusting the value of the parameter num_units several times to make the model optimal, as shown in Table 1. The input variable time_step of LSTM can also be changed. In this experiment, the optimal combination of time_step value and num_units value is selected by grid search to make the best prediction of the model.

5. Model evaluation. The root mean square error (RMSE) and mean absolute percentage error are the metrics used to assess the model performance (MAPE). Following are the formulas.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_{predict,i} - x_{real,i}\right)^2} \quad (7)\ [11]$$

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{x_{real,i} - x_{predict,i}}{x_{real,i}}\right| \quad (8)$$

5. Results and Analysis

5.1. Experiment Results

According to the RMSE values of each model, the optimal parameter combinations for the BTC, ETH, EOS, and SOL price prediction models are (time_step, num_units) = (30, 128), (10, 128), (30, 64), and (10, 128) respectively. And the evaluation metrics MAPE scores of these optimal models are shown in Table 2. As seen from the table, Bitcoin is best suited to use this single-layer multivariate LSTM model to predict the closing price. The acceptable ones are Ethereum and EOS, and the worst one is Solana.

Table 2: MAPE scores for the four cryptocurrencies.

Cryptocurrency name	MAPE score
Bitcoin	0.0299
Ethereum	0.0432
EOS	0.0475
Solana	0.0523

Figure 3, 4, 5, and 6 depict the comparison between the true and predicted close prices of the four cryptocurrencies.

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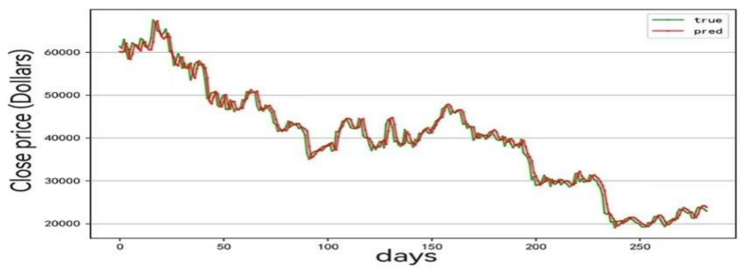

Figure 3: Bitcoin true price vs. predicted price.

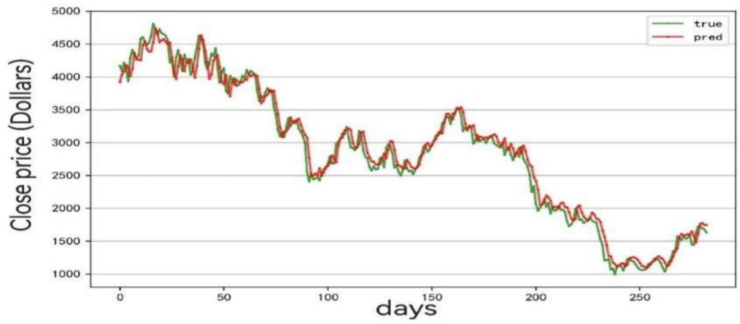

Figure 4: Ethereum true price vs. predicted price.

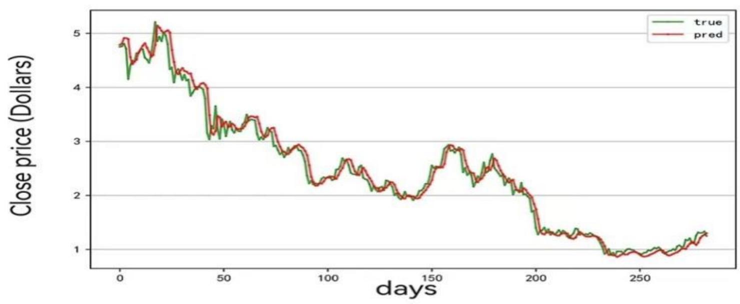

Figure 5: EOS true price vs. predicted price.

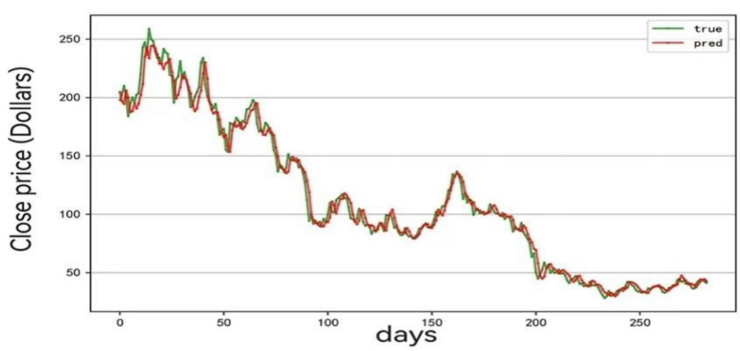

Figure 6: Solana true price vs. predicted price.

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In conclusion, the LSTM model is best suited for the Bitcoin dataset and can accurately forecast future prices, allowing investors to make the most profitable investments.

5.2. Analysis

Next, this paper discusses the factors affecting the accuracy of LSTM prediction models in terms of the nature and characteristics of the four cryptocurrencies.

Volatility. The historical volatility of each cryptocurrency can be calculated based on its close price from January 1, 2020, to August 1, 2022. Bitcoin at 123.45%, Ether at 162.78%, EOS at 193.70%, and Solana at 235.24%. The higher the historical volatility, the greater the variability in cryptocurrency prices and the greater the number of significant ups and downs. Then, the close price of cryptocurrencies is less likely to be accurately predicted [11].

Liquidity. Adding up the daily trading volume in each cryptocurrency dataset, we can get the total trading volume of the four cryptocurrencies respectively, from January 1, 2020, to August 1, 2022. The ranking of the total trading volume of cryptocurrencies is largest for Bitcoin, followed by Ethereum, then EOS, and the smallest is Solana. The larger the total trading volume of cryptocurrencies in the same period, the more liquid they are. Then, it can be concluded that the more fluid the cryptocurrency is, the more suitable it is for price prediction with LSTM model.

Technology level. Bitcoin, Ethereum, EOS, and Solana all have different consensus mechanisms. Based on the level of technical sophistication of the consensus mechanism, they are ranked as Solana, EOS, Ethereum, and Bitcoin. This is the opposite of their models' MAPE value ranking. It can be concluded that the more advanced the consensus mechanism technology used by a cryptocurrency, the worse the accuracy of its LSTM prediction model.

6. Conclusion

In this study, the close prices of four cryptocurrencies—Bitcoin, Ethereum, EOS, and Solana—were predicted using LSTM models. For the same cryptocurrency, RMSE was used to compare models based on various parameters and choose the best model. MAPE was used to assess and compare the four best models. Based on the MAPE values, it can be concluded that Bitcoin is the most appropriate for prediction using the LSTM model to get an accurate close price, while Solana is the least appropriate for the LSTM model.

Next, this paper analyzes the impact of cryptocurrency volatility, liquidity, and technology level on the accuracy of the LSTM model. It can be concluded that the less volatile and more liquid the cryptocurrency is, and the less technologically advanced the consensus mechanism is, i.e., the more secure the consensus mechanism is, the more accurate its LSTM price prediction model will be.

Only single-layer LSTM models are used in this study. In the future, multi-layer LSTM models can be constructed, and the most appropriate network layers of the model can be explored to predict cryptocurrency prices. Additionally, new features, such as macro policies and investor attractiveness that impact volatility and liquidity, can be added to train the model based on the factors proposed in this paper that may impact the LSTM model's accuracy. This will improve the model's accuracy for predicting the close price of cryptocurrencies and provide investors with more useful references.

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