Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 8, S. 367-376, 2, 2024

Araştırma Makalesi

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 8, pp. 367-376, 2, 2024

Research Article

https://as-proceeding.com/index.php/ijanser
ISSN: 2980-0811

Cryptocurrency Price Forecasting using LSTM with Short Time Series Data

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(Received: 08 March 2024, Accepted: 12 March 2024)

(4th International Conference on Innovative Academic Studies ICIAS 2024, March 12-13, 2024)

ATIF/REFERENCE: Korkmaz, E. & Altınoz, O. T. (2024). Cryptocurrency Price Forecasting using LSTM with Short Time Series Data. *International Journal of Advanced Natural Sciences and Engineering Researches, 8(2), 367-376.*

Abstract **–** After the discovery of RNN's lack of long-term memory storage, the LSTM (Long Short-Term Memory) concept was developed. LSTM's ability to retain past values from further steps within a sequence or pattern made it a very useful method to analyze past currency values and attempt to estimate their future values. In this report, this concept is applied to cryptocurrency market to determine if it is indeed possible to forecast its future values using an LSTM-based deep learning algorithm. In this study, 100 cryptocurrencies will be estimated using short-term, hourly data. When the results obtained are analyzed, 98% accuracy is obtained on average. However, for some cryptocurrencies, performances far above this rate and for some cryptocurrencies, performances far below this rate were obtained.

Keywords – Estimation, Deep Learning, RNN, LSTM.

I. INTRODUCTION

The price forecasting is an emerging science topic where the prediction of the future quantity of any real-world object, as an example for power price prediction [14], power load prediction [15], portfolio [16], etc. Recently with the definition of the crypto currency, the prediction of the coin prices is becoming the important issue. The difference of the prediction of the coins is their numbers and dynamic behavior. There are more than 8000 coins and cryptocurrencies are traded 24/7. For this reason, prices can change instantly and there can be large changes during the day. As a result, cryptocurrency price prediction is both a very difficult problem and one where it is not always possible to capture instant changes. In recent years, different studies have been carried out for this problem.

Most of the studies in the literature focus on Bitcoin price prediction. In [8] only Bitcoin is predicted by using the machine learning methods. Per day data is recorded with lowest highest closed and opened price of the Bitcoin. Kaggle dataset Bitcoin Historical Dataset is predicted. The SVM gives highest performance against LSTM and NN for 4 days of data. The study given in [10] prediction of 1-60min is proposed for Bitcoin prediction with the aid of additional data from oil prices, currency etc. The data is collected from Bloomberg, Twitter and Blockchain.com ranging from March 4, 2019, to December 10, 2019. The LSTM, GRU and NN methods are applied to the problem set. It is explained the paper that the LSTM performs best on the 1-min prediction and has more accuracy. Another paper presented in both [2, 11] the price of the BTC is estimated by using the LSTM algorithm. The data is from the last five years with daily basis. The gain accuracy of the prediction is more than 95%. The prediction is based on the data from 30 days and the price of the next day Bitcoin price. The research in [3], another study on LSTM prediction of the coin prices is given. Like [2], only the price of the Bitcoin is predicted. The highest and lowest of each day is recorded. The results represent more realistic to the dynamic change on the prices that it is hard to follow the results per day.

Some studies are focus on many coins; In [1], the price of three coins is predicted by using the three different types of Recurrent Neural Networks (RNN). These coins are Bitcoin (BTC), Litecoin (LTC), and Ethereum (ETH). The applied RNNs are gated recurrent unit (GRU), long short-term memory (LSTM) and bidirectional LSTM (bi-LSTM) models. The results indicated that GRU gives the best results among these three models. In this paper the training dataset is composed from 22 January 2018 until 22 October 2020 and the testing dataset (20% of the data) is form 22 October 2020 until 30 June 2021 (time series data of 1277 records). This paper gives a long-term prediction of the prices. In [1], a long-term prediction is evaluated for RNN, however the cryptocurrency is a dynamic system works 24/7. The price changes are very rapid, and a long-term prediction may not be possible in real-word applications. A shorter prediction is given in [2] that predicts the net days price.

A similar study reported in [4] that unlike other papers the price of the Ethereum is predicted by using seven models the recurrent neural network, ensemble stacked recurrent neural network, gradient boosting machine, generalized linear model, distributed random forest, deep neural networks, and stacked ensemble for gradient boosting machine, generalized linear model, distributed random forest and deep neural networks. The data is collected from CoinDesk from the 1st of August 2022 to the 8th of August 2022 with closing prices (highest and lowest prices). It is reported on this paper that According to MAE, RNN forecasts outperform the other model's performance. In [5], three coins are predicted Bitcoin, Digital Cash and Ripple. The data is collected for Bitcoin, from 16 July 2010 to 01 October 2018, Digital Cash spanning 8 February 2010 to 1 October 2018 and the Ripple from 21 January 2015 to 1 October 2018. The prediction is calculated with many prediction methods, among them long-short term memory neural network topologies (LSTM) is significantly higher when compared to the generalized regression neural architecture, under higher computational burden of LSTM. In [12] Bitcoin, Ethereum, and Litecoin are predicted from the data is at the period from August 15, 2015, to March 03, 2019, with the test sample beginning on April 13, 2018. In [6] four coins are considered Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), and FTX (FTT). The bet performance obtained from Gated Recurrent Unit (GRU). When compared with linear regression, decision tree, support vector regression, random forests, and XGBoost. The data is collected from Yahoo throughout a three-year period, from 30 November 2019 to 30 November 2022. In [9] prediction of a day ahead of the bitcoins is discussed these coins are Bitcoin, Dogecoin, Namecoin, Litecoin, Gridcoin, Peercoin, Ripple, NXT, Ethereum and Binance coin. A large set of methods are compared these methods are LSTM, CNN-TA, ARIMA, Rao-ANN, MFNN, N-Beasts, DeepAR, TFT, RDL, ARIMA. Among them LSTM gives the best performance with respect to the MAPE. In [7] both long term and short-term data is collected to prediction of Bitcoin and Ethereum by using Bi-LSTM. In [13] price prediction of cryptocurrency using a three layers of Gated Recurrent Units network with multi features is proposed for over a 21-day forecasting window at Bitcoin, Ethereum and Dogecoin. It is obtained that the proposed method is better than LSTM and GRU models.

In this study, as in other studies, we will focus on the estimation of cryptocurrencies. However, it has major differences from other studies. The first difference is the number of crypto assets estimated. In this study, 100 cryptocurrencies will be estimated. Another difference is the time interval for forecasting. Since cryptocurrencies change very rapidly, the authors believe that long-term forecasting is not feasible. Therefore, forecasting will be done on an hourly basis. LSTM will be used in the prediction process due to its performance in other studies. The performance of the LSTM method will be demonstrated on these 100 crypto assets.

This paper begins with the introduction of the research. Then the method and material section are presented. In that section the information related to the preferred tool LSTM will be given. Then methodology of the implementation will be given with the generation of the data and the results will be reported. Finally with the conclusion of the research the paper finalized.

II. MATERIAL AND METHOD

A recurrent neural network (RNN) is a type of artificial neural network that takes the output from the previous step as an input to the next step. It can retain information from the past and use that information to process new input. RNNs are well-suited to tasks that involve sequential data, such as natural language processing, speech recognition, and time series forecasting. They have been used to achieve state-of-the-art results in many of these tasks and have become a popular choice for building machine-learning models that operate on sequential data. Even RNN is a popular method, there are some fundamental problems related to that method. The first problem is related to memory problem so that at some activation functions and their derivatives makes is harder to remember long sequences. The other problem is the computational resources. That means it takes time to train this network. To get rid of these problems a method called long short memory or simply LSTM is proposed. This algorithm solves the vanishing gradient problem by forgetting some unnecessary information of the network. The LSTM contains four components which are memory cell, forget gate, input, and output gates.

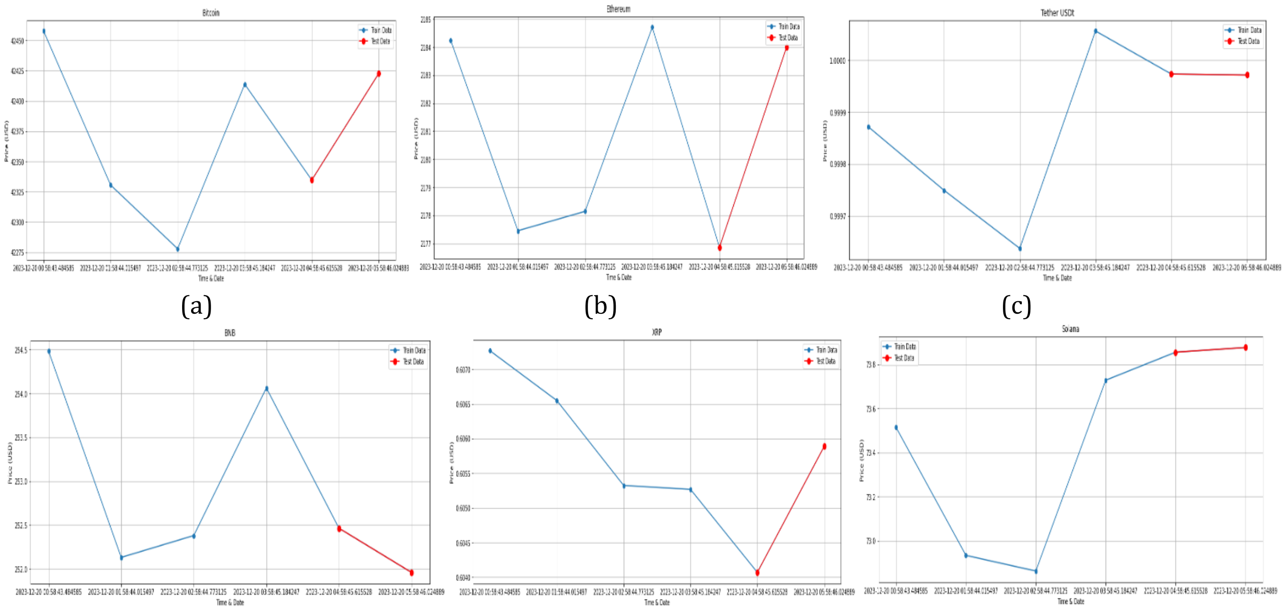
The first component is the memory cell. This is the calculation for remembering or forgetting the previous information. This component has a summation and multiplication. With the summation new information is added and with the multiplication the previous information may forgotten. Therefore, multiplication is prior than summation. The second component is the forget gate. The output of this component is feed to the memory cell with multiplication. For this reason, it is called the forget gate. The sigmoid function is calculated with the weighted multiplication of the new state and the previous hidden state. In LSTM there are hidden state, memory, and the input. The sigmoid of this component is feed to the memory cell as multiplication. The third component is the input component that the memory is calculated with tanh function and multiplied with the sigmoid function and feed to the memory cell. The final component is the output gate. The hidden state is update at this gate The previous hidden state applied to sigmoid function and multiplied with the tanh value of the memory and considered as the next hidden state.

III. METHODOLOGY

Preprocessing historical crypto coin price data, standardizing the values, and organizing it into sequences suited for training LSTM models are all part of the methodology. The data is separated into two sets: training and testing. Using the training data, LSTM models with varied layouts and hyperparameters are built and trained.

IV. DATA COLLECTION & ANALYSIS

To begin with, to observe and put data into the deep learning algorithm, we retrieve coin names and values from the website "CoinMarketCap.com" using an API key. In this research, we analyze only the top 100 coins with the largest market capitalization values in USD. Unlike the stock market, the cryptocurrency market operates without specific opening or closing times. To simplify the visualization of our analysis, we collect hourly values over a span of six hours for data on BTC, ETH, Tether USDt, BNB, XRP, and Solana. The figure 1 display the datasets of coins divided into training and testing datasets.



(a) (b) (c)

(d) (e) (f)

Figure 1. Six hours of time series of (a) BTC, (b) ETH, (c) Tether USDt, (d) BNB, (e) XRP and (f) Solana

Next, as a subsequent step, the datasets are selected and prepared for the LSTM model. This project is conducted in Spider Integrated Development Environment. Initially, it is scaled to a range of -1, 0, and 1 using the ***tanh*** function, facilitating preparation for the cell state and other gates within the hidden layers of the LSTM model. Following this process, the model's window size is determined, which is crucial as it represents the amount of data considered before estimation. The subsequent step involves allocating 80% of the data for training the LSTM model and reserving the remaining 20% for testing purposes.

The dataset is then reshaped because the LSTM model expects 3D input in the form of a time series. These three dimensions encompass Sample Size, Time Step, and Feature Size. Subsequently, a 2-layered LSTM model with 1000 neurons each, along with 1 layer of dropout, is coded and compiled using the 'Adam' optimizer and 'mean absolute error' loss function. Finally, the model undergoes training, and the training loss as well as the validation loss are determined and graphically visualized as depicted below.

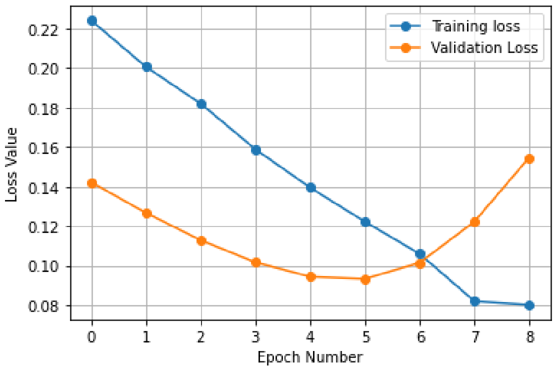


Figure 2. Training loss vs. Validation loss

Figure 2 presents the loss value vs epoch number for training loss and validation loss. The Training Loss is defined that it might start high but should decrease over time as the model learns. Lower loss values indicate better model performance. However, getting the loss down to zero might not always be possible. Similarly, the validation Loss's crucial to evaluate your model's performance on a separate validation set during training. Ideally, the validation loss decreases along with the training loss. If the training loss decreases but the validation loss increases, the model might be overfitting and not generalizing well. Finally, the epoch number is the number of times the learning algorithm processes the complete training dataset is indicated by the epoch count in a machine learning model training procedure. To put it another way, every epoch is one full run of the training dataset. When training a neural network, selecting the number of epochs is a crucial hyperparameter. The ideal number of epochs is determined by the neural network's design, dataset size, and task difficulty. It is standard procedure to keep an eye on the model's performance on a validation set while it is being trained, and to halt when the model reaches its maximum learning capacity as shown by a decline in performance on the validation set. It is possible to detect the epoch number from the plot in Figure 2.

To measure the performance of LSTM model there are several methods such as MSE, MAE and RMSE. Mean Squared Error (MSE) is a commonly used metric in statistics and machine learning to quantify the average squared difference between predicted values and actual values. It is calculated by taking the sum of the squared differences for each data point and then dividing this sum by the total number of data points. MSE is particularly valuable for assessing the accuracy and precision of predictive models, as it emphasizes the impact of larger errors due to squaring. A lower MSE value indicates that the model's predictions are closer to the actual values, while a higher MSE suggests a greater overall discrepancy between predicted and actual outcomes.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - y'_i)^2 \quad (1)$$

Mean Absolute Error (MAE) is a fundamental metric utilized in statistics and machine learning to measure the average absolute difference between predicted values and actual values. It is calculated by taking the sum of the absolute differences for each data point and then dividing this sum by the total number of data points. Unlike Mean Squared Error (MSE), which squares the errors, MAE treats all errors equally by considering only their absolute values. This makes MAE less sensitive to outliers, as extreme errors do not disproportionately influence the overall metric. A lower MAE value indicates a closer match between predictions and actual values, while a higher MAE suggests a greater overall discrepancy.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - y'_i|^2 \quad (2)$$

Root Mean Squared Error (RMSE) is a widely used metric in statistics and machine learning that provides a measure of the average magnitude of the errors between predicted values and actual values. It is derived from Mean Squared Error (MSE) by taking the square root of the MSE. RMSE is particularly useful because it retains the same scale as the original data, offering an interpretable and meaningful assessment of prediction accuracy. Like MSE, RMSE penalizes larger errors more significantly due to the squaring operation in MSE. Lower RMSE values indicate a closer alignment between predictions and actual values, reflecting better model performance. Conversely, higher RMSE values suggest a greater overall deviation between predicted and actual outcomes.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y'_i)^2} \quad (3)$$

V. OPTIMIZER

An optimizer is an essential part of the training procedure in machine learning, as it controls how the weights of the model are updated throughout training. An optimizer's job is to minimize the loss function by guiding the model towards convergence by modifying the model's parameters. A crucial choice in neural network construction and training is the optimizer to choose. In the iterative process of updating model parameters based on the gradients of the loss function with respect to those parameters, optimizers are essential. Gradient descent is a popular optimization technique. Different optimizers, including ***Adam, RMSprop, Adagrad,*** and ***Stochastic Gradient Descent (SGD)***, are variations made to handle distinct training issues.

VI. RESULTS

In this research because of the quantity of the data set epoch number is chosen to be 200 and batch size is chosen to be 4 and optimizer is chosen to be “Adam optimizer”. When the LSTM model is executed in Spider IDE results are shown and tabulated in Table 1 and Table 2.

Table 1. The MAE for all the crypto coins in this research (1-50)

Coins	***MAE***	***Coins***	***MAE***	***Coins***	***MAE***	***Coins***	***MAE***	***Coins***	***MAE***
Bitcoin	3.5345e-5	TRON	5.1312e-4	Cosmos	1.2245e-3	NEAR Protocol	7.3223e-2	Celestia	1.4790e-4
Ethereum	3.9911e-4	Polkadot	2.7358e-5	UNUS SED LEO	5.1057e-4	Filecoin	9.1098e-5	Mantle	1.0019e-2
Tether USDt	1.3291e-4	Chainlink	6.4969e-5	Uniswap	1.5318e-5	Aptos	4.3314e-4	THORChain	5.5903e-4
BNB	1.3889e-2	Toncoin	1.3542e-4	Stellar	8.8810e-6	TrueUSD	4.4620e-2	Stacks	1.7316e-2
XRP	7.3909e-5	Polygon	4.9728e-3	**OKB**	**1.054e-1**	Cronos	2.8252e-4	Render	5.7208e-4
Solana	7.8678e-6	Shiba Inu	1.9928e-3	Monero	8.4623e-5	VeChain	8.3446e-7	Algorand	1.0977e-2
USDC	2.5600e-5	Dai	2.6417e-3	Injective	6.6293e-3	Kaspa	7.2352e-3	MultiversX	3.6352e-2
Cardano	6.7353e-6	Litecoin	3.3676e-6	Ethereum Classic	9.6082e-5	Optimism	4.3585e-4	SATS	3.8981e-5
Avalanche	9.1302e-4	Bitcoin Cash	1.2019e-4	Hedera	3.4952e-4	Lido DAO	1.6009e-4	Aave	1.5729e-3
Dogecoin	9.8412e-3	Internet Computer	1.1551e-4	Immutable	4.7159e-4	**First Digital USD**	**2.5353e-1**	The Graph	2.3460e-4

Table 2. The MAE for all the crypto coins in this research (50-100)

Coins	***MAE***	***Coins***	***MAE***	***Coins***	***MAE***	***Coins***	***MAE***	***Coins***	***MAE***
Helium	1.0491e-2	BitTorrent	2.2470e-5	Beam	3.6776e-5	Klaytn	6.3419e-5	Chiliz	5.0884e-2
Arbitrum	1.5211e-4	ORDI	6.3052e-4	Decentraland	1.4072e-2	Gala	6.0558e-5	Blur	1.8433e-2
Quant	1.6528e-4	Sandbox	2.4331e-3	Neo	4.1842e-5	Sui	5.2027e-3	Fetch.ai	3.3140e-5
FTX	1.6376e-3	KuCoin	8.8435e-2	EOS	8.6665e-5	USDD	2.7390e-2	Terra	1.7702e-5
Maker	1.7350e-2	Theta	1.2406e-2	Tezos	5.3644e-5	**Osmosis**	**1.5369e-1**	ApeCoin	3.6537e-5
Bonk	1.5100e-3	BUSD	1.7960e-3	Sei	3.1844e-3	XDC	8.7079e-2	Arweave	1.7261e-4
Flow	3.3275e-3	Terra Classic	8.3339e-4	WOO	6.5565e-5	Oasis	2.9671e-4	Pancake	8.6404e-2
Fantom	7.9655e-4	Bitcoin SV	1.8900e-4	IOTA	2.5701e-4	Conflux	9.1195e-6	aelf	1.8715e-4
WEMIX	1.7172e-3	Bitget	2.1761e-3	Kava	1.3220e-4	eCash	2.7158e-4	**Gnosis**	**1.9519e-1**
Synthetix	2.2636e-4	Axie	2.5582e-4	Mina	6.5886e-4	Frax	7.1001e-4	Curve	1.2052e-4

Accuracy values is another concept in LSTM, normally accuracy concept is used in situations where classification is used so in this model if a coin's value is estimated with MAE value less than 0.001 when inspected individually then that estimation is accepted as "correct estimation". With this approach it can be said that this LSTM model estimated 96-coin values correctly.

$$Accuracy = (number\ of\ correct\ samples)/(number\ of\ all\ samples) \quad (4)$$

This LSTM model is used to predict future values of cryptocurrency prices accurately. Performance metrics such as Mean Absolute Error (MAE) is used to assess model performance. The results are tabulated and evaluated. Alternative methods are suggested to improve the performance of the model. The accuracy and the average MSE is reported in Table 3.

Table 3. The average mean absolute error value and accuracy

	Mean Absolute Error Value of LSTM model	Accuracy of LSTM model
	0.01499739	0.98 (%98)

VII. DISCUSSION AND CONCLUSION

In order to forecast future cryptocurrency values, we used Long Short-Term Memory (LSTM) neural networks in this study. Our results provide a few significant new insights into the viability and efficiency of LSTM models for price prediction of cryptocurrencies. The findings show that long short-term memory (LSTM) models perform admirably when it comes to capturing the complex dynamics and patterns present in cryptocurrency markets.

However, it's important to acknowledge the inherent volatility and unpredictability of cryptocurrency markets, which pose challenges for accurate price forecasting. While LSTM models offer promising results, they are not immune to the limitations and uncertainties associated with cryptocurrency trading. Factors such as regulatory developments, market sentiment shifts, and technological advancements can introduce significant uncertainties that may impact the reliability of our predictions.

In conclusion, the findings suggest that LSTM neural networks hold promise as valuable tools for predicting cryptocurrency prices. Despite the inherent challenges and uncertainties, LSTM models offer a viable approach to gaining insights into the future trends and behaviors of cryptocurrency markets. Future research efforts should focus on addressing the limitations identified in this study and further refining LSTM models for more accurate and reliable price forecasting. However, as future study the performance will be improved with respect to given methods.

1.Modifying the complexity of the model can help prevent issues like overfitting or underfitting. Model complexity is related to factors such as the number of layers, the number of neurons, and the parameters used. A more complex model often has more learning capacity but may increase the risk of overfitting.

2.If possible, training a model with more and diverse data can enhance its generalization ability and reduce error rates.

3.Trying different optimization algorithms or adjusting the learning rate can help the model learn more efficiently and effectively.

4.Identifying important features in a dataset and removing unnecessary ones can aid the model in better learning.

5.Employing techniques like dropout, where some neurons are randomly "dropped," can mitigate the risk of overfitting. Regularization techniques can also enhance the model's generalization ability.

6.Halting the training process when the validation error starts to increase can prevent overfitting.

7.Determining the optimal batch size and epoch count can help the model learn more effectively.

8.Normalizing or standardizing input data can contribute to better model performance.

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