Bitcoin Price Prediction and Analysis Using Deep Learning Models

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Temesgen Awoke Muniye
KIIT University

Minakhi Rout
KIIT University

Suresh Satapathy
Institute of Electrical and Electronics Engineers

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Temesgen Awoke, Minakhi Rout, Lipika Mohanty, and Suresh Chandra Satapathy

Abstract Cryptocurrencies are a digital way of money in which all transactions are held electronically. It is a soft currency which doesn't exist in the form of hard notes physically. Here, we are emphasizing the difference of fiat currency which is decentralized that without any third-party intervention all virtual currency users can get the services. However, getting services of these cryptocurrencies impacts on international relations and trade, due to its high price volatility. There are several virtual currencies such as bitcoin, ripple, ethereum, ethereum classic, lite coin, etc. In our study, we especially focused on a popular cryptocurrency, i.e., bitcoin. From many types of virtual currencies, bitcoin has a great acceptance by different bodies such as investors, researchers, traders, and policy-makers. To the best of our knowledge, our target is to implement the efficient deep learning-based prediction models specifically long short-term memory (LSTM) and gated recurrent unit (GRU) to handle the price volatility of bitcoin and to obtain high accuracy. Our study involves comparing these two time series deep learning techniques and proved the efficacy in forecasting the price of bitcoin.

1 Introduction

Virtual currencies are a form of cryptocurrency which is an impressive technical achievement in digital marketing, nevertheless. Virtual currencies live on, and they couldn't fully replace fiat or conventional currencies. In the current study, we

T. Awoke · M. Rout (✉) · L. Mohanty · S. C. Satapathy
School of Computer Engineering, KIIT Deemed to be University, Bhubaneswar, Odisha, India
e-mail: minakhi.rout@gmail.com

T. Awoke
e-mail: temesgenawoke5@gmail.com

L. Mohanty
e-mail: mohanty.lipika93@gmail.com

S. C. Satapathy
e-mail: sureshsatapathy@gmail.com

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are trying to show an interesting new perspective from which view of economics questions surrounding currency governance, the characteristics of money, political economy of financial intermediaries, and the nature of currency computation.

Virtual currencies become the most favorable and used for commercial enterprise transactions all over the world [1, 2]. The popularity is due to its innovative characteristics such as transparency, simplicity, and increasing acceptance through the world [3]. In the current time, bitcoin is the popular flourishing virtual currency. Reported to the website https://bitcoin.org, viewed on April 19, 2019, the virtual currency market value is close to 90 billions of dollars, but it varies from time to time. Bitcoin is a peer-to-peer cryptocurrency in which all transactions are not regulated or controlled by any third party. Third-party intervention between customers is impossible. It is highly volatile market price working 24/7. Market capitalization of bitcoin is increased through time to time. In the current time, more than 71 billions of dollars publicly traded. Due to its open-source nature, clear, transparent, simple, and time is saving which leads all virtual currencies in the world.

Bitcoin is a worldwide and most popular cryptocurrency, first introduced in 2008 and exploited as open source in 2009 by a person called Satoshi Nakamoto, but it became highly popular in 2017. Bitcoin functions as a decentralized moderate of electronic cash, with transactions proved and transcribed in a public distributed ledger (blockchain) without any third-party intervention. Transaction blocks consist of secure shell algorithm which is used to connect each other, and blocks are served as a non-editable data which is recorded when the transaction is being held. Then any virtual currency especially bitcoin has been adopted by the people, and the virtual currency market trend has been growing up.

The popularity of bitcoin is increased within a short period of time. Different technologies and business companies are joined with bitcoin. As different researchers assured that after 2015 around 100,000 technology and business companies have started the bitcoin market. Some of the popular companies which are joined with bitcoin are Amazon, Microsoft, Overstock, Dell, and others [1]. Many works have been done to predict time series, as well as BTC value. However, any deep learning models have not been much used yet to predict the BTC price value. Knowing the deep learning models become state-of-the-art neural network architecture that improves prediction accuracy in various domains including time series, we consider applications of deep learning to predict the BTC price value. In coming sections, we will explore previous works done on BTC price prediction, discuss deep learning models to predict the time series, and focus on three main articles which will serve as foundation of our work.

Primarily, the main challenge of bitcoin exchange rate is its high rate of price fluctuation. High price volatility implies a certain measure should be taken to predict the price of bitcoin accurately. Knowing the forecasting activity is necessary to tell about the future price of bitcoin and build trust as well as acceptance throughout the world. Influenced by a variety of factors, such as political system, public relations, and market policy of a country, can determine economical role of bitcoin and international relation of countries on different market strategies. Lastly, doesn't have an official road map: few key challenges and developments coming up for bitcoin prediction are in consistent, because there is no clear description of the exchange platform on which the transactions related to buying and selling are not regulated. The objective of our current study is to forecast the bitcoin price with improved efficiency using deep learning models and minimizing the risks for investors as well as policy-makers.

2 Related Works

Researches on the prediction of cryptocurrencies using machine learning are not much enough, especially on deep learning models. According to the research of 2016, more than 600 papers have been published on this topic. Our literature survey covers work done on bitcoin (BTC) price prediction using different techniques, the need, and evaluation of recurrent neural network (RNN) and its system architecture. Dennys et al. [4] used different attribute selection mechanisms to get the most important features and applied machine learning methods such as artificial neural network (ANN), support vector machine (SVM), and recurrent neural network (RNN) as well as k-means clustering in the bitcoin price prediction. However, one limitation of this study is only focused on the investors. Policy-makers should be considered as a major partner of the system because cryptocurrency can change the dynamics of world economy. Sean McNally et al. [5] used Bayesian optimized recurrent neural network and LSTM to predict the direction of Bitcoin price in USD. They also used ARIMA model to compare the deep learning methods. In Atsalakis et al. [6], this research focuses on computational intelligence method especially hybrid neuro-fuzzy controller in order to predict the exchange rate of bitcoin. This model used neuro-fuzzy approach and artificial neural networks. Goodfellow et al. [7] proposed a deep direct reinforcement learning framework for financial signal representation and trading. They combined the reinforcement learning (RL), deep learning (DL), and their current deep neural network (NN) to generate precise prediction results. They validate the proposed approach using commodity future markets as well as stock market data. Madan et al. [8] tried to predict the price of bitcoin using machine learning and investigate the trends of BTC surrounding. They used 25 attributes relating to bitcoin to forecast the daily price variation. In Lahmiri et al. [9], they implemented machine learning algorithms to predict the exchange rate of daily price of high data availability cryptocurrencies such as BTC, ripple, and digital cash. They applied RNN and GRNN (Generalized Regression Neural Network) to get the accurate prediction rate of high liquidity cryptocurrencies. Saxena et al. [10] investigated the minimum accuracy of bitcoin price using LSTM and ARIMA model. Paresh kumar et al. [11] suggested that bitcoin has a negative impact on market inflation. It is not predictable; therefore, bank of Indonesia should warn not to invest on bitcoin. Not only this but also different government authorities including police should prevent bitcoin marketing in Indonesia, and the objective of this study is to control the effects of cryptocurrency on the monetary system. Pant et al. [12] state that socially constructed ideas in a twitter about virtual currency have straight or sidelong impact over all the market analyses of virtual currencies. This study focuses on forecasting the fluctuated value of bitcoin by sentiment analysis and identifying the relationship between positive and negative sentiments. Nivethitha et al. [13] proposed the future stock price prediction using LSTM machine learning algorithm. They especially focused on time series prediction because it is a basic for share price prediction and other financial prediction models. And comparing with that of existing model ARIMA, LSTM algorithm provides efficient and accurate results. Roth et al. [14] assured that bitcoin is the new and most popular virtual currencies, while the security and its volatility rate are debatable. This study makes it functional for the peer-to-peer transaction of bitcoin through the network and the blockchain technology. Phaladisailoed et al. [15] used various machine learning algorithms to predict the bitcoin price more efficiently.

3 Proposed Methodology

The proposed methodology considers two different deep learning-based prediction models to forecast daily price of bitcoin by identifying and evaluating relevant features by the model itself. After applying both the models for bitcoin prediction, we can determine which model is much more accurate for the future fulfillment of our target and select appropriate parameters to obtain a better performance. In this work, we have proposed deep learning mechanisms such as LSTM and GRU which are the latest and efficient techniques for the forecasting of bitcoin price. As bitcoin is the most popular cryptocurrency, the price volatility issue should be handled within a short period of time. The process of prediction starting from collecting data till the forecasting of bitcoin price is depicted in Fig. 1.

3.1 RNN

RNN is a deep neural network characterized as a recurrent connection between the input and output of its neurons or layers and capable of learning sequences designed to capture temporal contextual information along time series data. They have recently gained popularity in deep learning due to their ability to overcome the limitation of existing neural network architecture where it comes to learn over long sequences. Two common RNN networks are LSTM and GRU and presented in the subsequent sections.

3.1.1 LSTM

LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior, not something they struggle to learn. All recurrent neural networks have the form of

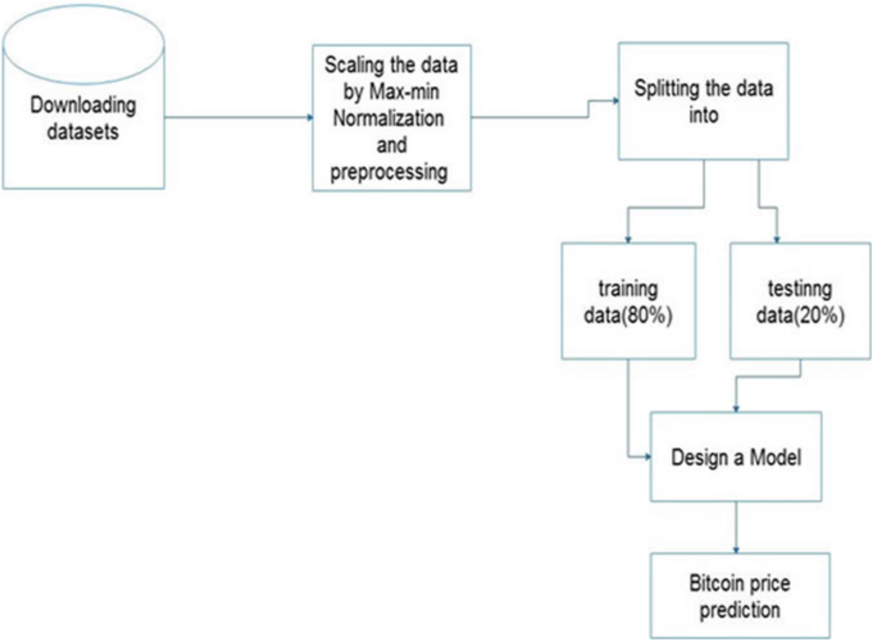
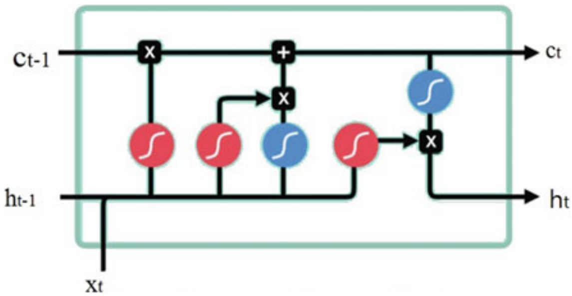


Fig. 1 Block diagram of proposed workflow

a chain of repeating modules of neural network. In standard RNNs, this repeating module will have a very simple structure, such as a single *tan h* layer.

The deep learning LSTM neural networks overcome the problems with RNN related to vanishing gradients, by replacing nodes in the RNN with memory cells and gating mechanism. In this regard, it is an attractive deep learning neural architecture mostly on the account of its efficacy in memorizing long- and short-term temporal information simultaneously, and it can be viewed the same in LSTM architecture depicted in Fig. 2.

Fig. 2 LSTM architecture



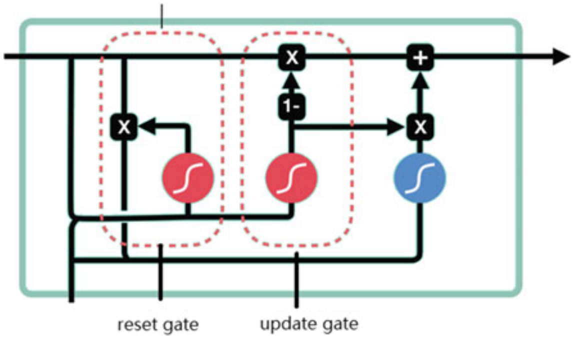


Fig. 3 GRU architecture

3.1.2 GRU

The GRU is the newer generation of recurrent neural networks and is pretty similar to an LSTM. GRU got rid of the cell state and used the hidden state to transfer information. It has also only two gates, a reset gate and update gate as shown in Fig. 3.

Reset Gate: The reset gate is another gate that is used to decide how much past information to forget.

Update Gate: The update gate acts similar to the forget and input gate of an LSTM. It decides what information to throw away and what new information to be added.

4 Simulation Results and Analysis

4.1 Data and Data Set Preparation Method

Data preparation is the process of collecting, combining, organizing, and structuring data, and then it can be considered as data visualization, analytics, and data mining with machine learning applications. It is critical to feed accurate data for the problem we want to solve.

Data set preparation is a crucial step in machine learning. As we mentioned before, the data preparation impacts the accuracy of the predictions. Therefore, in this section, we should explain the details of the data sets. We will expose the methods used to prepare the data in scope of our model. The dataset used for this research consists of daily price value collected from Kaggle website https://www.kaggle.com.

The overall data collection period is from January 1, 2014 to February 20, 2018. In this dataset, there are seven attributes such as opening price, high price, low price, and closing prices and also the market cap of publicly traded outstanding shares.

Table 1 Comparision of compilation time required by both the deep learning-based models

Model	Compilation time (ms)	Epoch
LSTM	53	100
GRU	5	100

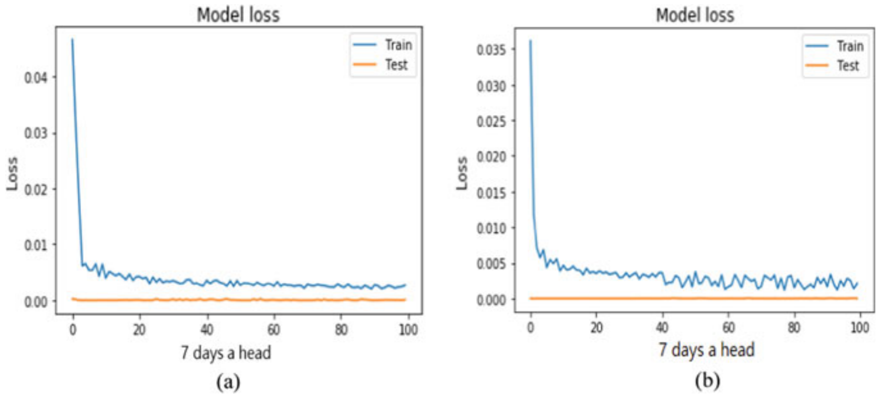


Fig. 4 **a** MSE graph obtained using LSTM model **b** MSE graph obtained using GRU model

4.2 Results and Discussion

The proposed model of LSTM and GRU price prediction of bitcoin was trained, and the predictions were carried out for popular cryptocurrency. The accuracy of the proposed LSTM as well as GRU model is investigated by finding the root mean square error (RMSE) and mean absolute percentage error (MAPE) to determine which model has better accuracy. We observed from the resultant Table 1 that LSTM takes greater compilation time than GRU model.

The MSE value obtained for 7 days ahead from both the models is plotted and shown in Fig. 4, and it is clearly observed that GRU is converging faster and steady than the LSTM model. From Fig. 5a, b, it is discovered that the variation of actual price and predicted price is more in LSTM than the GRU.

4.3 Performance Measures

One of the common ways to compare the time series models is to measure their performance for short- and long-term prediction. To validate the performance of these two models, we have used MAPE (Mean Absolute Percentage Error) and RMSE (Root Mean Square Error) as performance measure. These error values are obtained using LSTM and GRU and listed in Table 2.

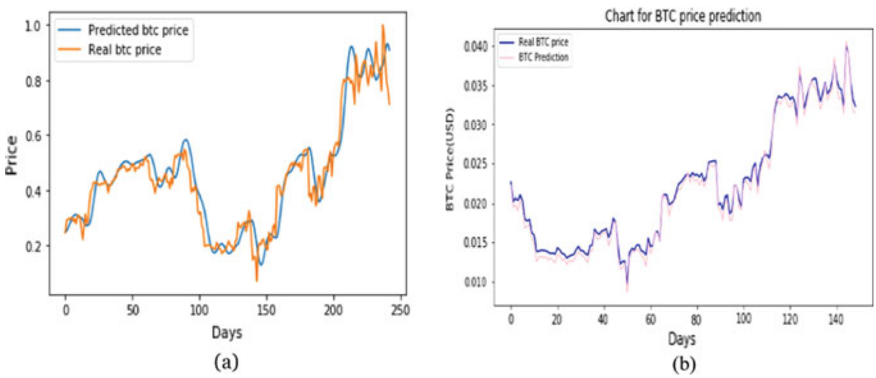


Fig. 5 Comparison of actual and predicted bitcoin price during training phase of LSTM (**a**) and GRU (**b**)

Table 2 Comparison of RMSE and MAPE value obtained using LSTM and GRU models

Window size	Number of days ahead	LSTM		GRU	
		RMSE	MAPE	RMSE	MAPE
1	1	0.092	0.068	0.075	0.065
5	3	0.079	0.057	0.065	0.046
7	5	0.081	0.060	0.087	0.062
12	7	0.045	0.030	0.051	0.035
15	15	0.067	0.048	0.067	0.058

From this study, we found that the GRU-based forecasting model is more appropriate in order to forecast time series data of highest price volatility. As we have observed, from Table 2 and Fig. 6 the prediction accuracy of the LSTM is better at window size of 12 and days ahead of 7. However, in the rest of window sizes and days ahead, GRU model is more efficient than that of LSTM models and the comparison actual and predicted bitcoin price obtained.

5 Conclusion and Future Work

Bitcoin is the most popular decentralized way of virtual currency which has a great role in the free market economy and avoids the intermediary of another third party between customers. The main objective of our study is to forecast the bitcoin price with improved efficiency using deep learning models and minimizing the risks for the investors as well as policy-makers. We have implemented two deep learning techniques such as LSTM and GRU as prediction models. The study reveals that the GRU model is the better mechanism for time series cryptocurrency price prediction

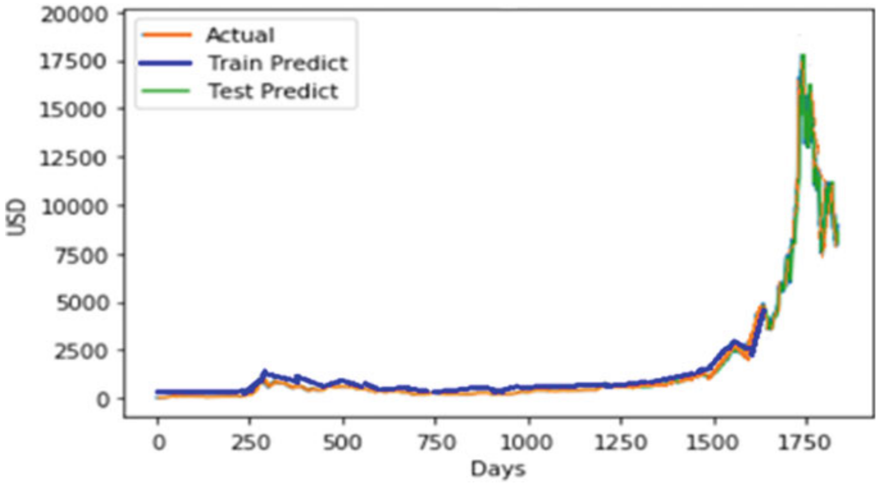


Fig. 6 Actual and predicted bitcoin price in terms of USD obtained using LSTM model

and takes lower compilation time. LSTM and GRU models are more capable of recognizing long-term dependencies. In this study, we have only compared to basic deep learning-based models, i.e., LSTM and GRU. However, it needs to investigate further to enhance the accuracy of the deep learning-based prediction models by considering different parameters in addition to the previous one. Features such as political system, public relations, and market policy of a country can affect and determine the price volatility of cryptocurrency. In our study, we have not considered other cryptocurrencies such as ripple, ethereum, lite coin, and others. We will enhance the model by applying on these cryptocurrencies so the model becomes a stable one. Fuzzification can also be incorporated at the input layer by considering the degree of participation of each of the features in the prediction.

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