Bitcoin Price Trend Prediction Using Deep Neural Network

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Abstract
Bitcoin is a kind of cryptocurrency that has become a popular stock market investment and it has been steadily rising in recent years, and occasionally falling without warning, on the stock market. Because of its fluctuations, an automated tool for predicting bitcoin on the stock market is required. However, because of its volatility, investors will need a prediction tool to help them make investment decisions in bitcoin or other cryptocurrencies. In this paper, Deep learning mechanisms like Recurrent Neural Network (RNN) and Long short-term memory (LSTM) are proposed to develop a model to forecast the bitcoin price trend in the market. Finally, the predictions result for the Bitcoin price trend are presented over the next 15, 30, and 60 days. Each model is evaluated in terms of Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) forecasting error values. The LSTM model is found to be the better mechanism for time-series cryptocurrency price prediction, but it takes longer to compile.

Keywords  Bitcoin, Blockchain, Cryptocurrency, Long Short Term Memory(LSTM), Machine Learning, Prediction, Recurrent Neural Network (RNN)

Introduction
With the introduction of Bitcoin ten years ago, the world of economics underwent and continues to undergo a revolution, albeit on a small scale.

Bitcoin is a cryptocurrency and a type of electronic money [1]. It is a digital currency that can be sent from user to user on the Bitcoin peer-to-peer network without the use of intermediaries. It keeps a record of peer-to-peer transactions, and each record is encrypted. Each new record contains the cryptographic hash of the previous block. Each record includes a timestamp as well as information about the sender, receiver, and amount of money transferred.

Bitcoin is the most popular cryptocurrency in the world [2]. It was first introduced in 2008 and exploited as open-source in 2009 by a person known as Satoshi Nakamoto, but it became extremely popular in 2017. Bitcoin operates as a decentralized electronic cash channel, with transactions...
proven and transcribed in a public distributed ledger (blockchain) without the intervention of a third party. Transaction blocks are made up of a secure shell algorithm that is used to connect them, and blocks are served as non-editable data that is recorded when the transaction is held. Then, any virtual currency, particularly bitcoin, was adopted by the public, and the virtual currency market trend grew.

Bitcoin was introduced as the system that solved the Double Spend problem [3], a common issue with inherent Digital Cash systems. Nonetheless, the impact in the following years was greater. Distributed Ledger Technologies (DLT), Smart Contracts, Cryptocurrencies, and other technologies all appeared from the "Bitcoin idea." This is due to the distinct decentralization combined with intuitive incentives.

Bitcoin's popularity has risen in a short period of time. Bitcoin is linked to a variety of technologies and businesses. According to various researchers, around 100,000 technology and business companies joined the bitcoin market after 2015 [4]. Amazon, Microsoft, Overstock, Dell, and other well-known companies have partnered with bitcoin [5].

The primary challenge of the bitcoin exchange rate is its high rate of price fluctuation. Because of the high price volatility, certain precautions must be taken in order to accurately predict the price of bitcoin. Knowing the forecasting activity is required to tell about the future price of bitcoin and to build trust and acceptance all over the world. A variety of factors, such as a country’s political system, public relations, and market policy, can influence the economic role of bitcoin and the international relations of countries on various market strategies.

Finally, there is no official road map: a few key challenges and developments for bitcoin prediction are consistent because there is no clear description of the exchange platform on which transactions related to buying and selling are not regulated. The goal of this paper is to forecast the bitcoin price more precisely using deep learning models while minimizing risks for investors and decision-makers.

**Related Work**

Many studies have been conducted in order to predict time series as well as Bitcoin (BTC) value. Deep learning models, on the other hand, have not been widely used to forecast the value of Bitcoin. Knowing that deep learning models have evolved into state-of-the-art neural network architecture that improves prediction accuracy in a variety of domains, including time series, we consider deep learning applications to predict the BTC price value. In the following sections, previous work on Bitcoin price prediction will be reviewed, and deep learning models for time series prediction will be discussed.
Madan et al. [6] attempted to predict the price of bitcoin using machine learning and to investigate the BTC surrounding trends. They forecasted the daily price variation using 25 bitcoin-related attributes.

According to Roth et al. [7], bitcoin is the new and most popular virtual currency, but its security and volatility rate are debatable. This research makes it possible to conduct peer-to-peer bitcoin transactions using the network and blockchain technology.

Goodfellow et al. [8] suggested a deep direct reinforcement learning paradigm for financial signal encoding and trading. They utilized reinforcement learning (RL), deep learning (DL), and their current deep neural network (NN) to obtain exact prediction results. They validate the suggested approach using data from commodity futures markets as well as the stock market.

According to Pant et al. [9], socially constructed ideas about virtual currency on Twitter have a direct or indirect impact on all market analyses of virtual currencies. The purpose of this research is to forecast the fluctuating value of bitcoin using sentiment analysis and to identify the relationship between positive and negative sentiments.

Dennys et al. [10] used various attribute selection mechanisms to obtain the most important features and machine learning methods such as artificial neural network (ANN), support vector machine (SVM), and recurrent neural network (RNN), and k-means clustering in bitcoin price prediction.

S. Lahmiri and S. Bekiros [11] predicted the direction of the Bitcoin price in USD using a Bayesian optimized recurrent neural network and LSTM. They also compared deep learning methods using the ARIMA model.

According to Atsalakis et al. [12], this study focuses on computational intelligence methods, specifically hybrid neuro-fuzzy controllers, to predict bitcoin exchange rates. The neuro-fuzzy approach and artificial neural networks were used in this model.

According to R. Nikita, S. J. Subhashini [13], The research is devoted to the problems related to predicting cryptocurrency prices using machine learning and data science. The main algorithms used are RNN and GRU. The main goal is to combine RNN and GRU Algorithms to form a hybrid and possibly increase the accuracy of the predictions.

**Background**

**3.1 RNN**
RNN is a deep neural network that can learn sequences designed to capture temporal contextual information along with time-series data. It is distinguished by a recurrent connection between the input and output of its neurons or layers. They have recently gained popularity in deep learning because of their ability to overcome the limitations of existing neural network architecture when learning over long sequences.

### 3.2 LSTM

LSTMs are explicitly designed to avoid the problem of long-term dependency. Remembering information for extended periods of time is practically their default behavior; it is not something they have to work hard to learn. All recurrent neural networks take the form of a chain of repeating neural network modules. This repeating module in standard RNNs will have a very simple structure, such as a single tanh layer.

Deep learning LSTM neural networks solve the problem of vanishing gradients in RNNs by replacing nodes in the RNN with memory cells and a gating mechanism. In this regard, it is an appealing deep learning neural architecture owing to its efficacy in simultaneously memorizing long- and short-term temporal information, which can be seen in the LSTM architecture depicted in Fig 1.

![LSTM Architecture](http://www.webology.org)

**Fig. 1. LSTM Architecture**

### 3.3 Accuracy Measures

MAPE is a measure of the prediction accuracy of a forecasting method in statistics. It usually expresses the accuracy as a ratio. RMSE is the square root of the average of squared differences between prediction and actual observation. A lower value for both measures implies better prediction accuracy.
Using $F_t$ as the forecast value, $A_t$ as the actual value, and $n$ the number of time steps. The MAE [14], MAPE, and RMSE [15] can be defined as follows:

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |A_t - F_t|$$  \hspace{1cm} (1)

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \frac{|A_t - F_t|}{A_t} \times 100\%$$  \hspace{1cm} (2)

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (A_t - F_t)^2}$$  \hspace{1cm} (3)

**Proposed Methodology**

The proposed methodology uses two different deep learning-based prediction models to forecast the daily price of bitcoin by identifying and evaluating relevant features. We can determine which model is much more accurate for the future fulfillment of our target after applying both models for bitcoin prediction and selecting appropriate parameters to obtain a better performance. In this paper, deep learning mechanisms are proposed like RNN and LSTM, which are the most recent and efficient techniques for forecasting bitcoin prices. Because bitcoin is the most popular cryptocurrency, the price volatility issue should be resolved quickly. The prediction process, from data collection to bitcoin price forecasting, is depicted in Fig. 2.
Fig. 2. Model Block Diagram

Data Preprocessing

5.1 Data Gathering
Data preparation is the process of gathering, combining, organizing, and structuring data, which can then be used for data visualization, analytics, and data mining. It is critical to provide accurate data for the problem we want to solve. Preparing data sets is an important step in machine learning. As previously stated, data preparation has an impact on prediction accuracy.

The dataset used for this research consists of daily price values collected from the “Kaggle” website https://www.kaggle.com. The overall data collection period is from 1 January 2012 to 31 March 2021. 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.

5.2 Data Cleansing
Data cleansing can be done by simply examining the associated Volume, Close, Unlock, higher prices, and market capitalization from exchange data. If the NaN values are found to be correct in any data set, they are replaced with a description of the appropriate attribute. Following that, all datasets are merged into one, based on the magnitude of the time.
When we examine the Bitcoin price fluctuation over the period from 2012 to 2017, we have seen it is better to remove data points prior to 2017, which is why the details that will be transferred to the neural network are dormant from 2012 to September 2017.

5.3 Data Normalization
Deciding how to get used to the timeline, particularly in finance, is not an easy task. Aside from that, the neural network must load data from a large number of different time series scales. This can result in significant gradient updates that prevent the network from changing. Data should have the following characteristics for easy reading on the network:

- Use small values- Most values should be in the 0-1 range.
- Be homogeneous, which means that all features should have values in the same range.

So we used Min-max normalization, which is one of the most common ways to normalize data. For every feature, the minimum value of that feature gets transformed into a 0, the maximum value gets transformed into a 1, and every other value gets transformed into a decimal between 0 and 1.

For example, if the minimum value of a feature was 20, and the maximum value was 40, then 30 would be transformed to about 0.5 since it is halfway between 20 and 40. The formula is as follows:

\[ X' = \frac{x - \min(x)}{\max(x) - \min(x)} \] (4)

5.4 Data Training and Splitting
The main goal is to test the ability of the algorithm to predict the next 15, 30 and 60 days and calculate the MAE error and RMSE for both RNN and LSTM algorithms. So I split the time series into training and validation sets with ratios of 80% and 20% respectively.

The experiment was repeated again several times but the dataset was truncated to consider historical data from only the last year, 2 years, 3 years, and 4 years to remove monotonic data from the initial bitcoin years then the same algorithm was used again to calculate the MAE and RMSE errors and compare between the 4-time series periods to determine the best period performance.

MACHINE LEARNING PIPELINE
This section explains how to adapt time series data for supervised machine learning problems. Price predictions are treated as regression rather than classification and then demonstrated how LSTM can be used in such cases.

6.1 Architecture of Network
The overall architecture is as follows:
1 Input Layer: The input layer is the inner one and it will be RNN or LSTM with 32 nodes and a sigmoid activation function.

- Dropout Layer: Typically, this is used before the Dense layer. As for Keras, a dropout can be added after any hidden layer, in our case, it is after the input layer.

- Dense Layer: This is the regular fully connected layer.

- Activation Layer: Because we are solving a regression problem, the last layer should give the linear combination of the activations of the previous layer with the weight vectors. Therefore, this activation is a linear one. Alternatively, it could be passed as a parameter to the previous Dense layer.

6.2 Software Used
Data preparation and handling were conducted in Python 3.8, relying on the packages NumPy and pandas. The deep learning LSTM networks are developed with Keras on top of Google TensorFlow. Moreover, the Sci-kit learn library (also known as sklearn) was used to make min-max standardization and classification metrics. Finally, matplotlib is used to display charts.

6.3 Time Series Data

<table>
<thead>
<tr>
<th>TABLE 1 DATA SET SAMPLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timestamp</td>
</tr>
<tr>
<td>------------</td>
</tr>
<tr>
<td>3528720</td>
</tr>
<tr>
<td>1303746</td>
</tr>
<tr>
<td>4321484</td>
</tr>
<tr>
<td>3432882</td>
</tr>
<tr>
<td>770464</td>
</tr>
</tbody>
</table>
RESULTS AND ANALYSIS
In this section, we show the results of the RNN and LSTM models. On the full dataset, Fig. 3 & Fig. 4 demonstrate how RNN and LSTM models perform when forecasting bitcoin prices by comparing the predicted BTC price with the real BTC price for the next 30 days.

Fig. 3. Bitcoin Price History

Fig. 4. Full Dataset - RNN Results for the next 30 days
It is clear that the LSTM algorithm performs better than the RNN algorithm but it consumes more time to compile.

A complete comparison is introduced in Table 2 which summarizes the predicted results of the three periods for both RNN and LSTM as well as the consumed time.

**TABLE 2 Comparison of RMSE and MAPE values obtained using RNN and LSTM models of Full Dataset**

<table>
<thead>
<tr>
<th>Prediction Period</th>
<th>MAPE</th>
<th>RMSE</th>
<th>Time (Min.)</th>
<th>MAPE</th>
<th>RMSE</th>
<th>Time (Min.)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Next 15 Days</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNN</td>
<td>7.93%</td>
<td>4,485.277</td>
<td>2.381</td>
<td>1.37%</td>
<td>775.082</td>
<td>8.394</td>
</tr>
<tr>
<td>LSTM</td>
<td></td>
<td>3,938.001</td>
<td>1.932</td>
<td></td>
<td>1,297.3</td>
<td>61</td>
</tr>
<tr>
<td><strong>Next 30 Days</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNN</td>
<td>7.10%</td>
<td>2,592.872</td>
<td>2.108</td>
<td>2.34%</td>
<td>1,611.9</td>
<td>64</td>
</tr>
<tr>
<td>LSTM</td>
<td></td>
<td>1,782.912</td>
<td>1.835</td>
<td></td>
<td>1,611.9</td>
<td>64</td>
</tr>
<tr>
<td><strong>Next 60 Days</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNN</td>
<td>7.10%</td>
<td>1,782.912</td>
<td>1.835</td>
<td>3.01%</td>
<td>1,611.9</td>
<td>64</td>
</tr>
<tr>
<td>LSTM</td>
<td></td>
<td>1,782.912</td>
<td>1.835</td>
<td></td>
<td>1,611.9</td>
<td>64</td>
</tr>
</tbody>
</table>

The experiment will be repeated again several times to improve the results by truncating the dataset to consider data from only the last year, 2 years, 3 years, or 4 years to decide which one will improve the result and be faster in prediction. Then we repeated the experiment three times to predict the next 15, 30, and 60 days for both RNN and LSTM algorithms.

Finally, to determine which model is more accurate, the root means square error (RMSE) and mean absolute percentage error (MAPE) are calculated for each of the proposed models. A complete comparison is introduced in Table 3, Table 4, and Table 5 which summarizes the predicted results of the three periods for both RNN and LSTM as well as the consumed time.
### TABLE 3b Comparison of RMSE and MAPE values obtained using RNN and LSTM models of Partial Dataset 24 Months

<table>
<thead>
<tr>
<th>Prediction Period</th>
<th>RNN - MAPE (%)</th>
<th>RNN - RMSE (Min)</th>
<th>LSTM - MAPE (%)</th>
<th>LSTM - RMSE (Min)</th>
<th>Time (Min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Next 15 Days</td>
<td>3.67%</td>
<td>2,079.60</td>
<td>1.33%</td>
<td>752.474</td>
<td>2.244</td>
</tr>
<tr>
<td>Next 30 Days</td>
<td>4.58%</td>
<td>2,539.11</td>
<td>1.31%</td>
<td>728.450</td>
<td>2.219</td>
</tr>
<tr>
<td>Next 60 Days</td>
<td>4.54%</td>
<td>2,414.43</td>
<td>1.87%</td>
<td>987.352</td>
<td>2.049</td>
</tr>
</tbody>
</table>

### TABLE 4 Comparison of RMSE and MAPE values obtained using RNN and LSTM models of Partial Dataset 36 Months

<table>
<thead>
<tr>
<th>Prediction Period</th>
<th>RNN - MAPE (%)</th>
<th>RNN - RMSE (Min)</th>
<th>LSTM - MAPE (%)</th>
<th>LSTM - RMSE (Min)</th>
<th>Time (Min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Next 15 Days</td>
<td>6.10%</td>
<td>5,452.039</td>
<td>0.72%</td>
<td>410.617</td>
<td>2.563</td>
</tr>
<tr>
<td>Next 30 Days</td>
<td>5.31%</td>
<td>2,949.343</td>
<td>0.10%</td>
<td>65.607</td>
<td>2.450</td>
</tr>
<tr>
<td>Next 60 Days</td>
<td>5.51%</td>
<td>2,929.175</td>
<td>1.55%</td>
<td>725.967</td>
<td>3.400</td>
</tr>
</tbody>
</table>

### TABLE 5 Comparison of RMSE and MAPE values obtained using RNN and LSTM models of Partial Dataset 48 Months
By studying those results, it is obvious that truncating the full dataset and removing monotonic data from the initial bitcoin years has improved the prediction results error and speed especially since the last 3 years’ partial dataset has achieved the best results.

The final sample of results using the last 3 years' partial dataset is shown in Fig. 6, and Fig. 7.
Fig. 7. Partial Dataset Last 36 Months - LSTM Results for the next 30 days

Each model predicts the bitcoin price in terms of its forecasting error value for both MAPE and RMSE. The best results are achieved by RNN and LSTM models when predicting the next 30 days which had RMSEs of 2949.343 and 65.607, respectively. According to the RMSE, the LSTM model improved RNN predictions by 97.7 percent.

To summarize, both the proposed models RNN and LSTM have succeeded in predicting the bitcoin price trend. However, the LSTM algorithm performs better than the RNN algorithm but it consumes more time to compile.

Conclusion and Future Work

Bitcoin is the most widely used decentralized virtual currency, which plays a significant role in the market economy and eliminates the need for a third party to act as an intermediary between customers. The main goal of our research is to improve the accuracy of bitcoin price forecasting using deep learning models while lowering risks for investors and policymakers. As prediction models, we used two deep learning techniques such as RNN and LSTM.

The LSTM model is found to be the better mechanism for time-series cryptocurrency price prediction, but it takes longer to compile. Basic deep learning-based models, such as RNN and LSTM are only compared in this study. However, more research is needed to improve the accuracy of deep learning-based prediction models by taking into account additional parameters. Other cryptocurrencies such as Ripple, Ethereum, Lite Coin, and others were not considered in our research. We'll improve the model by applying it to these cryptocurrencies, making it more stable.

References