

# Bit coin-Price-Prediction-Using-RNN-LSTM

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## Abstract

The world has more than 5000 digital-currencies, bitcoin is one of it, which has more than 5.8 million dynamic client and approximately more than 111 exchanges throughout the world. So, the aim for this paper is to do the near prediction of the price of Bitcoin in USD. Precious details are taken from the price index of Bitcoin. A Bayesian recurrent hierarchical (RNN) neural network and a long-term memory (LSTM) network can accomplish this function. The total identification accuracy of 52% and an 8% RMSE is obtained by the LSTM. In contrast to the profound training systems, the common ARIMA method for the prediction of time series. This model have not much efficient as deep learning model can be performed. The deep learning methods were predicted to outperform the poorly performing ARIMA prediction. So here we used Gated Recurrent Network model (GRU) to forecasting Bitcoin price eventually, all deep learning models have a GPU and

CPU that beat the GPU implemented by 94.70 percent for their GPU training time.

## INTRODUCTION

### 1.1 Aim of study

The machine learning technique we have proposed for prediction of bitcoin price is recurrent neural networks and LSTM (Long Short-Term Memory) to predict the price of bitcoin. The main goal of the system is to analyze and study the hidden patterns and relationships between the data present in bitcoin dataset.

### 1.2 Objective

The objective of Bitcoin Prediction is to ascertain with what accuracy can the price of Bitcoin be predicted using different machine learning algorithm and compare their accuracy. LSTM can process not only single data points, but also entire sequences of data.

### 1.3 Scope

They predicted that Bitcoin could fall to \$5,000 levels in 2023. Experts

believe that the rising interest rates and tighter monetary policy will not allow Bitcoin to rebound sharply in the near future. As in this kind of uncertain market, investors will not prefer to invest or buy risky assets such as Bitcoin.

#### 1.4 Introduction

Recurrent neural networks (RNN) are the state-of-the-art algorithm for sequential data and are used by Apple's Siri and Google's voice search. It is an algorithm that remembers its input due to its internal memory, which makes the algorithm perfectly suited for solving machine learning problems involving sequential data. It is one of the algorithms that have great results in deep learning. In this article, it is discussed how to predict the price of Bitcoin by analyzing the information of the last 6 years. We implemented a simple model that helps us better understand how time series works using Python and RNNs.

Digital currencies have become the favourable and most used for commercial money transactions all over the world. The rising usage is because of its innovative characteristics such as transparency thus increasing acceptance throughout the

world. El Salvador became the first country to do this. Furthermore, Bitcoin is the leading cryptocurrency in the world with adoption growing consistently over time. First introduced in 2008, and deployed as open source in 2009 by Satoshi Nakamoto [1] whose identity is still unknown.

Currently, the virtual currency market value is close to 1.4 trillion INR, but it varies from time to time. Digital currency especially bitcoin has been adopted by the people, and since then the digital currency market has been growing up. Bitcoin is a peer-to-peer cryptocurrency in which all transactions are not regulated or controlled by any third party. It has highly volatile market price working 24/7[2]. It operates on a decentralised, peer-to-peer and trustless system in which all transactions are posted to an open ledger called the Blockchain.

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 done [3]. This type of transparency is not seen in other financial markets. The popularity of bitcoin has increased within a short period of time. Different technologies and

businesses are joined with bitcoin. Some of the companies which are joined with bitcoin are Microsoft, Dell, PayPal, Wikipedia and others. Prediction of time series is not a new thing.

Prediction of most financial markets such as the stock market has been researched at a very large scale. Bitcoin presents an interesting parallel to this as it is a time series prediction problem in a market that is still in its early stage. As a consequence, there is high volatility in the market and this provides an opportunity in terms of prediction. Many works have been done to predict time series, as well as bitcoin price. However, any deep learning models have not been much used yet to predict the bitcoin price.

The main challenge of bitcoin is its high rate of price fluctuation. Given the complexity of the task, deep learning makes for an interesting technological solution based on its performance in similar areas [4]. The objective of our study is to predict the future price of bitcoin efficiently using machine learning (Recurrent neural networks and long short-term memory) which will eventually minimize the risk for investors.

Bitcoin drives the digital currency market with 58% piece of exchanges; comparing to \$4.9 Billion USD exchange volume and more than 5.8 million dynamic clients. In October 2008, Bitcoin was first presented by Satoshi Nakamoto through his white paper entitled "Bitcoin: peer-to-peer Electronic Cash System" [1]. Bitcoin is the first decentralized cryptographic money while other advanced monetary forms (otherwise known as Altcoin or option virtual monetary forms) are made by cloning or modifying the instrument of Bitcoin [2].

## LITERATURE SURVEY

1. S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system," 2008.

A purely peer-to-peer version of electronic cash would allow online payments to be sent directly from one party to another without going through a financial institution. Digital signatures provide part of the solution, but the main benefits are lost if a trusted third party is still required to prevent double-spending. We propose a solution to the double-spending problem using a peer-to-peer network. The network timestamps transactions by hashing them into an

ongoing chain of hash-based proof-of-work, forming a record that cannot be changed without redoing the proof-of-work. The longest chain not only serves as proof of the sequence of events witnessed, but proof that it came from the largest pool of CPU power.

**2. G. Heleman, M. Rauchs, "Global crypto-currency benchmarking case study," SCambridge Centre for Alternative Finance (2017).**

The first global cryptocurrency benchmarking study presents a systematic and comprehensive picture of a rapidly evolving industry, illustrating how cryptocurrencies are being used, stored, transacted and mined. The study gathered non-public data from more than 100 cryptocurrency companies and over 30 individual cryptocurrency miners in 38 countries around the world via secure web-based questionnaires, capturing an estimated 75 per cent of the cryptocurrency industry. The study breaks down the cryptocurrency industry into four key sectors – exchanges, wallets, payments and mining. Key findings and highlights from the study include our estimate that

over three million unique individuals are actively using cryptocurrency today, data on regulation and compliance practices and costs at firms, and a global map of cryptocurrency mining.

**3. G. Neil, H. Halaburda. " Can we predict the winner in a market with network effects?? Competition in crypto-currency market," Games, vol.7 no.3 , 2016, p.p: 16.**

We analyze how network effects affect competition in the nascent cryptocurrency market. We do so by examining early dynamics of exchange rates among different cryptocurrencies. While Bitcoin essentially dominates this market, our data suggest no evidence of a winner-take-all effect early in the market. Indeed, for a relatively long period, a few other cryptocurrencies competing with Bitcoin (the early industry leader) appreciated much more quickly than Bitcoin. The data in this period are consistent with the use of cryptocurrencies as financial assets (popularized by Bitcoin), and not consistent with winner-take-all dynamics.

4. **M. Bri  re, K. Oosterlinck, and A. Szafarz, “Virtual currency, tangible return: Portfolio diversification with bitcoins,” Tangible Return: Portfolio Diversification with Bitcoins (September 12, 2013), 2013.**

Bitcoin is a major virtual currency. Using weekly data over the 2010-2013 period, we analyze a Bitcoin investment from the standpoint of a U.S. investor with a diversified portfolio including both traditional assets (worldwide stocks, bonds, hard currencies) and alternative investments (commodities, hedge funds, real estate). Over the period under consideration, Bitcoin investment had highly distinctive features, including exceptionally high average return and volatility.

5. **I. Kaastra and M. Boyd, “Designing a neural network for forecasting financial and economic time series,” Neurocomputing, vol. 10, no. 3, pp. 215–236, 1996.**

Artificial neural networks are universal and highly flexible function approximators first used in the fields of cognitive science and engineering. In recent years, neural

network applications in finance for such tasks as pattern recognition, classification, and time series forecasting have dramatically increased. However, the large number of parameters that must be selected to develop a neural network forecasting model have meant that the design process still involves much trial and error. The objective of this paper is to provide a practical introductory guide in the design of a neural network for forecasting economic time series data.

### EXISTING WORK

This researched work[8] based on blockchain toward characterized cryptocurrency for high accuracy in blockchain, in blockchain which connected to other block it is decentralize network this paper defined that it gather data and analyze user network end monitoring activity of user that has changed over time to time which relate to economic so recognize the features that estimate the requirement of cryptocurrency so for this purpose used machine learning predict attributes on user activiry like number of wallet, unspent transaction, output block size, income transaction per day and wallet and unique address estimate how many user join network each day.

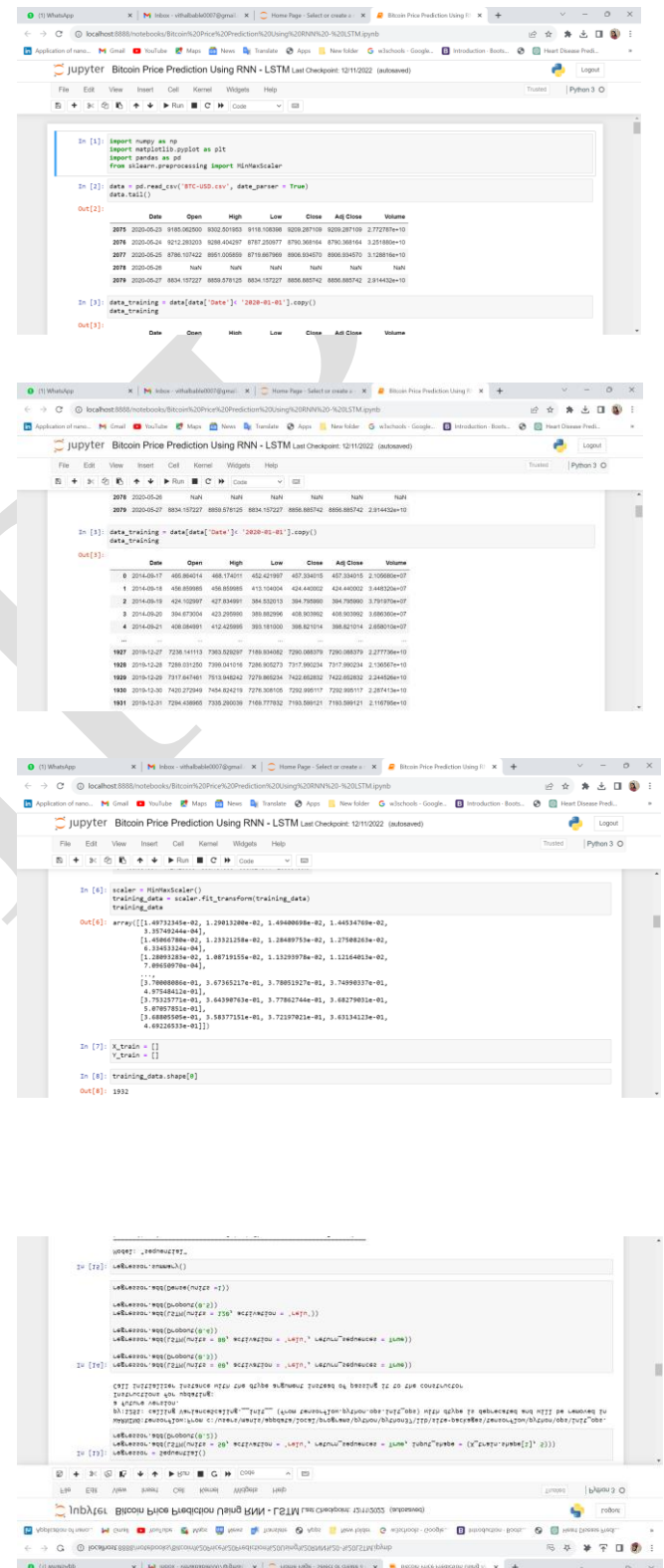
## PROPOSED METHOD

## RESULT

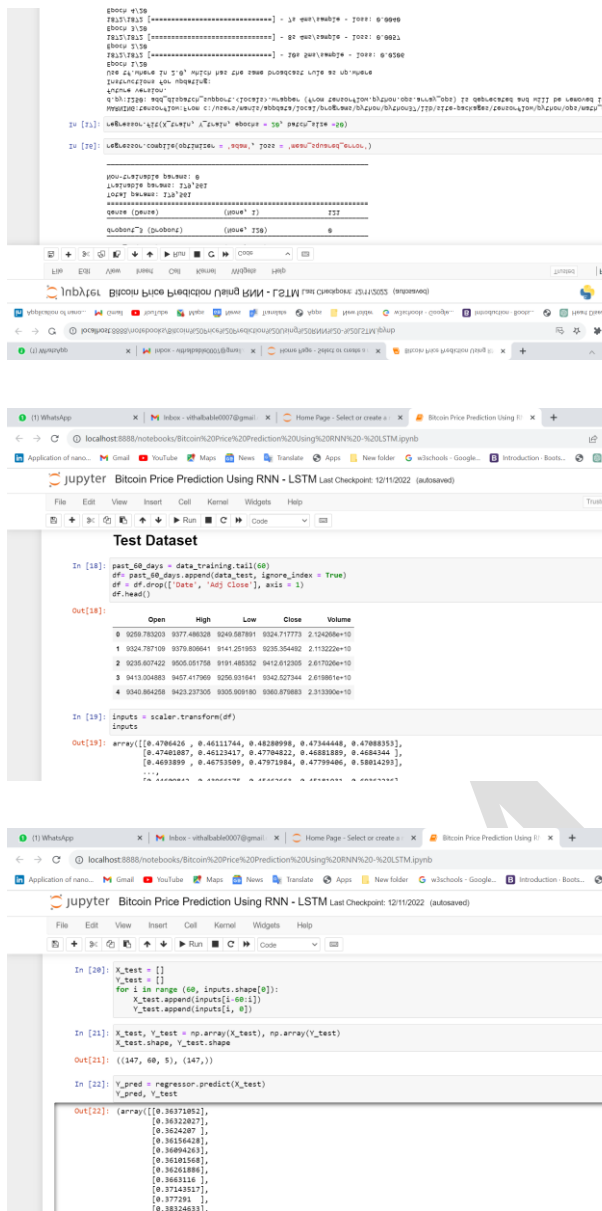
### 4.1 Methodology

This paper reflects the CRISP technique of data mining. The CRISP-DM motivation for the traditional KDD[26] focuses on the company-level of the forecasting task. The data set is used by Bitcoin covers the period 19 August 2013 to 19 July 2016. Figure 1 displays a time series graph of this. Data is omitted from prior to August 2013 as they no longer represent the network correctly. Dataset is used in bitcoin Ethereum Historical Data and Bitcoin Historical Data.

CSV files for bitcoin exchanges from Jan 2014 to July 2019, with by-the-minute updates of OHLC (Open, High, Low, Close), Volume in BTC and currency, as well as weighted bitcoin price. The information was also normalized in order for it to have a mean of 0 and default of 1.







```

In [18]:
past_60_days = data_training.tail(60)
df = df.drop(['date', 'Adj Close', 'axis = 1])
df.head()

Out[18]:
Open      High      Low      Close      Volume
0  9268.763203  9377.486328  9249.587891  9324.717773  2.154208e+10
1  9324.767109  9379.806641  9141.251953  9235.354492  2.113222e+10
2  9235.807422  9305.051758  9191.488392  9412.812305  2.617320e+10
3  9413.024883  9437.417969  9296.931841  9342.527344  2.619801e+10
4  9340.884298  9423.237305  9305.608180  9365.879883  2.313390e+10

In [19]:
inputs = scaler.transform(df)

Out[19]:
array([[0.4786426, 0.4611744, 0.48288998, 0.47864448, 0.47888353],
       [0.4786426, 0.4611744, 0.47794822, 0.46885889, 0.4686244 ],
       [0.4693889, 0.46735589, 0.47971584, 0.47789486, 0.58814293],
       ...,
       [0.36371852, 0.3632821, 0.3624287, 0.36156428, 0.36094263],
       [0.36181568, 0.36261886, 0.3663116, 0.3745357, 0.377391 ],
       [0.38324633, ...]])

In [20]:
X_test = []
for i in range(60, inputs.shape[0]):
    X_test.append(inputs[i-60:i])

In [21]:
X_test, Y_test = np.array(X_test), np.array(Y_test)
X_test.shape, Y_test.shape

Out[21]:
((147, 60, 5), (147,))

In [22]:
Y_pred = regressor.predict(X_test)
Y_pred, Y_test

Out[22]:
(array([[0.36371852, 0.3632821, 0.3624287, 0.36156428, 0.36094263, 0.36181568, 0.36261886, 0.3663116, 0.3745357, 0.377391 ],
       [0.38324633, ...]])

```

## CONCLUSION

Our aim of study is to develop model which predict bitcoin price using deep learning. Since deep learning is used to select the parameter to get successive outcomes in developing model. In this latter we implemented for three proposed model RNN, LSTM and GRU we found

that total parameter and dataset can influence result. The Previous model developed using RNN and LSTM which had less predicted accuracy that is 52% approximately. Whereas in our comparative analysis GRU model result better as comparatively LSTM model. The Optimal model for GRU result accuracy is 94.70%. The proposed model shows about 42.3% of accuracy improvement. The tests of all our GRUs show the highest detailed outcomes which take time. Furthermore, Selected features: Low, High, Close and Open can't be enough to predict the Bitcoin value, as various factors, including social media responses, legislation and laws each country advertises for handling the digital currency won help to increase and lower the Bitcoin price. Therefore, modified information should always be gathered and applied for the best results of all models.

## REFERENCES

1. S. Nakamoto, "Bitcoin: A peer \_to\_peer electronic cash system," 2008.
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  4. M. Brie`re, K. Oosterlinck, and A. Szafarz, "Virtual currency, tangible return: Portfolio diversification with bitcoins," Tangible Return: Portfolio Diversification with Bitcoins (September 12, 2013), 2013.
  5. H. Kaastra and M. Boyd, "Designing a neural network for forecasting financial and economic time series," Neurocomputing, vol. 10, no. 3, pp. 215–236, 1996.
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  7. C. Chatfield and M. Yar, "Holt-winters forecasting: some practical issues," The Statistician, pp. 129–140, 1988.