# BIT COIN PREDICTION USING RECURRENT NEURAL NETWORK

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***Abstract:*** Over the last few years the interest in machine learning and AI-assisted trade have been increasing. We use this approach here to test the hypothesis that to produce abnormal income, the inefficiency of the crypto-currency market can be exploited. We review daily data for the period between Nov. 2015 and Apr. 2018 for 1, 681 crypto currencies. We prove that basic market methods, enabled by sophisticated machine learning algorithms, surpass traditional requirements. The findings suggest that algorithmic processes that are not trivial but essentially easy will help predict the growth of the crypto currency industry in the foreseeable future. In 2017, the interest of crypto currencies increased because of the mega- exponential rise in market capitalization for several consecutive months. There are currently more than 1,500 publicly trading crypto currencies capitalizing over $300 billion, with a market capitalization record in January 2018 totaling more than $800 billion. According to a recent study, between 2.9 million and 5.8 million private and institutional investors are working in the various transaction networks. In a variety of online markets, big crypto currencies can be acquired using fiat currency and then used to buy less common crypto currencies in turn. The regular trading amount is reportedly in excess of $15 billion. More than 170 hedge funds investing in crypto currencies have appeared since 2017 and bitcoin futures were released to meet investor appetite for Bitcoin trading and hedging.

***Index Terms* –** Crypto Currency, Bitcoin , Machine Learning.

## I. OBJECTIVE AND SCOPE OF THE PROJECT

To predict the price of bitcoin using machine learning.In this project we will predict the daily price change with highest possible accuracy.

In this proposed project we designed a protocol or a model to detect the bitcoin activities. This system is capable of providing most of the essential features required to predict the level of bitcoin in feature. With the growth in computer learning, artificial intelligence and other related areas in information technology , it is possible to simplify this process and save some of the intensive quantities of bitcoin.

## II. EXISTING SYSTEM

In existing system we analyzed stock markets prediction, suggests that these methods could be effective also in predicting crypto currencies prices. After all, the application of machine learning algorithms to the crypto currency market has so far been limited to the study of Bitcoin values, using random forests, the Bayesian neural network, the long-term neural memory network and other algorithms. These experiments have been able to forecast, to differing degrees, the price fluctuations in Bitcoin and have shown that the best outcomes have been obtained by neural network-based algorithms. Deep reinforcement learning has been shown to overcome the uniform purchasing and hold technique by projecting the values of 12 crypto currencies over a one-year span.

## DISTADVANTAGE

Other efforts to use machine learning to forecast crypto currency values other than Bitcoin come from non-academic sources. The bulk of those analyses centered on a small number of currencies and did not include the effects of benchmarking.

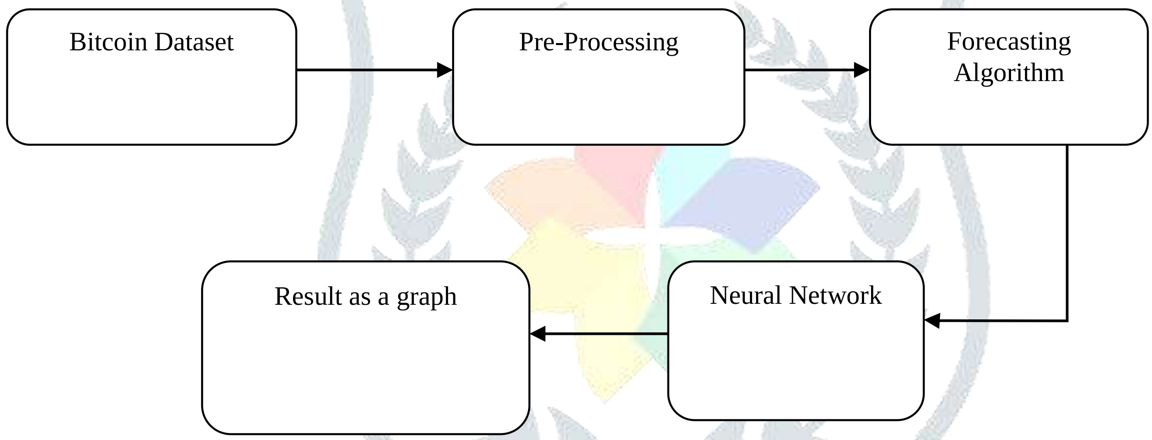
## III. PROPOSED SYSTEM

Here, we measure the efficiency of three models in forecasting the regular crypto currency price of 1,681 currencies. Two models are based on gradient-boosting decision trees and one is based on long-term memory (LSTM) recurring neural networks. In all cases, we construct investment portfolios based on forecasts and measure their success in terms of return on investment. We notice that all three methods do better than the basic 'easy moving average' model, where the price of a currency is expected to be the average price over the intervening days, and that the long-term memory-based approach is recurrent neural networks systematically yields the best return on investment

## ADVANTAGE

1. The results obtained are discussed and compared with the three forecasting algorithms and the baseline process.
2. Currency prices are predicted on a regular basis for all currencies used between January 1 , 2016 and April 24, 2018..
3. The analysis considers all currencies whose age is larger than 50 days since their first appearance and whose volume is larger than $100000.
4. To discount the impact of the overall market trend (i.e. business increase, for much of the time considered), we consider the crypto currency values represented in Bitcoin.

## III. SYSTEM ARCHITECTURE




## IV. PURPOSE OF THE PROJECT

The aim of this analysis is to figure out with what accuracy the trajectory of the Bitcoin price can be forecast using machine learning methods. This is essentially time series prediction challenge. While much literature occurs on the use of various machine learning approaches for time series prediction, there is a lack of research in this field directly applicable to Bitcoin. This forecast provides tremendous promise and motivates study in this area. An review of the current literature reveals that running machine learning algorithms on a GPU can deliver substantial improvements in performance. The training bench of the RNN and LSTM network is investigated using GPU and CPU, which addresses the corresponding testing query. Any variable significance is evaluated using an algorithm of the random forestry in order to examine the selected dependent variables.

## V. MODULES

1. Dataset Collection
2. Data Processing
3. Predicting Polarity using RNN
4. Deep Learning

**Dataset Collection:**

We first started with Bit coin market data that was publicly available on Kaggle2. The dataset consists of Bit coin historical data from December 1st, 2014 to January 8th, 2018 divided into one-minute increments.It consists of 1,574,274 minutes in this time span. Data on the opening value, the closing value, the highest value, the lowest value, the amount exchanged and the weighted price is included with each timestamp. In an effort to iterate quickly and build an initial model, we opted to first analyse the polarity trends in the market. The dataset was labelled as true if the price went up at the end of the minute timestamp and false if it stayed the same or decreased.

**Data Processing:**

Scraping the data produces a 2D tensor of n properties of m samples. To translate this into a collection of window data with window size w=50, we used a time-series transformation to produce a 3D tensor of shape (m-w) samples by n characteristics by window size w day. For eg, for each of the 0-49 days, our first data point m=0 had a 2D tensor of m characteristics. We normalised the info, then. Finally, by deleting the last day and making it the source data, we divided this into the input and output data. For a visualisation of this, see below.

**Predicting Polarity using RNN:**

The obvious end-goal of building a neural network based on cryptocurrencies is to predict price volatility in real time. We were eager to start with a highly temporally resolved dataset with this goal in mind. We could do an even better job of forecasting inflation and keeping ahead of the competition if we could get details on a minute-by - minute or second-by-second time scale. In comparison, millions of data points will be available and it will be the size of a dataset it neural networks excel at. However, we noticed, as we referred to above, that there are still problems with highly resolved results.

It was very small and loud. The above graph reveals that inside the third bin, which reflected price increases below 0.003 percent, almost all the 1.5 million minutes dropped. As a result, because it would mainly suit noisy data and any noticeable change would be blurred out, our model would not be able to interpret the price adjustment. To remember, at this early point in the project, we had not yet binned our "y-values" but chose to turn the minute dataset into a regular dataset based on our instincts. The graph above is made to display the distribution after the truth.

**Deep Learning:**

3 layer bidirectional RNN to predict the closing price of Bit coin given a variety of data from previous days. Code for scraping crypto currency data is included, as well as the LSTM model.

**Result:**

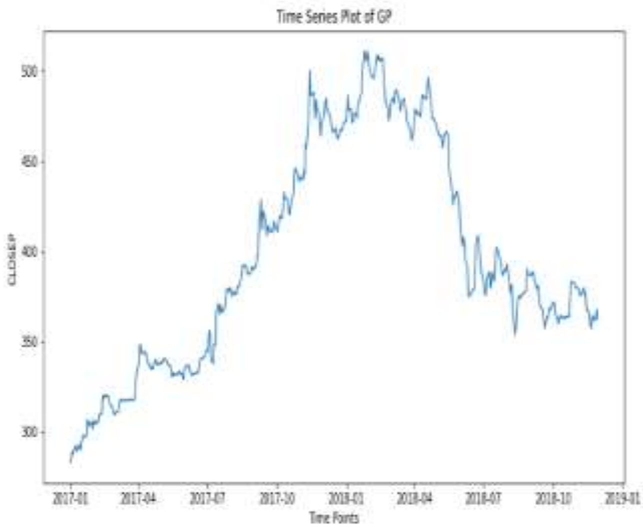



Fig 1. Time series analysis between closing price and dates

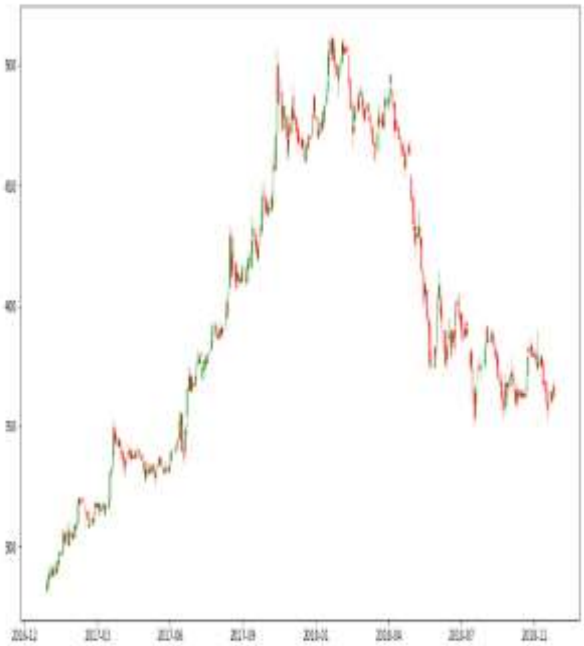


Fig 2. Candlestick analysis between closing price vs opening price vs high vs low and dates

## CONCLUSION AND FUTURE WORK

Deep learning models such as the RNN and LSTM, with the LSTM more capable of understanding longer-term dependencies, are clearly successful learners on training results. A high variance function of this type, though, makes it impossible to transpose this into amazing validation outcomes. As a consequence, it remains a hard job. The distinction between overfitting a model and keeping it from knowing enough is a fine line. After setting up the learning system and completing the normalisation, we plan to use the above two methods and use the best way to solve the problem of Bitcoin prediction. In terms of the dataset, the complexity and hash rate variables may be considered for pruning based on an interpretation of the model's weights. Deep learning models require a large amount of data from which to learn efficiently. The dataset used included 1066 steps in time reflecting each day. If the granularity of data is changed to per minute, 512,640 data points would be given in a year. Data of this type is not valid for the past but for potential use is currently being obtained from CoinDesk on a regular basis.

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