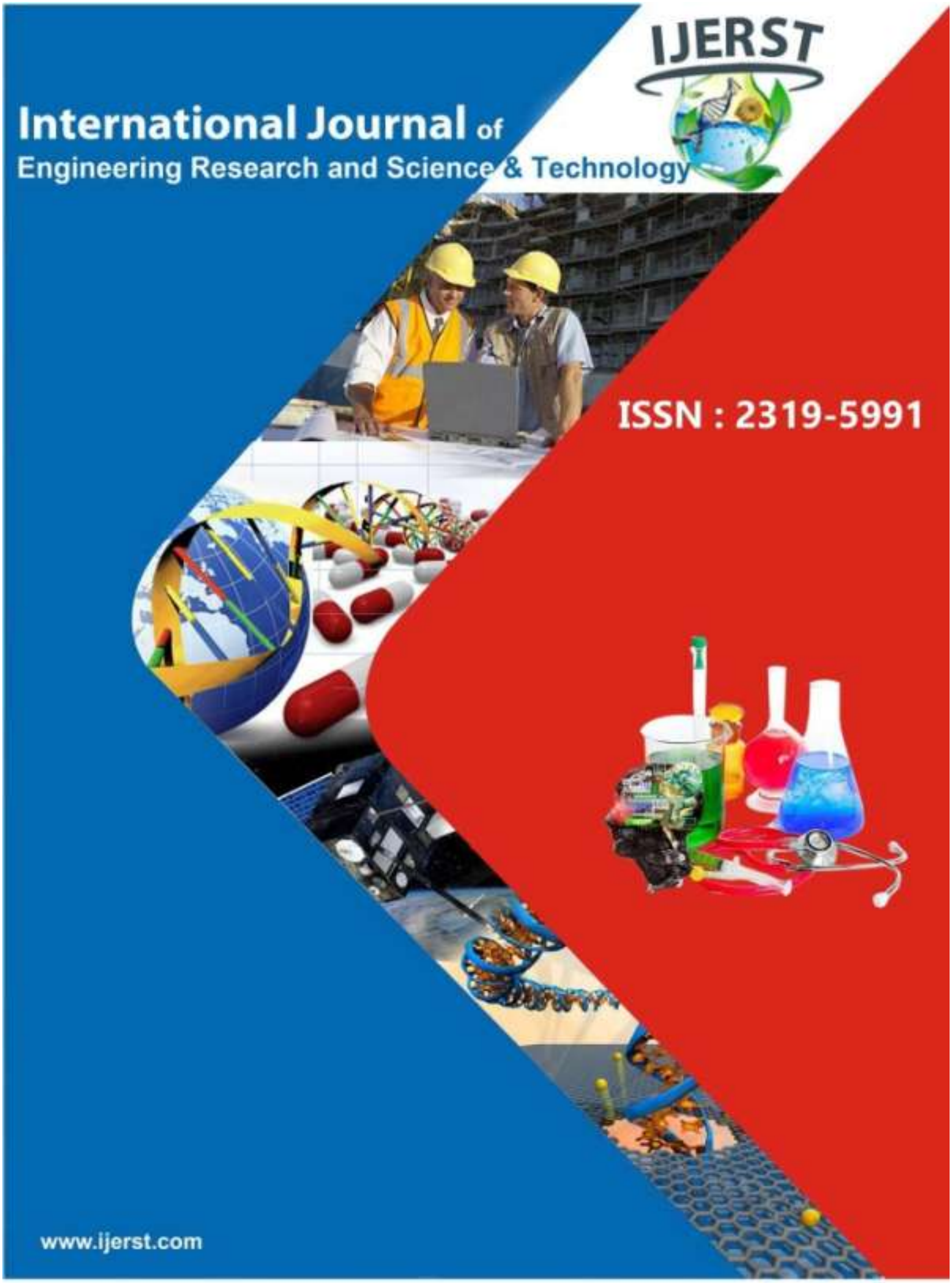

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Bit Coin Price Prediction Using Deep Learning and Supervised Learning Methodologies

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Abstract

Recent years have seen a rise in interest in the use of machine learning and artificial intelligence to aid in trading. Specifically, we put this method to use here by examining whether or not the inefficiency of the

The cryptocurrency market may be gamed to produce irrational gains. Between November 2015 and April 2018, we examine daily data for 1,681 different cryptocurrencies. We demonstrate that, when combined with modern machine learning algorithms, even the simplest trading strategies may significantly surpass industry norms. Our findings demonstrate the viability of using non-trivial, but ultimately straightforward, algorithmic processes for forecasting the near-term trajectory of the cryptocurrency market.

Introduction

Cryptocurrencies' meteoric rise to fame in 2017 may be traced to their market capitalization increasing at an exponential rate for several months in a row. There are now over 1,500 crypto currencies that are regularly traded, with a total market valuation of over $300 billion. This is down from a high of over $800 billion in January of 2018. Among the range of Recent research indicates that millions of individual and institutional investors participate in various transaction networks, including The market has grown more accessible. Numerous online exchanges accept fiat cash for the purchase of major cryptocurrencies, which may subsequently be used to purchase secondary, less liquid cryptocurrencies. At now, daily trading volume is in excess of $15 billion. To meet the needs of institutional investors interested in trading and hedging Bitcoin, the futures market for this cryptocurrency was introduced in December of 2017, and since then, more than 170 cryptocurrency-focused hedge funds have arisen.

Current Structure

Predicting the price of cryptocurrencies may be possible using approaches similar to those used to examine financial markets. The study of Bitcoin values is the only area where machine learning algorithms have been applied to the cryptocurrency market so far. Other areas of application include random forests, Bayesian neural networks, and long short-term memory neural networks. It was shown that neural network based algorithms performed the best in predicting Bitcoin price changes. Uniform purchase and wear was shown to be inferior to deep reinforcement learning.

the use of a hold approach to forecast the values of 12 different cryptocurrencies over the course of a year.

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Disadvantage

First, efforts to apply machine learning to forecast the value of Bitcoin and other cryptocurrencies have come mostly from sources outside of academia.

The majority of these studies looked at only a few different currencies and did not provide any kind of comparative data.

Conceptualized Scheme

We put three algorithms to the test to see how well they can forecast the price of 1,681 different cryptocurrencies every day.

One model uses long short-term memory (LSTM) recurrent neural networks, while the other two are based on gradient boosting decision trees.

In each scenario, we construct investment portfolios using the forecasts and evaluate their returns.

All three methods improve upon the performance of the basic moving average model for predicting the value of a currency.

arithmetic mean of prices over the prior days, and that the approach based on lengthy short-term memory recurrent neural networks consistently produces the highest return on investment

Advantage

First, we show the outcomes from running the three forecasting algorithms alongside the baseline technique.

We provide daily predictions for the value of all currencies between January 1, 2016, and April 24, 2018.

Third, the study includes all currencies with a volume more than $100,000 and an age of more than 50 days from their initial appearance.

We reduce the Bitcoin price of cryptocurrencies to account for the impact of the general market movement (i.e., market expansion, over most of the investigated time).

System Architecture

 Python

"Anaconda Navigator"

Hardware:

It works on Windows 7, 8, and 10 (64 bit)

 RAM 3GB

Pi 3 B+ Raspberry

Pi Raspberry

The Raspberry Pi foundation in the United Kingdom designed the inexpensive Raspberry Pi single-board computer to expand access to computer science education in underprivileged communities.

The original design has seen explosive growth in demand for applications like as robotics, much beyond its initial scope.

Processor

The brains of the Raspberry Pi are Broadcom BCM28XX processors.

The Broadcom System-on-Chip (SOC) is the chip used in the Raspberry Pi. From the first to the third generation of processors, we find:

The first Raspberry Pi used a 700MHz Single-Chip Microcontroller (SOC) from Broadcom called the BCM2835.

a 32-bit RISC processor with 128kb of cache that is compatible with the ARM architecture (specifically the ARM1176JZF-S).

Raspberry Pi 2 has a Broadcom BCM 2836 system-on-a-chip (SoC) with a 900MHz CPU speed, 256kb of L2 cache, and a 32-bit quad-core ARM cortex-A7 CPU (ARMv7).

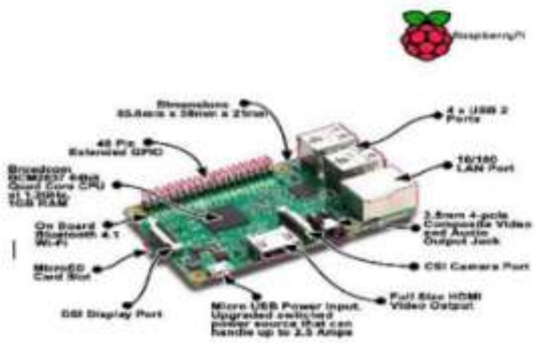
With the Raspberry Pi 3, you get a system-on-a-chip (SoC) powered by a Broadcom BCM2837 that has a 1.2GHz 64-bit quad-core - A53 with 512 kb shared L2 cache (64-bit instruction set ARMv8).

Computer System Board, Raspberry Pi 3

The latest Raspberry Pi, the Pi 3, is being used in this endeavour.

The Broadcom BCM2837 is the brains of the Raspberry Pi 3, as it was of the subsequent Raspberry Pi 2 variants. The BCM2837 is functionally equivalent to the BCM2836 in terms of its underlying architecture. Changes include upgrading from a quad-core ARMv7 cluster to a quad-core ARM Cortex A53 (ARMv8) cluster, which is the only major change.

With 1.2GHz ARM processors and 1GB of RAM on board, this gadget is almost twice as fast as the Raspberry Pi 2. The speed of the videocoreIV is 400MHz.



GPIO: Raspberry Pi 3:-

PURPOSE OF THE PROJECT

The goal of this analysis is to see how well machine learning techniques can forecast the future course of the bitcoin price. The underlying issue here is one of time series prediction. Though there is a plenty of data on the benefits of

There is a dearth of work in this field concerning bitcoin and the many machine learning algorithms for time series prediction.

Furthermore, bitcoin is a currency in a transitional phase, therefore its value is far more volatile than that of established currencies like the US dollar.

Among major currencies, it has shown the best performance over the last five years.

As a result, there is a lot riding on its forecast, which is encouraging study in the field.

An examination of the current literature reveals that executing machine learning algorithms on a graphics processing unit (GPU) rather than a central processing unit (CPU) may provide substantial performance gains.

To investigate this, we compare the results of training an RNN and an LSTM network on a graphics processing unit and a central processing unit.

It answers the secondary question of the study.

Finally, a random forest technique is used to rank the relevance of each of the dependent variables.

MODULES

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

Dataset Collection:

To begin, we used Kaggle2's freely accessible data on the Bitcoin market. The dataset contains one-minute intervals of historical data for Bitcoin from December 1, 2014, to January 8, 2018. There are a total of 1,574,274 minutes in this window of time. The data includes the starting price, closing price, highest price, lowest price, volume traded, and weighted price for each time stamp. As a first step toward rapid iteration and prototype creation, we decided to study market polarity tendencies. If the price increased by the end of the minute timestamp, it was marked as true in the dataset, otherwise it was marked as false.

Information Retrieval:

In the end, the data scraping process produces a 2D tensor of m samples by n features. We applied a time-series transform to this information, resulting in a collection of windows data with window size w=50 days, and therefore a three-dimensional tensor of shape (m - w) samples by n features by w day window size. To cite just one illustration:

Our initial data point, m=0, consisted of a 2D tensor of m characteristics for each of the first 49 days. The data was then standardised. After deleting the last day and designating it as output data, we have completed the process of decoupling the input and output data. Please see the image below for clarification.

Making RNN Polarity Predictions:

The eventual purpose of using a neural network to analyse cryptocurrency prices is, of course, to anticipate future price changes. Since this was our starting point, we were keen to begin with a dataset that was very well resolved in time. We could perform much better at price forecasting and keeping ahead of the market if we had access to information on a minute-by-minute or second-by-second basis. In addition, there would be millions of data points, the ideal size for training neural networks. However, we discovered that there are also problems with highly resolved data, as we referred to above. Our intuition told us there wouldn't be any change on a minute timeline, or if there was, it would be extremely minor and noisy based on our dataset's minute resolution. Nearly majority of the 1.5 million minutes (indicated by the "third bin" in the above graph) correspond to price fluctuations of less than 0.003%. Since our model would be largely fitting to noisy data, any important change in the price would be lost in the noise and the model would not be able to learn it.

out. It is important to remember that we opted to transform the minute dataset into the daily dataset based on pure intuition rather than having actually binned our "y-values" at this stage in the project. This distribution graph was created after the fact.

Learning at a Deep Level:

Predicting the Bitcoin price at market close using historical data and a 3-layer bidirectional RNN. The LSTM model and the code for scraping cryptocurrency data are provided.

SUMMARY AND FUTURE STUDIES

Both the RNN and the LSTM are excellent learners on training data, with the latter being better able to spot long-term dependencies. However, it is challenging to translate this into remarkable validation findings since this is a high variance job. So the challenge persists. Overfitting a model and preventing it from learning enough are two extremes that must be carefully balanced. We plan to employ the aforementioned two approaches to tackle the Bitcoin prediction issue when we have established the learning framework and finished normalisation. Specifically, a study of the dataset's weights reveals that

the model, the factors of difficulty and hash rate might be taken into account for thinning. For optimal learning, deep learning models need a large quantity of data. In the dataset that was used, there were 1066 discrete time points for each day. This would result in 512,640 data points each year if the data granularity was increased to one minute. This kind of information is unavailable for the past, but it is being collected on a daily basis from CoinDesk in preparation for the future.

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