

# BITCOIN PRICE PREDICTION USING MACHINE LEARNING

<sup>1</sup>G.Naga Jyothi, <sup>2</sup>Dr.M.Jahir Pasha

<sup>1</sup>M.Tech Student, <sup>2</sup>Professor & HOD  
Department of CSE,  
Ashoka women's Engineering College

**Abstract:** Crypto currencies, such as Bit coin, are one of the most controversial and complex technological innovations in today's financial system. This study aims to forecast the movements of Bit coin prices at a high degree of accuracy. In order to test these algorithms, besides existing continuous dataset, discrete dataset was also created and used. For the evaluations of algorithm performances, the F statistic, accuracy statistic, the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and the Root Absolute Error (RAE) metrics were used. The test was used to compare the performances of the SVM, ANN, NB and RF with the performance of the LR. Empirical findings reveal that, while the RF has the highest forecasting performance in the continuous dataset, the NB has the lowest. On the other hand, while the ANN has the highest and the NB the lowest performance in the discrete dataset. Furthermore, the discrete dataset improves the overall forecasting performance in all algorithms (models) estimated.

## INTRODUCTION:

Some statistical tests can be carried out on the close price of financial instruments (to ascertain key metrics which can further be used to better understand market behavior); one of which is the Augmented Dickey-Fuller test. This test is used to check if a particular asset or instrument will revert to its rolling mean after a market swing (in upwards or downwards direction).

The Bitcoin stock-to-flow model makes it possible to trade it against a base currency on the foreign exchange market. This means that as with the Volatility 10 index above, bitcoin can be represented (on the charts) by its open, high, low and close prices and consequently traded with leverage at varying trade volumes.

## IMPLEMENTATION:

LSTM (Long Short-Term Memory) is a deep learning model that helps with prediction of sequential data. LSTM models prevail significantly where there is a need to make predictions on a sequence of data. The daily OHLC (Open, High, Low and Close) price of any financial asset constitutes a good example of a sequential data.

LSTM's are an extension of the classic recurrent networks, which address the (the gradient tends to zero as the error propagates through many layers recursively). The long-short term memory cell uses an input, a forget and an output gate. Those gates help the network learn what to save, what to forget, what to remember, what to pay attention and what to output. Pretty neat right? Remember that a gate is nothing more than a simple multilayer perceptron, but a smart combination of them can provide amazing results. Each LSTM cell has its cell state (c) and has the ability to add or remove information to it. The forget gate decides what to remove from the cell state(f), while the input gate (i) decides which values it will update.

## Output Screens

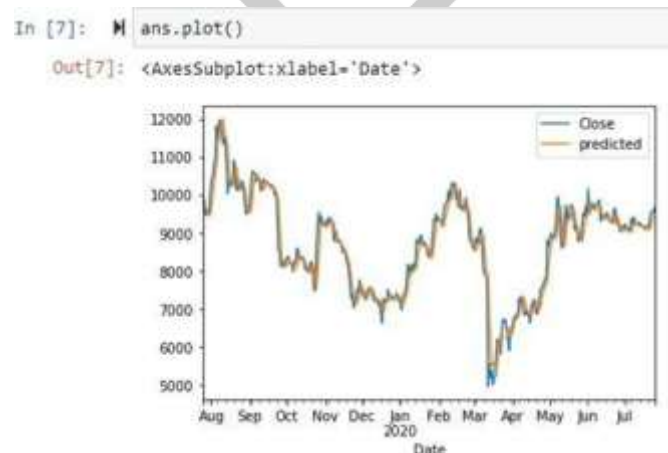


Fig.1: Graph of 2020

```
Epoch 11/50  
5/5 [=====] - 0s 15ms/step - loss: 0.0007  
Epoch 12/50  
5/5 [=====] - 0s 15ms/step - loss: 0.0014  
Epoch 13/50  
5/5 [=====] - 0s 17ms/step - loss: 0.0048  
Epoch 14/50  
5/5 [=====] - 0s 17ms/step - loss: 0.0052  
Epoch 15/50  
5/5 [=====] - 0s 17ms/step - loss: 0.0019  
Epoch 16/50  
5/5 [=====] - 0s 17ms/step - loss: 0.0014  
Epoch 17/50  
5/5 [=====] - 0s 18ms/step - loss: 0.0046  
Epoch 18/50  
5/5 [=====] - 0s 18ms/step - loss: 0.0042  
Epoch 19/50  
5/5 [=====] - 0s 18ms/step - loss: 0.0041  
Epoch 20/50  
5/5 [=====] - 0s 18ms/step - loss: 0.0029  
Epoch 42/50  
5/5 [=====] - 0s 15ms/step - loss: 0.0028  
Epoch 43/50  
5/5 [=====] - 0s 15ms/step - loss: 0.0028  
Epoch 44/50  
5/5 [=====] - 0s 15ms/step - loss: 0.0028  
Epoch 45/50  
5/5 [=====] - 0s 19ms/step - loss: 0.0028  
Epoch 46/50  
5/5 [=====] - 0s 16ms/step - loss: 0.0028  
Epoch 47/50  
5/5 [=====] - 0s 15ms/step - loss: 0.0028  
Epoch 48/50  
5/5 [=====] - 0s 16ms/step - loss: 0.0028  
Epoch 49/50  
5/5 [=====] - 0s 18ms/step - loss: 0.0028  
Epoch 50/50  
5/5 [=====] - 0s 17ms/step - loss: 0.0027  
Train Score: 388.47 ROISE
```

Fig.2: Epoch Graph

	time	high	low	open	volume from	volume to	close	conversionType	conversionSymbol	time/UTC
0	1629880400	50377.42	48814.06	50093.55	5500.25	2.730188e+08	49205.58	direct		2021-05-13 14:30:00
1	1629900000	50245.19	48943.19	49205.00	4835.77	2.327157e+08	49205.50	direct		2021-05-13 15:30:00
2	1629920000	49915.17	48484.16	49206.50	4595.54	2.260429e+08	48779.02	direct		2021-05-13 16:30:00
3	1629940000	50371.18	49557.96	48779.02	3301.84	1.893618e+08	50108.17	direct		2021-05-13 17:30:00
4	1629960000	50613.68	49665.36	50108.17	3823.06	1.918258e+08	50661.28	direct		2021-05-13 18:30:00
...	...	...	...	...	...	...	...	...	...	...
3900	1624490400	33342.94	32973.28	33202.12	2328.42	7.858876e+07	32930.05	direct		2021-06-24 08:30:00
3901	1624500000	32871.88	32344.07	32839.05	2490.58	8.133467e+07	32514.41	direct		2021-06-24 09:30:00
3902	1624503600	32681.84	32405.75	32514.41	1967.78	5.450832e+07	32612.85	direct		2021-06-24 09:30:00
3903	1624507200	32773.58	32348.83	32612.85	1879.51	5.515483e+07	32554.08	direct		2021-06-24 09:30:00
3904	1624510800	32908.61	32501.16	32554.09	1905.79	3.991388e+07	32882.05	direct		2021-06-24 10:30:00

Fig.3: Daily Price Rate

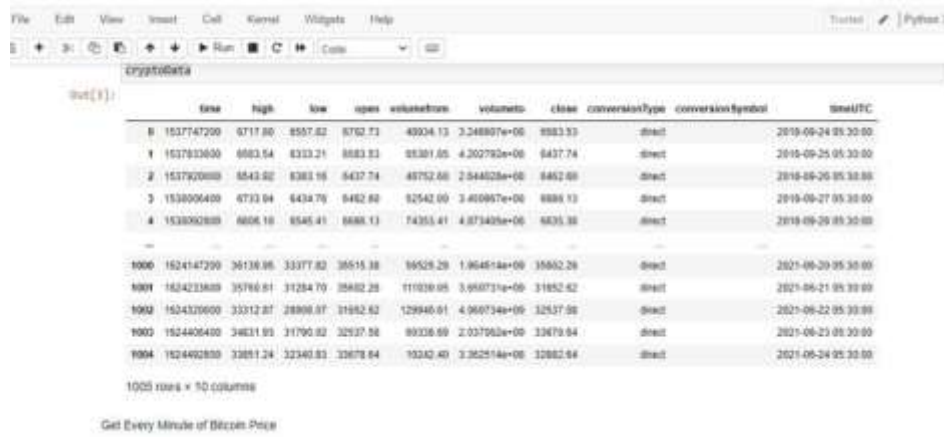


Fig.4: Minute Price Rate

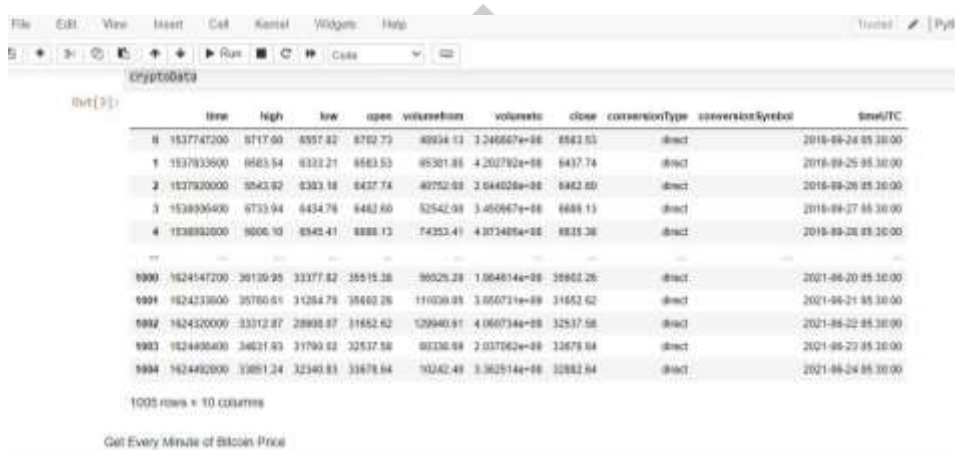


Fig.5: Minute Price Rate

**TESTING STRATEGIES:**

A Strategy for software testing integrates software test cases into a series of well-planned steps that result in the successful construction of software. Software testing is a broader topic for what is referred to as Verification and Validation. Verification refers to the set of activities that ensure that the software correctly implements a specific function. Validation refers the set of activities that ensure that the software that has been built is traceable to customer’s requirements

**Unit Testing**

Unit testing focuses verification effort on the smallest unit of software design that is the module. Using procedural design description as a guide, important control paths are tested to uncover errors within the boundaries of the module. The unit test is normally white box testing oriented and the step can be conducted in parallel for multiple modules.

**Integration Testing**

Integration testing is a systematic technique for constructing the program structure, while conducting test to uncover errors associated with the interface. The objective is to take unit tested methods and build a program structure that has been dictated by design.

**Top-down Integration**

Top down integrations is an incremental approach for construction of program structure. Modules are integrated by moving downward through the control hierarchy, beginning with the main control program. Modules subordinate to the main program are incorporated in the structure either in the breath-first or depth-first manner.

**Bottom-up Integration**

This method as the name suggests, begins construction and testing with atomic modules i.e., modules at the lowest level. Because the modules are integrated in the bottom up manner the processing required for the modules subordinate to a given level is always available and the need for stubs is eliminated.

**Validation Testing**

At the end of integration testing software is completely assembled as a package. Validation testing is the next stage, which can be defined as successful when the software functions in the manner reasonably expected by the customer. Reasonable expectations are those defined in the software requirements specifications. Information contained in those sections form a basis for validation testing approach.

**System Testing**

System testing is actually a series of different tests whose primary purpose is to fully exercise the computer-based system. Although each test has a different purpose, all work to verify that all system elements have been properly integrated to perform allocated functions.

**Security Testing**

Attempts to verify the protection mechanisms built into the system.

**Performance Testing**

This method is designed to test runtime performance of software within the context of an integrated system.

**CONCLUSION:**

In this project we conclude that survey report will be just introducing modules of Bitcoin price prediction and machine algorithms. Hear the Comparison table of ML algorithm model accuracy which tells that the linear regression model will have most accuracy then the other algorithms. In this project we conclude that the linear regression algorithm is more efficient than the other algorithms. By taking help from that linear regression algorithm, we can implement the LASSO also. The time complexity reduction in bit coin price prediction using LASSO algorithm is tested by referring all other algorithms and came to a conclusion that LASSO is the best among all. The machine learning algorithms will improve that feature idea of crypto currencies. That will improve the market price of globule investments. In this paper we proposed the new algorithm to find the feature price accuracy. That helps the customer increments and profits.

**FUTURE ENHANCEMENT:**

- With the help of real time data it can further be predicted for upcoming years.
- It can be predicted accurately with help of API key this project can be improvised to predict next years price.

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