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# Forecast Bitcoin Price Prediction Using Time Series Analysis through Machine Learning

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**Abstract:**
Following the rise and fall of cryptocurrency fees in recent years, Bitcoin has increasingly become a source of finance. There might be a need for great projections on which to base financing decisions due to its incredibly unstable nature. While the current study used system mastery to anticipate Bitcoin charges with more accuracy, few studies have examined the practicality of applying alternative modelling approaches to samples with different fact systems and dimensional capacities. We first divide the Bitcoin charge into daily and high-frequency components in order to predict it at various frequencies by employing system mastering techniques. Logistic Regression and Linear Discriminant Analysis are two statistical techniques for Bitcoin. Daily charge prediction with high-dimensional capabilities performs better than more difficult system mastering techniques with a 66 percent accuracy rate. With the best statistical techniques and system mastery algorithms with accuracy rates of 66 percent and 65.3 percent, respectively, we outperform benchmark effects for daily charge prediction. Statistics are updated from ML, models including "Random Forest, XG Boost, Quadratic Discriminant Analysis, Support Vector Machine, and Long Short-term Memory for Bitcoin 5-minute C language charge prediction, and they achieve an accuracy of 67.2 percent". When examining the significance of pattern measurement in system mastering tactics, our research on the prediction of Bitcoin charges may be taken into account.

**Keywords:** Recurrent Neural Network (RNN), Bitcoin, Long Short-Term Memory (LSTM), Blockchain, Machine Learning, Crypto Currency.

## I. INTRODUCTION:

### Bitcoin

Cryptocurrencies like Bitcoin are used all around the world for transactions and investments. Since Bitcoin is decentralized, nobody owns it. Since no specific country is now associated with bitcoin transactions, they are secure.

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Through a variety of marketplaces referred to as "bitcoin exchanges," investments can be made. These enable the sale and purchase of bitcoin using precious metals. Mt Gox has the biggest Bitcoin exchange. A digital wallet, which resembles a virtual economic group account in many ways, is where bitcoins are kept. A site called Blockchain is where the timestamp data and database of all transactions are kept. A block is a single file in a blockchain.

**Prediction**

The price of a Bitcoin varies similarly to an inventory, albeit in a different way. For charge prediction, certain algorithms are applied to inventory market statistics. But Bitcoin is affected by different factors. Therefore, it's critical to anticipate the price of Bitcoin in order to make precise financial decisions [5]. The price of Bitcoin is no longer dependent on business operations or interfering governments, unlike the stock market. As a result, in order to anticipate the price, we believe it's critical to make use of modern technology for knowledge generation.

The organization of this article is in following manner i.e., Section-II describes the research background, where we reviewed and analyzed about all the literatures, Section-III denotes about the existing regime, Proposed methodology explained in Section-IV, results and discussions are demonstrated in Section-V and finally conclusions are noted in Section-VI.

## II. Research Background:

**Observation 1:**

The research paper entitled "Predicting the price of the Bitcoin Using Machine Learning", by the author's Simon CatonJason Roche, Sean McNally, stated that Distributed, Network - processing based. The goal of this article is to anticipate how accurately the path of the Bitcoin fee in USD will take. The Bitcoin Price Index is the source of the fee data. Using a Bayesian optimal recurrent neural network and a Long Short-Term Memory network, the project is being carried out with varying degrees of success. The LSTM delivers the maximum level of type correctness, with an RMSE of 8% and a type accuracy of 52%. Deep mastery trends are evaluated using the well-known ARIMA version for time collection forecasting. The ARIMA forecast performs worse than expected and is outperformed by non-linear deep learning algorithms. Finally, the efficiency of each deep learning model is evaluated on both a GPU and a CPU. The GPU version performed 67.7% better than the CPU version.

**Observation 2:**

The research paper entitled "A New Forecasting Framework for Bitcoin price with LSTM" Wu Chih – Hung, Ma Yu – Feng, Lu Chih –Long short-term memory networks, according to Chiang, are a brand-new series learning in deep learning for time collection forecasting [2]. But there hasn't been as much study on financial time series forecasting, especially in terms of predicting bitcoin prices. In order to estimate the daily price of bitcoin, we therefore offer a new forecasting framework that uses two LSTM models: the regular LSTM version and the LSTM with ARIMA version. The effectiveness of the suggested models is assessed using daily bitcoin transaction data from 208 records from 2018/1/1 and 2018/7/28. The

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outcomes demonstrated the proposed version's astoundingly accurate predictions thanks to ARIMA [1].For the forecast of bitcoin charges, the analysis of the proposed squared error (MSE), the suggested absolute percent error (MAPE), and the suggested absolute error (MAE) is shown.The LSTM with AR[2] variant we suggested performed better than the original LSTM. This paper makes a contribution by offering a novel forecasting framework for predicting bitcoin prices that can improve and overcome the difficulty of entry variable selection in LSTM without making stringent statistical assumptions [2]. The outcomes demonstrated that it could be used to make accurate predictions about a range of cryptocurrencies, as well as commercial scenarios, scientific statistics, and financial time-collection statistics.

**Observation 3:**

The research paper entitled “A Study of Opinion Mining and Data Mining Techniquesto Analyze the Cryptocurrency Market”- Akhilesh P. Patil, T.S. Akarsh, According to A. Parkavi stated that many cryptocurrencies' prices, including those of Bitcoin, Litecoin, and Ethereum, are frequently illusory. Therefore, if a version can forecast what the bitcoin market will look like tomorrow, it would be a greatfee addition for buyers.In order to forecast the future price of cryptocurrencies, this article creates a time-collection model utilizing Long Short-Term Memory Networks. Three digital currencies—Bitcoin, Litecoin, and Ethereum—were considered for the study. The results of employing opinion mining to assess the market conditions for various currencies have been looked at.In the version that is utilized for predictions, sentiment ratings from the natural language processing of text data are used. Plotly, a Python utility for creating graphed plots, is used to create the time-collection charts [3]. Uncertainty is measured using a technique called the Mean Absolute Error, which is derived between the actual and projected values. These methods for quantifying uncertainty are compared to opinion mining, which is used to evaluate the situation of the market at the moment.

## III. Existing Regime:

According to an analysis of stock market forecasting under the current system, these techniques might work well to forecast the prices of crypto currencies. Long short-term memory neural networks, Bayesian neural networks, and random forests are just a few of the machine learning methods that have lately begun to be utilized to analyses Bitcoin prices. These experiments showed that for varying degrees of price prediction, neural network-based algorithms produced the best results. In predicting the prices of 12 crypto currencies over a year, deep reinforcement learning surpassed the traditional buy and hold strategy. The majority of these research concentrated on a restricted set of currencies and did not support their findings with benchmark comparisons.

## IV. Methodology being proposed:

We evaluate the precision with which three algorithms forecast the daily crypto FX rate for 1,681 various currencies. One of the models is based mostly on long short-term memory (LSTM) recurrent neural networks, while the other two are based primarily on gradient boosting decision bushes.The typical "easy transferring common" model, which presumes that a

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currency's rate will be the average rate over the prior days, is outperformed by each of the three models. We also discover that the approach based only on long short-term memory recurrent neural networks consistently yields the highest ROI. We share and examine the conclusions drawn by the three forecasting algorithms, additional data, and the baseline approach.

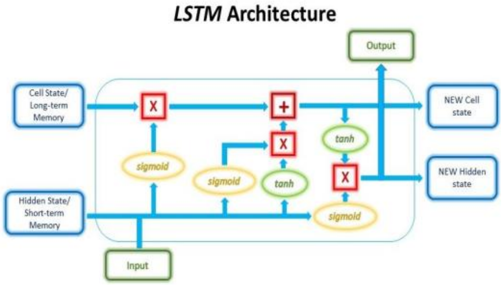


**Figure 4.1. LSTM Architecture**

## Dataset collection

Bitcoin DatasetA dataset, like a relational database desk, is a collection of records. Records are similar to table rows, but the columns can now include nested statistical systems such as lists, maps, and other records in addition to just texts or numbers. The term "Dataset" refers to a set or series of statistics. Typically, this set is presented in a tabular format. A particular variable is described in each column. Additionally, each row is associated with a certain statistician from the statistics collection, according to the stated question. The handling of statistics includes this. Data units are used to describe values for each variable for unknowable components of an item, such as height, weight, temperature, volume, and so on, or random number values.

| | timestamp | open | high | low | close | volume |
|---|---|---|---|---|---|---|
| **0** | 6/4/2021 19:20 | 147.680 | 147.680 | 147.6800 | 147.680 | 100 |
| **1** | 6/4/2021 18:45 | 147.270 | 147.270 | 147.2500 | 147.250 | 637 |
| **2** | 6/4/2021 18:40 | 147.300 | 147.300 | 147.3000 | 147.300 | 100 |
| **3** | 6/4/2021 18:20 | 147.360 | 147.360 | 147.3600 | 147.360 | 200 |
| **4** | 6/4/2021 18:15 | 147.400 | 147.400 | 147.4000 | 147.400 | 100 |
| **...** | ... | ... | ... | ... | ... | ... |
| **95** | 6/3/2021 16:05 | 145.550 | 145.550 | 144.9686 | 145.550 | 660063 |
| **96** | 6/3/2021 16:00 | 145.590 | 145.690 | 145.5400 | 145.550 | 231997 |
| **97** | 6/3/2021 15:55 | 145.490 | 145.630 | 145.4600 | 145.580 | 122646 |
| **98** | 6/3/2021 15:50 | 145.665 | 145.665 | 145.4600 | 145.500 | 95908 |
| **99** | 6/3/2021 15:45 | 145.740 | 145.800 | 145.6500 | 145.665 | 61512 |

100 rows × 6 columns

**Figure 4.2.Bitcoin Dataset**

## Pre-Processing

Data pre-processing is the process of preparing the raw statistics and altering them for a machine learning model. The first and most important step in creating a machine learning model is this one. When developing a project for a device study, we don't always come across the clear-cut and prepared statistics. Additionally, any process involving statistics must be facilitated and installed in a proper manner. Therefore, we use the statistics pre-processing task for this.

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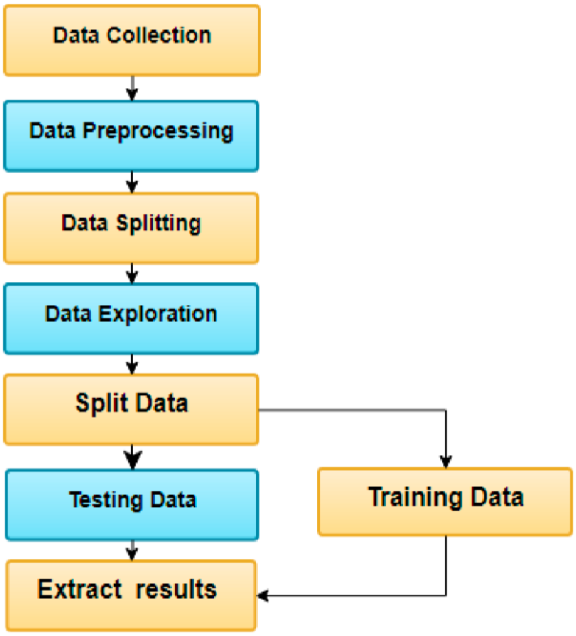


**Figure 4.3.Pre-Processing**

## Long short-term memory (LSTM) RNN

The artificial Recurrent Neural Network (RNN) shape known as long short-term memory is employed in the deep learning field. With the assistance of Sepp Hochreiter and Jurgen Schmid Huber, it was modified and proposed in 1997. The LSTM has feedback connections, in contrast to common feed-in advance neural networks. It can now be more enjoyable to view entire records sequences rather than just single records points (which include images) (which incorporates speech or video). For instance, LSTM is a piece of software that carries out tasks and recognizes handwriting or voice in conjunction with unsegmented handwriting. A desired LSTM unit consists of a molecule, an input gate, an output gate, and a neglect gate. The molecule retains values across arbitrary time intervals and has three gates that can change the flow of statistics into and out of it.For categorizing, predicting, and managing time series with unclear duration, the LSTM is a viable alternative. We have opted to forgo what functions in favor of the Sequential Kera's API. The production's overall setup is voiced:

**LSTM Layer:** According to Kera's (2015), all of the gates that had previously been recorded using auto-sigmoid automation had already been used in the LSTM Layer, which is internal. The number of neurons and entrance mode make up the LSTM parameters, as was previously mentioned.

**Dropout Layout:** Since we are resolving a problem involving retreat, the final layer must provide an aggregate of the road performance for the previous layer and weight vectors. The previous dense layer can be changed as a parameter in either case.

**Dense Layer:**This layer is very common and completely incorporate.

**Background Layout:**Since we are attempting to solve a retreat problem, the final layer must provide an aggregate of the weight vectors and previous layer's road performance.The previous dense layer can be changed as a parameter in either case.

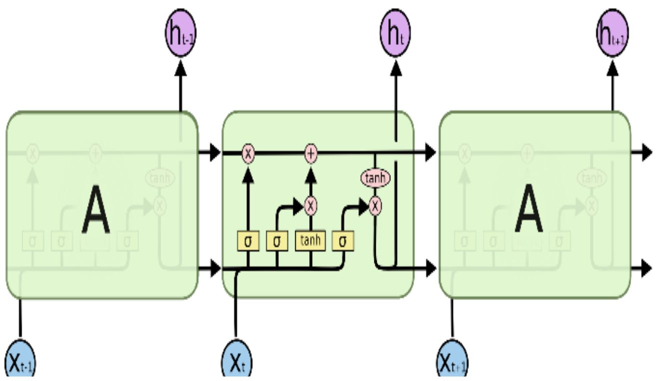


**Figure 4.4. LSTM layers/layouts**

**Input gate: -**To modify the memory, the input gate chooses. Which input value to utilize. The sigmoid functionselects 0 or 1

**JOURNAL OF ALGEBRAIC STATISTICS**
Volume 13, No. 3, 2022, p.2113-2123
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as the value to pass through. The tanh function, which rates the relevance of the provided values on a scale from -1 to 1, adds weight to the passed values as well.

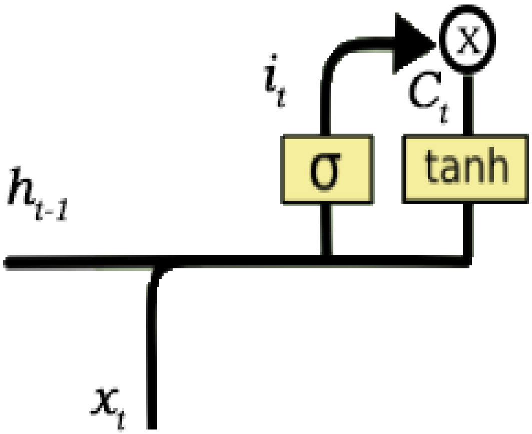


**Figure 4.5.Input Gate**

**Forget gate:** -The forget gate is taught the information that hasto be removed from the block. The sigmoidfunction is used to make the decision. By looking at the previous state (ht-1) and the content input, it outputs a number between 0 (omit this) and 1 (keep this) for each number in the cell state Ct-1 (XT).

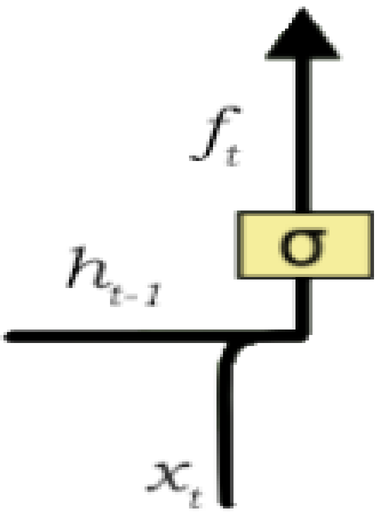


**Figure 4.6.Forget Gate**

**Output gate:** -The output is determined by the block's input and memory. The sigmoid function selects 0 or 1 as the value to pass through. Furthermore, the tanh function decides which values, such as 0, 1, are to be passed through. Along with sorting the values provided from -1 to 1, the tanh function assesses their importance and multiplies them with a sigmoid output.

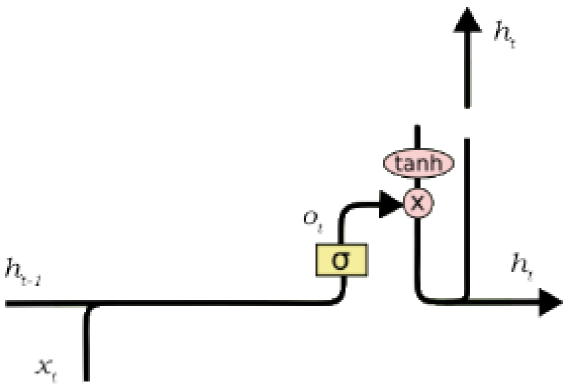


**Figure 4.7.Output Gate**

**Mean Square Error**

Equation1:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t' - y_t)^2$$

Where $y_t'$ is the predicted value,

$y_t$ is the actual value, and

n is the total number of values in test set.

**Root Mean Square Error**

Equation2:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t' - y_t)^2}$$

Where, $y_t'$ is predicted value

$y_t$ is actual value, and

n is total number of values in test set.

**Mean Absolute Error**

**JOURNAL OF ALGEBRAIC STATISTICS**
Volume 13, No. 3, 2022, p.2113-2123
https://publishoa.com
ISSN: 1309-3452

Equation 3:

$$MAE = \frac{1}{n}\sum_{t=1}^{t=n}|y't - y_t|$$

Where, $y_t'$ is predicted value,

$y_t$ is actual value, and

n is total number of values in test set.

**Mean Percentage Error**

Equation 4:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{y_t' - y_t}{y_t} * 100\,\%$$

Where, $y_t'$ is predicted value,

$y_t$ is actual value and n is total number of values in test set.

**Mean Absolute Percentage Error**

Equation 5:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|y_t' - y_t|}{y_t} * 100\,\%$$

Where $y_t'$ is predicted value

$y_t$ is actual value, and

n is total number of values in test set.

**Software Used:**

TensorFlow and Kera's were selected for the Deep Learning backend programmer because they are the front-stop layer for building neural networks more quickly [10]. The performance of matrices and vectors, as well as the preservation of data and training sets, are handled by NumPy, and min-max standardization is produced through Scikit-learn (also known as Sk-learn). Pandas was created primarily for tasks involving records. Charts are then shown using Plotly.

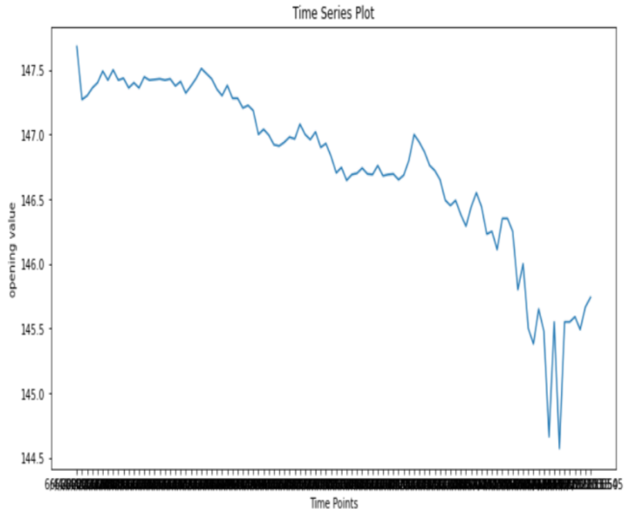


**Figure 4.8. Accurate Graph**

**V Results Analysis:**

We show the effects of our LSTM version in this part. For the period of schooling, it was stated that the worse the prediction at the check set, the longer the batch length. That should come as no surprise, given that the more educated a person is, the more prone they are to the version being overfitted. While predicting the price of Bitcoin is difficult, it is clear that the algorithm's functions are crucial. Future work will focus on evaluating the RNN's Gated Recurrent Unit model and fine-tuning currently used hyper-parameters. The loss from the Mean Absolute Error characteristic while using the version to predict the education and check data is depicted in the graph below.

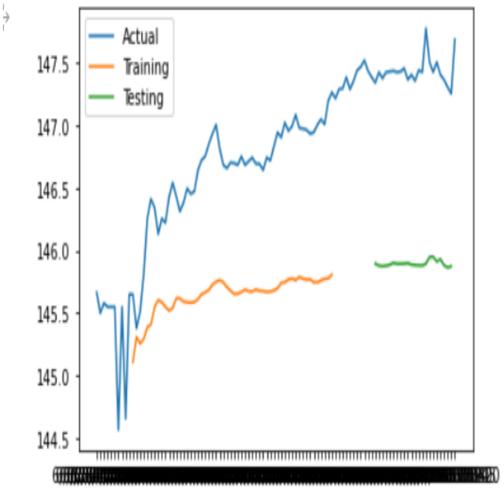


**Figure 5.1. Accuracy of LSTM on the Dataset**

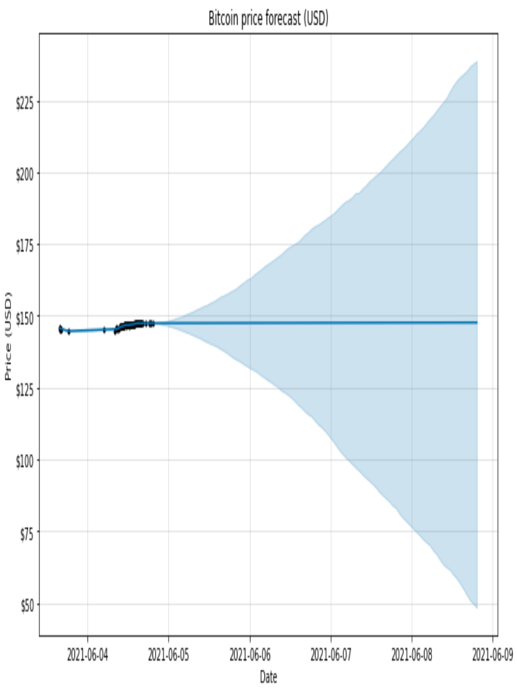


**Figure 5.2. Forecasting Graph**

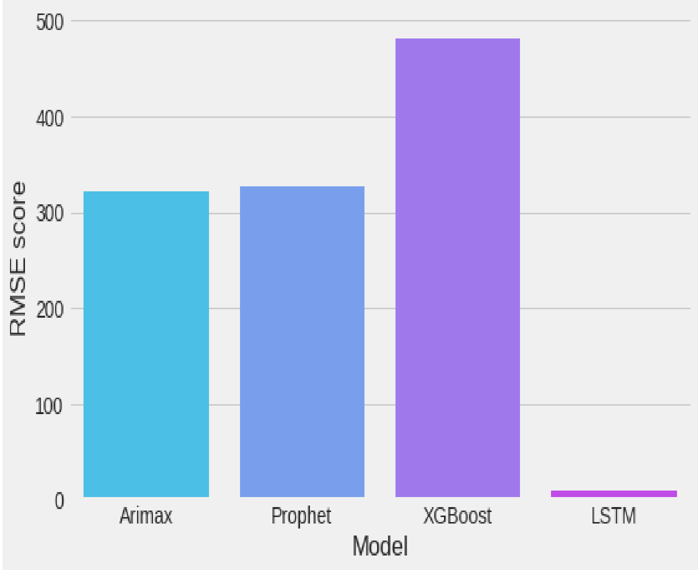


**Figure 5.3. RMSE score of LSTM model**

**Table 1. Representing Accuracies of five Algorithms**

| S. No | Algorithm used | Accuracy |
|---|---|---|
| 1 | LSTM | 0.7820773930753564 |
| 2 | Logistic regression | 0.7317073170731707 |
| 3 | Gradient boosting machine | 0.43089430894308944 |
| 4 | Random forest classifier | 0.7317073170731707 |
| 5 | Facebook Prophet | 0.7642276422764228 |

**JOURNAL OF ALGEBRAIC STATISTICS**
Volume 13, No. 3, 2022, p.2113-2123
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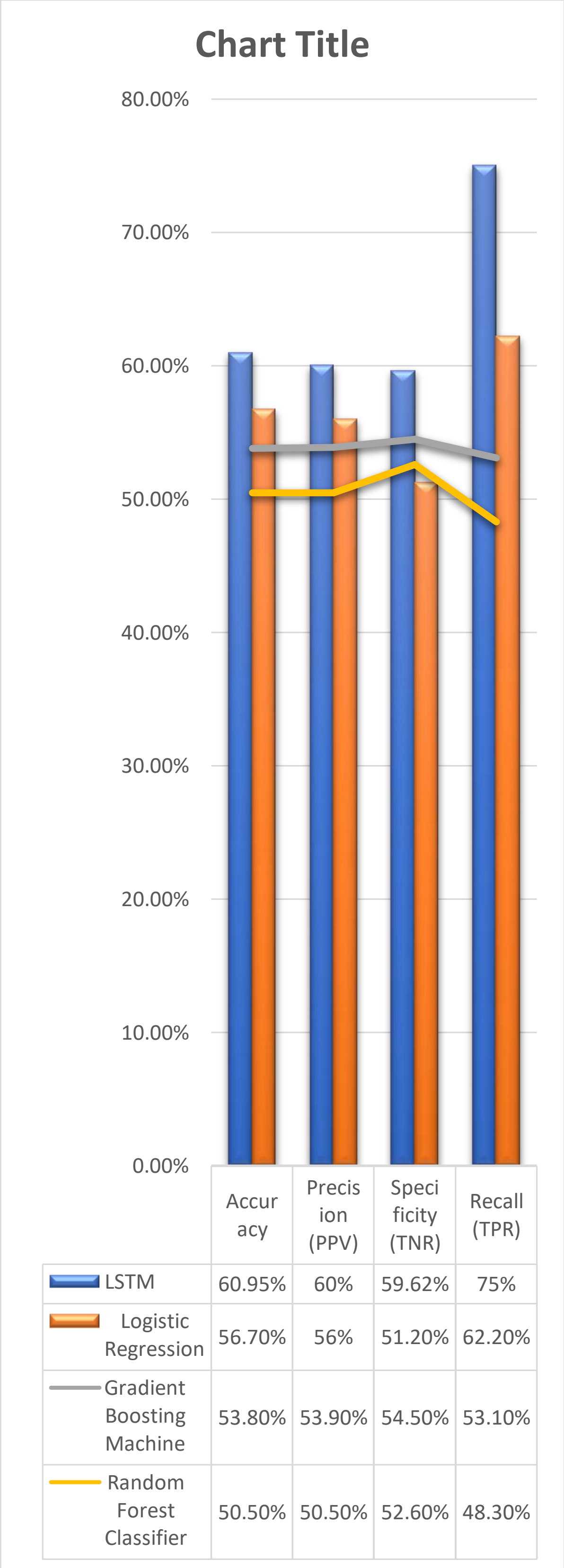


| | Accuracy | Precision (PPV) | Specificity (TNR) | Recall (TPR) |
|---|---|---|---|---|
| LSTM | 60.95% | 60% | 59.62% | 75% |
| Logistic Regression | 56.70% | 56% | 51.20% | 62.20% |
| Gradient Boosting Machine | 53.80% | 53.90% | 54.50% | 53.10% |
| Random Forest Classifier | 50.50% | 50.50% | 52.60% | 48.30% |

**Figure 5.4. LSTM accuracy**

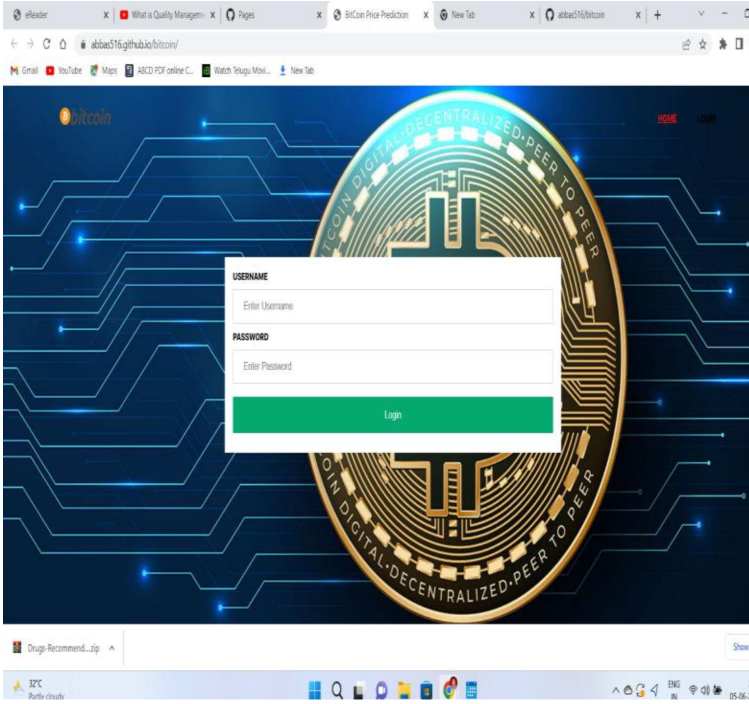


**Figure 5.5. Login page for user**

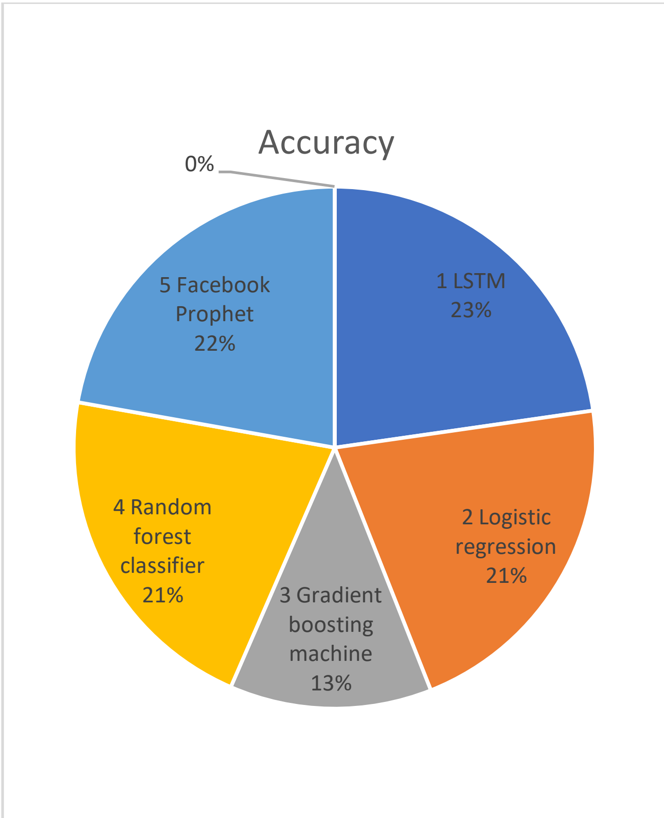


**Figure 5.6.The accuracy percentages of the five algorithms depicted in a Pie chart.**

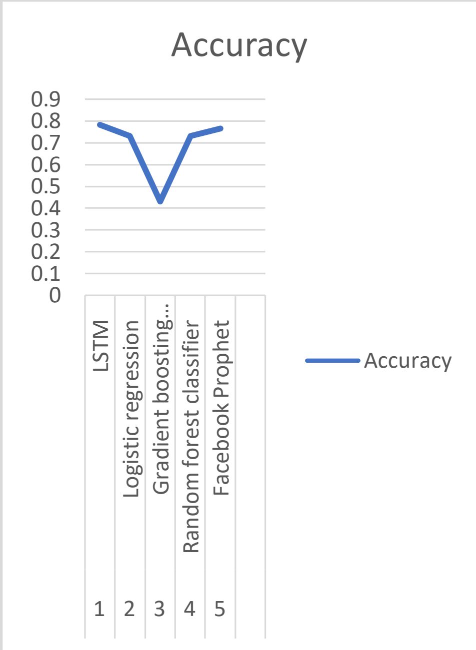


**Figure 5.7. The accuracy percentages of the five algorithms depicted in a line chart.**

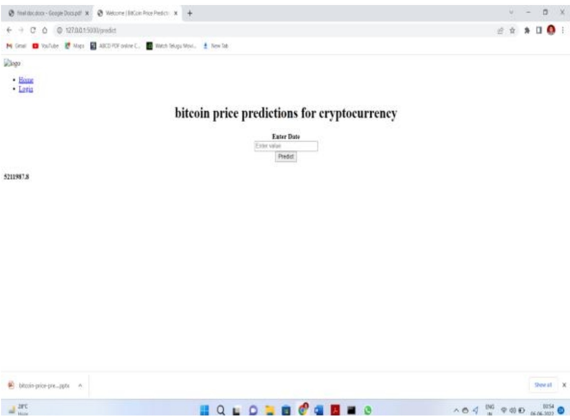


**Figure 5.8. Bitcoin price prediction**

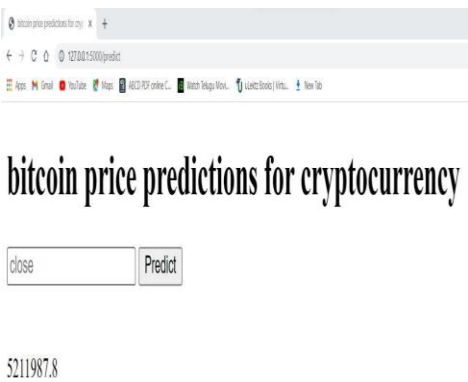


**Figure 5.9. Bitcoin predicted value**

## VI Conclusion:

Overall, because there are so many market-influencing factors, it is difficult to anticipate a price-related variable. Additionally, keep in mind that expenses nowadays heavily rely on possibilities rather than historical facts. But employing deep neural networks has helped us comprehend how LSTM and Bitcoin work. To achieve a more accurate community design, the work in progress entails enforcing hyperparameter adjustment. Additional considerations include various capabilities (despite the fact that from our experiments with Bitcoin, extra capabilities have now no longer continually caused higher results).

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