International Journal of Research Publication and Reviews, Vol 4, no 12, pp 4565-4570 December 2023

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Bitcoin Price Prediction using Machine Learning

Kella Lokeshwar

B. Tech Student, Department of IT, GMR Institute of Technology, Rajam-532127, Andhra Pradesh, India
Email: 21341A1258@gmrit.edu.in

ABSTRACT

Bitcoin is an Internet currency that was invented by Pseudonymous Satoshi Nakamoto in the year 2009. It is also a popular payment mechanism for online illegal activity where there exists an anonymous payment from one person to other. Hence it is both a digital asset and payment method. Bitcoin usually uses peer-to-peer network which rely on the Blockchain technology instead of the central authorities. Nowadays bitcoin becoming the most popular and expensive cryptocurrency. The absence of government regulation results in uncontrollable price of the Bitcoin and frequent large fluctuations. Due to these fluctuations, there is a need of automation tool to predict the price of the bitcoin in the stock market. In last few years, ML algorithms and some deep learning methods have played a crucial role in predicting the price of the bitcoin. But the main consideration is the algorithm or method. This research focuses on the methods or algorithms that are used to predict Price of the Bitcoin. Considering the methods used in recent years, LSTM(Long Short Term Memory) have given the predictions with high accuracy. And we also have GRU(Gated Recurrent Unit), RNN(Recurrent Neural Network), HMM(Hidden Markov Model) which predicts the price of the bitcoin effectively. But through the research from recent years, LSTM has been outperformed all the deep learning algorithms. LSTM could have a better performance with indispensable time for training, especially happens via the CPU.

Keywords: Machine Learning, Deep Learning techniques, Bitcoin, LSTM, MSE, R-Squared.

INTRODUCTION

Bitcoin is a digital coin that has been reason for the deadlines over a decade. It was created by a mysterious person named Satoshi Nakamoto in 2009. It was a most popular cryptocurrency. It enables the anonymous payment from person to person called peer-to-peer transactions without the need of the intermediaries such as banks. But everyone's mind had struck with a question that What will be the future price of the Bitcoin and How Bitcoin's price will affect the business and the world?

As different researchers have been found that after 2015, around 1,00,000 technologies and business companies have started the bitcoin market. The companies that are joined with the bitcoin are Amazon, Microsoft, Overstock, Dell, etc. Bitcoin was the most popular cryptocurrency market that was declared by the market capitalization in 2017. One reason that bitcoin has raised its fame in the world is that it can be exchanged, spent conveniently and globally with a low transaction fee.

The unique characteristic of the bitcoin is its daily price fluctuations. There is a need of an automation tool to make predictions that help investors and businessmen decide for bitcoin. The main challenge of the exchange rate of the bitcoin is its high rate of fluctuation. This high price volatility says that a certain measure must be taken to predict the accurate price of the bitcoin. The main thing is to know the every forecasting value that affects the fluctuation and exchange rate.

This paper studies about the future prediction of the price of bitcoin using the deep learning method called LSTM(Long Short Term Memory)..

RESEARCH APPROACH

This paper presents the prediction of the future price of the bitcoin using Hidden Markov Model(HMM) and two machine learning methods namely Long Short Term Memory(LSTM) and Gated Recurrent Unit(GRU). This study aims to predict the closing price of the Bitcoin of next time step based on the previous 300-minute information.

The system has been implemented three forecasting methods namely LSTM, GRU, HMM. Here the evaluation is done by RMSE and MAPE and the results obtained indicate that HMM with Guassian Mixture Model has been outperformed all the methods. And the GRU model too outperformed the LSTM, though sometimes it provide extreme results. Here the prices are mostly constant and changes steadily. But if it comes to fluctuation period, the HMM and GRU do not provide much precise results.

The proposed system has constant period with steady changes, so within that HMM is providing the best performance.

METHODOLOGY:

Dataset Overview

The raw dataset used in the study includes Bitcoin information from the European-based exchange, Bit-Stamp, starting from its first transaction in September 2011. The data was extracted using an API from the website Bitcoincharts.com, which is recommended by Bitcoin.org.

The dataset consists of eight variables, including price information and volume information, for every 15-minute time step. The dataset contains a total of 301,803 observations in chronological order .

While the specific names of the variables are not mentioned in the provided sources, it can be inferred that the dataset includes information such as the opening price, closing price, highest price, lowest price, trading volume, and possibly other relevant metrics.

Feature Selection

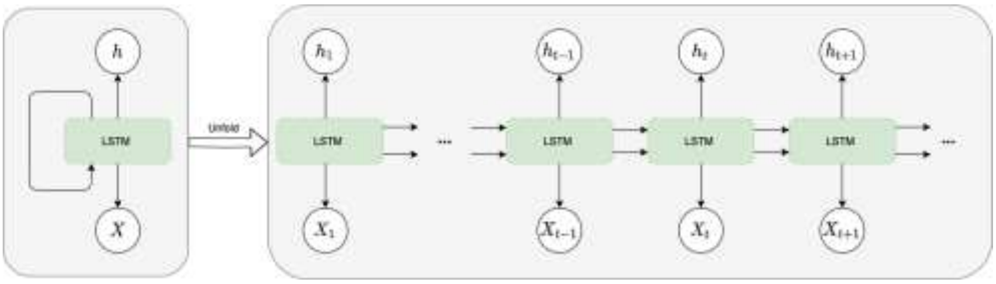
VARIABLE	MEANING
Open	Price (USD) of the first trade at the current time step
High	High Highest Price (USD) of trades at the current time step
Low	Low Lowest Price (USD) of trades at the current time step
Close	Close Price (USD) of the last trade before the next time step
Volume_BTC	Volume BTC Trade volume in Bitcoins
Volume_Currency	Volume Currency Trade volume in USD
Weighted_Price	Weighted Price Weighted Bitcoin price (USD)
Timestamp	Timestamp Ten digits integer that represents time

Long Short Term Memory

In Time series forecasting, the Long Short Term Memory is a type of popular deep learning method. LSTM was introduced by Hochreiter and Schmidhuber in 1997. The LSTM is a Recurrent Neural Network architecture which uses a loop to pass information from one step to next step of the network. From the above diagram, we can observe that the loops are unfolded or unrolled into a chain-like structure of the same network.

A Recurrent Neural Network have ability to memorize previous input in a memory when a huge set of sequential data is considered. For the RNN, if the necessary information is further back of the sequence, the gradients, which update neural network weights, can be minimal and leads to a short-term memory problem. And the problem with RNN is that the Long Term Dependency problem. Mainly, LSTM is capable of learning from sequence dependency while solving the traditional RNN's memory problem.

LSTM is a variation of the RNN with similar chain-like structure but more layers. There is a key of the LSTM, i.e., Ct that stores the memory and three different gates namely input gate, output gate and forget gate



A Recurrent Neural Network have ability to memorize previous input in a memory when a huge set of sequential data is considered. For the RNN, if the necessary information is further back of the sequence, the gradients, which update neural network weights, can be minimal and leads to a short-term memory problem. And the problem with RNN is that the Long Term Dependency problem. Mainly, LSTM is capable of learning from sequence dependency while solving the traditional RNN's memory problem.

LSTM is a variation of the RNN with similar chain-like structure but more layers. There is a key of the LSTM, i.e., Ct that stores the memory and three different gates namely input gate, output gate and forget gate. The LSTM has two activation functions which plays a n essential role, they are Sigmoid function and Tanh function. The Sigmoid function also known as a Logistic function and it regulates how much information to be passed through these gates. Sigmoid function is defined as:

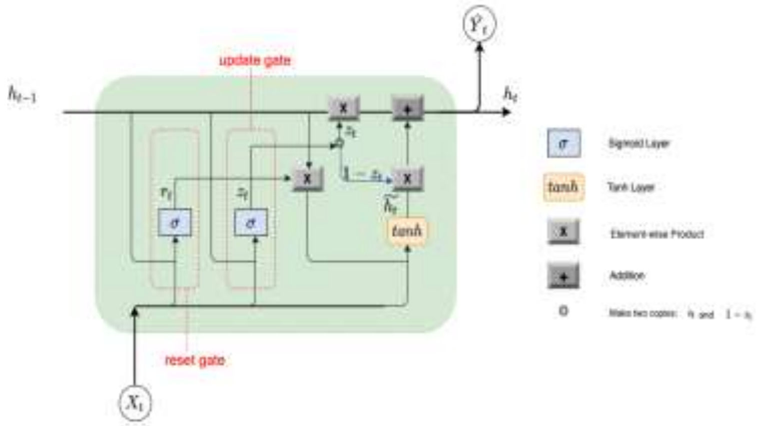
$\sigma(x) = ex /1+ ex$

Gated Recurrent Unit(GRU):

Gated Recurrent Unit or GRU is another variation of the RNN, which is introduced in 2014. Like LSTM, the GRU is proposed to solve the RNN's shrinking gradient issue, and it also includes the sigmoid layer, the tanh layer, and the hidden state. However, the GRU does not depend on the cell to store memory.

Simpler than the LSTM, the GRU has two gates, update gate and reset gate. The reset gate is similar to the LSTM's forget gate, which decides how much past information is ignored. Similar to the LSTM's forget gate, if the output vector's values rt is close to 0, little information from the previous hidden state is maintained, and the vector resets with the current input. The update gate determines what past information is used in the new hidden state, which serves as the similar function as the cell in the LSTM.

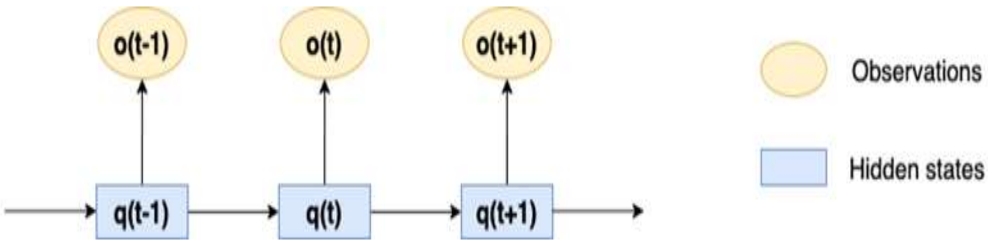
.



Hidden Markov Model(HMM):

A Hidden Markov Model (HMM) is a statistical model that is used to describe a system with hidden states that can only be observed through a series of observable outputs or observations. In an HMM, the observation at a given time depends only on the current hidden state, and the hidden state at a given time depends only on the previous hidden state.

The HMM assumes that the emission probabilities, which describe the likelihood of observing a particular output given a hidden state, can be modeled using a multivariate Gaussian distribution or Gaussian mixture models. The parameters of the HMM, including the emission probabilities, are trained using the Baum-Welch algorithm**.**



The closing price is forecasted using a Hidden Markov Model (HMM) in this study. The HMM model takes into account the previous 20-time step information to make predictions. Two emission probabilities are tried in the HMM model to determine the likelihood of observing a particular output given a hidden state. The parameters of the HMM, including the emission probabilities, are trained using the Baum-Welch algorithm.

RESULTS:

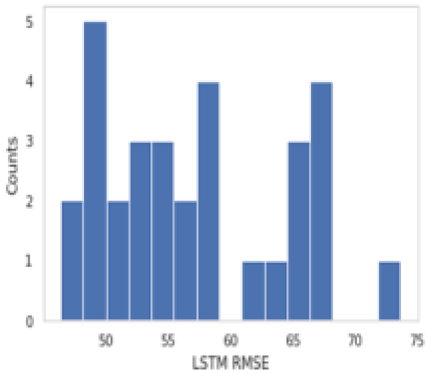
The paper evaluates the performance of three methods for predicting Bitcoin prices using the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics. The RMSE measures the squared root of the squared errors between the predicted price and the actual price, while the MAPE measures the absolute difference between the predicted price and the actual price in percentage.

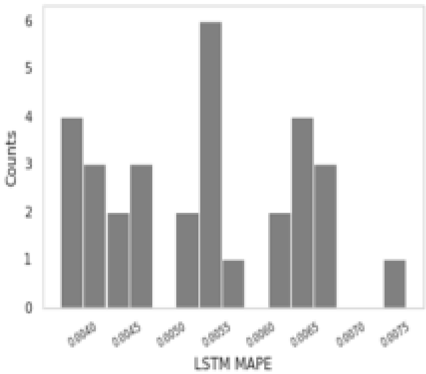
A smaller RMSE and MAPE indicate a better result, indicating that the prediction is close to the actual price. The MAPE is also used to decide the tuning hyperparameters. The study discusses the tuning results, predicted results from each method separately, and compares the predictions in the last section**.**

Using LSTM

The paper implements a stacked LSTM architecture with two hidden layers to increase the depth of the models. The LSTM model's performance is evaluated using metrics such as RMSE and MAPE. The optimal hyperparameters of the LSTM model are determined through experimentation.

The LSTM model has an almost identical performance evaluated by RMSE and MAPE. It has average RMSE value at 57 and average MAPE value at 0.0053 or 0.53%. For both evaluations, the medians are slightly lower than the means due to the maximum RMSE value 73.65, and the maximum MAPE value 0.0076 or 0.76%, that are much higher than other values.



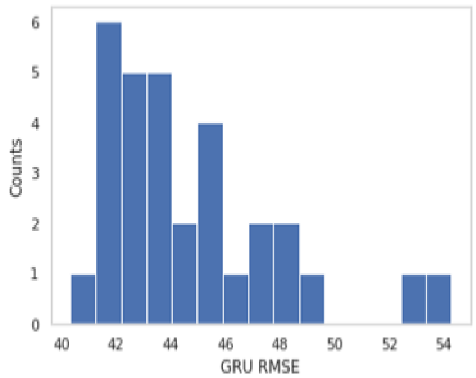


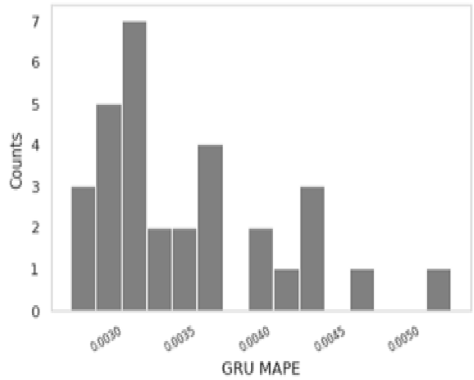
	RMSE	MAPE
Mean	57.2310	0.0053
Standard Deviation	7.4317	0.0011
Min	46.3745	0.0037
50% (Median)	57.0664	0.0053
Max	73.6512	0.0076

The overall performance indicates a distinguishable difference within repetitions' results, and the predictions from some repetitions are less accurate than others, resulting in higher RMSE and MAPE values.

Using GRU

Like the LSTM model, we tuned the hyperparameters in the GRU model following the earlier methods. According to the tuning results summarized, the final GRU model configured with 32 neurons, a batch size of 32, and trained for 500 epochs. The best optimization algorithm is RMSprop with a gradient norm clipping of 1.0 to avoid exploding gradient problem, meaning that the L2 vector norm for a gradient is limited to a threshold of 1.0.





The outlier prediction in MAPE has a value of 0.0053, and it is also the outlier measured by RMSE with a value of 54.27. Another outlier RMSE value is 52.50, while its corresponding MAPE value is 0.0046, which is considered the maximum of MAPE results.

	RMSE	MAPE
mean	44.7693	0.0035
std	3.2983	0.0006
min	40.3035	0.0028
50%	43.6422	0.0033
max	54.2775	0.0053

4.3 Using HMM

There are two choices of emission probabilities for the HMM model. Before implementing the single multivariate Gaussian distribution (GaussianHMM), we determined the number of hidden states (n). The HMM model with two different emission probabilities has similar predictions. The difference between GaussianHMM and GMMHMM is imperceptible. They have good performance even in the fluctuation period, such as the remarkable drop in mid-March 2020.

The RMSE values and the MAPE values indicate that the prediction from GMMHMM is slightly better than that of GaussianHMM, though the contrast is negligible.

Methods	RMSE	MAPE
GaussianHMM	37.8054	0.002814
GMMHMM	37.4856	0.002803

CONCLUSION:

In conclusion, the application of LSTM models for Bitcoin price prediction has shown promise in capturing complex patterns and dependencies within the cryptocurrency market. The utilization of historical price data to train the LSTM model has allowed for the identification of trends and potential future movements in Bitcoin prices. Our analysis revealed that LSTM models, with their ability to capture long-term dependencies, demonstrated reasonable accuracy in predicting short to medium-

term.Bitcoin price trends. However, it's crucial to acknowledge the inherent volatility and unpredictability of the cryptocurrency market, which can impact the model's performance.

While LSTM models have proven effective in capturing certain patterns, it is essential to consider various factors that can influence Bitcoin prices, such as regulatory developments, market sentiment, macroeconomic indicators, and technological advancements. These external factors may not be fully captured by historical price data alone, and incorporating additional features into the model could enhance its predictive capabilities.

Furthermore, it's important to note that past performance is not necessarily indicative of future results in the highly dynamic and speculative nature of the cryptocurrency market. Traders and investors should exercise caution and consider combining LSTM predictions with other analytical methods and risk management strategies.

In conclusion, while LSTM models provide a valuable tool for analysing Bitcoin price trends, they should be used as part of a broader decision-making framework. Continuous refinement of the model, incorporation of additional features, and ongoing evaluation against real market conditions are essential for improving predictive accuracy and making informed decisions in the ever-evolving landscape of cryptocurrency trading.

References

1. Xu, Yike. Bitcoin Price Forecast Using LSTM and GRU Recurrent networks, and Hidden Markov Model. University of California, Los Angeles, 2020.
2. Gunarto, Dzaki Mahadika, Siti Sa'adah, and Dody Qori Utama. "Predicting Cryptocurrency Price Using RNN and LSTM Method." Jurnal Sisfokom (Sistem Informasi dan Komputer) 12.1 (2023): 1-8.
3. Phaladisailoed, Thearasak, and Thanisa Numnonda. "Machine learning models comparison for bitcoin price prediction." 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE). IEEE, 2018.
4. Hua, Yiqing. "Bitcoin price prediction using ARIMA and LSTM." E3S Web of Conferences. Vol. 218. EDP Sciences, 2020.
5. Andi, Hari Krishnan. "An accurate bitcoin price prediction using logistic regression with LSTM machine learning model." Journal of Soft Computing Paradigm 3.3 (2021): 205-217.
6. S. Nithiya, G. Parimala (2023), "Bitcoin Price Prediction Using Machine Learning", International Conference on Computer Communication and Informatics (ICCCI), pp.1-6, 2023.
7. Shreyasi Periketi, Rajesh Kulkarni, Uma N Dulhare (2023), "LSTM and Prophet Model Fusion Framework for Bitcoin Candlestick Visualization and Price Prediction Forecasting", 2023 10th International Conference on Computing for Sustainable Global Development (INDIACom), pp.1190-1194, 2023.
8. G. Neil and H. Halaburda(2019), "Can we predict the winner in a market with network effects? Competition in cryptocurrency market", Games, vol. 7, no. 3, pp. 16.
9. S. McNally, J. Roche and S. Caton (2018), "Predicting the Price of Bitcoin Using Machine Learning", 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP), Cambridge, UK, 2018, pp. 339-343, doi: 10.1109/PDP2018.2018.00060.
10. Dhanya, N. M. (2021) "An Empirical Evaluation of Bitcoin Price Prediction Using Time Series Analysis and Roll Over." In Inventive Communication and Computational Technologies, pp. 327-339. Springer, Singapore, 2021.
11. Nurhayati Buslim, Imam Lutfi Rahmatullah, Bayu Aji Setyawan, Aryajaya Alamsyah (2021), "Comparing Bitcoin's Prediction Model Using GRU, RNN, and LSTM by Hyperparameter Optimization Grid Search and Random Search", 2021 9th International Conference on Cyber and IT Service Management (CITSM), pp.1-6, 2021.
12. C. -H. Wu, C. -C. Lu, Y. -F. Ma and R. -S. Lu, "A New Forecasting Framework for Bitcoin Price with LSTM," 2018 IEEE International Conference on Data Mining Workshops (ICDMW), Singapore, 2018, pp. 168-175, doi: 10.1109/ICDMW.2018.00032.
13. Awoke, T., Rout, M., Mohanty, L., Satapathy, S.C. (2021). Bitcoin Price Prediction and Analysis Using Deep Learning Models. In: Satapathy, S.C., Bhateja, V., Ramakrishna Murty, M., Gia Nhu, N., Jayasri Kotti (eds) Communication Software and Networks. Lecture Notes in Networks and Systems, vol 134. Springer, Singapore. https://doi.org/10.1007/978-981-15-5397-4_63.
14. Karakoyun, Ebru Seyma, and A. O. Cibikdiken. "Comparison of arima time series model and lstm deep learning algorithm for bitcoin price forecasting." The 13th multidisciplinary academic conference in Prague. Vol. 2018. 2018.
15. Jiang, Xiangxi. "Bitcoin price prediction based on deep learning methods." Journal of Mathematical Finance 10.1 (2019): 132-139.