

CRYPTO CURRENCY PRICE PREDICTION USING DEEP LEARNING

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ABSTRACT: Investors have recently become interested in cryptocurrency because of its inherent decentralization and transparency. In order to build efficient trading platforms, accurate value estimation is essential, given the cryptocurrencies' new features and volatility. The researchers propose a cutting-edge method for determining the value of Bitcoin (BTC), a well-known cryptocurrency, in order to accomplish this. The change point detection method is utilized to provide consistent prediction performance across previously unknown price ranges. Time-series data are split specifically so that segmentation-based normalization can be carried out separately. Price forecasting also makes use of on-chain data as an input variable. The various records that are contained in cryptocurrencies and saved on the blockchain are referred to as "on-chain data." Moreover, for on-chain variable assembles, this paper exhorts involving SAM-LSTM as the assumption model, which includes the thought part and a couple of LSTM modules. Self-consideration-based multiple long short-term memory is abbreviated as SAM-LSTM. Tests conducted with authentic BTC cost information and a variety of technique limits demonstrated that the proposed structure was effective in forecasting BTC prices. The highest individual values for the MAE, RMSE, MSE, and MAPE were 0.3462, 0.5035, 0.2536, and 1.3251, respectively. The outcomes are positive.

Keywords – *Bitcoin, deep learning, prediction methods, and change detection algorithms are all included.*

1. INTRODUCTION

The state of money and the concept of trade have been significantly altered by the growth of blockchain technology. Since its inception, cash has primarily served as a payment instrument and exchange mechanism for significant value. Faith in money, which is guaranteed and settled by a central organization, is necessary for its competence. such as the government or a bank). Focused power is extremely concerned about the possibility of wickedness threatening steady quality exchange. The open, tamper-proof, anti-counterfeiting blockchain gave rise to Bitcoin, a digital currency. By allowing confidence without the assurance of a centralized authority, Bitcoin breaks away from the usual connection. Bitcoin, which ensures decentralization and transparency [2], makes it possible to create a

monetary system that reduces the likelihood of fraud and safeguards privacy. In terms of how it differs from the conventional forms of money that are currently in use, the most widely used cryptocurrency, Bitcoin (BTC), is a model cryptocurrency currency. There is virtually no inflation caused by a central bank issuing money because of the 21 million Bitcoin issue limit [3]. By allowing cryptocurrencies to function as both a means of exchange and a method of value storage, the concept of decentralization is expanded. In point of fact, it is now accepted that investing resources in cryptocurrencies rather than traditional venture vehicles is one of the best ways to increase resource value.

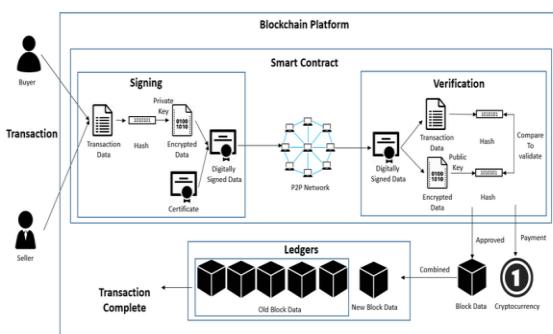


Fig.1: Example figure

Cryptocurrencies, in contrast to conventional resources like gold, values, government-issued currency, and so forth, are elusive and volatile. such as a partnership). The inclusion of on-chain information, which includes information gathered from the blockchain, is another feature that sets cryptocurrencies apart [6]. Basic information about the blockchain network, such as exchanges, block size, and mining difficulty, can be found in on-chain information. Because of this, it is challenging to initially apply standard indicators and criteria for asset classification to cryptocurrencies. Effective deployments necessitate a creative strategy that emphasizes the cryptocurrencies' unique characteristics in light of the aforementioned constraints.

2. LITERATURE REVIEW

Stochastic neural networks for cryptocurrency price prediction:

The use of cryptocurrencies as forms of currency has significantly increased recently as a result of advancements in blockchain technology. Due to the market's unpredictable behavior and extreme price volatility, bitcoin is not considered a viable business opportunity. On account of their deterministic design, the greatness of the methodologies gave in the article to computerized cash esteem expecting may not be suitable for consistent expense assumption. We propose a stochastic brain network model for calculating bitcoin values in light of the difficulties previously mentioned. The arbitrary walk concept, which is frequently utilized for stock price demonstration in financial industry sectors, serves as the

foundation for the suggested method. In order to imitate market volatility, the proposed method incorporates layer-wise randomization into the observed component enactments of neural networks. The ability of the expectation model to explain patterns of market response is well-known. For Bitcoin, Ethereum, and Litecoin, we developed the Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) models. The findings demonstrate that the proposed model performs better than the deterministic models. File TERMS includes stochasticity, multi-layer perceptrons, long short-term memory, irregular walks, and cryptocurrencies.

Privacy and cryptocurrencies—A systematic literature review

Our exchange history might uncover an enormous part of individual data about every hot shot under the ongoing incorporated monetary structure, both to the monetary system itself and to those that wall it in. (legislatures, businesses, and so on) The amounts spent, the items purchased with those funds, the places where we spend our money, and the people with whom we transfer money are all examples of leaked data. People who have this knowledge may put it to use in a variety of unfavorable ways. Cryptocurrencies, like Bitcoin, were offered as a way to avoid the problems of centralized financial systems while still offering customers conditional data security. We conduct a comprehensive literary analysis of the issue of security for electronic monetary standards in this exposition. We follow the development of computerized money, from electronic money to digital currencies, focusing on consumer security measures. Additionally, we draw attention to security risks posed by current bitcoin frameworks to customers. In the previous article, we examined three areas of research that have the potential to provide bitcoin users with additional levels of security: exchange proliferation procedures, brief ZK confirmation frameworks without a dependable arrangement, and specific trustless zero-information evidences are all examples of these.

Virtual currency bitcoin in the scope of money definition and store of value

The news often talks about it. Since it is decentralized and operates without the influence of governments to regulate the supply of currency, customers of untraceable cash appreciate it. The advantages of bitcoin are frequently emphasized, such as its speed at which money can be transferred around the world, its resistance to growth brought on by state-run administrations having to deal with their own problems, and its high level of exchange security. Because they have been thoroughly examined in numerous releases, the particulars of bitcoin and the operation of this framework are not the primary focus of this explanation. The economic ramifications of Bitcoin's technical aspects are emphasized when absolutely necessary. To accomplish this, the article is divided into two sections. The definition of bitcoin is the focus of the first section. It examines the legal, theoretical, and empirical definitions of money to see if bitcoin meets them. For the most part, Czech, German, and EU standards portray cash consistency;

However, the viewpoints of legislators from China and the United States are also mentioned. The results demonstrate that bitcoin cannot simply be considered money. The issue of currency hoarding is the subject of the following section. The fact that bitcoin is a more dependable way to store value than government-issued cash ought to be one of its major advantages. Bitcoin volatility evaluations, in addition to other monetary standards and resources, serve as the foundation for this competency assessment. At the point when the realities are thought of, obviously bitcoin's unpredictability (and thus risk) is basically more noteworthy than that of other money related structures and assets.

Bitcoin is not the new gold—A comparison of volatility, correlation, and portfolio performance

Bitcoin and other cryptocurrencies are becoming increasingly popular as business vehicles, earning them the moniker "New Gold." However, this investigation demonstrates that the two resources are in direct opposition to one another. The restricted fluctuation characteristics of Bitcoin, Gold, and other resources were first evaluated and analyzed in order to identify fundamental differences. We develop a BEKK-GARCH model to evaluate time-varying restrictive connections. Gold plays a crucial role in the financial sector's journey toward quality during market downturns. According to our data, Bitcoin's behavior is diverse and well correlated with market declines. Last but not least, we looked at the Bitcoin components as a part of a portfolio and found little evidence of sustaining capacity. Bitcoin and gold, in our opinion, share very distinct fundamental resource characteristics and connections to financial markets. Our findings are supported by the comprehensive cryptocurrency index CRIX. At the moment, Bitcoin only reflects the asymmetric variance response of gold.

Macroeconomic variables affecting the volatility of gold price

This study's examination of the macroeconomic parts affecting gold costs checks the world's biggest gold customer out. (Turkey, Saudi Arabia, China, and India). The Statistical Package for the Social Sciences (SPSS) was used to investigate the future relationships between gold prices and GDP, genuine loan fees, money rates, raw petroleum prices, and money rates. There were 20 years of annual information use from 1996 to 2015. The data revealed that there were also some links between raw petroleum costs and gold costs, despite the fact that there were negative links between the growth rate, GDP, genuine financing cost, swapping scale, and gold value. The consequences of the relapse demonstrated that the price of gold was influenced by factors other than the conversion scale.

An on-chain analysis-based approach to predict ethereum prices:

The Ethereum blockchain generates a significant amount of data due to its openness and decentralization. On-chain information is another name for it, and anyone can access it. An open record is likewise timestamped, reviews and approves chain data. We are able to evaluate the health and appearance of the organization thanks to this crucial blockchain feature. It is a huge data store for cutting-edge expectation

computations that can predict future behavior and recognize basic instances. By creating an LSTM-RNN (Long Short-Term Memory Recurrent Neural Network) with metrics typically strongly associated with cost as sources of information, we employ a quantitative method to characterize the true financial value of the business. Since a couple of hyperparameters impact how a RNN learns, its settings are basic. In this manner, choosing the fitting hyperparameters is basic for a plausible and fast planning. Testing and taking a lot of time are the most common ways to find the right bounds for an RNN model. Numerous self-versatile computations for determining the appropriate attributes for various limits have been developed as a result of previous research. In any case, the use of self-versatile computations and on-chain information in deep learning models to determine bitcoin costs has not been the subject of any prior research. We provide three independent estimates in this investigation, each of which is based on a set of ideal bounds for the specific hypothesis of Ethereum's cost. We contrast our outcomes with those of a standard LSTM model. With a low rate of error, our method is 86.94 percent accurate.

3. METHODOLOGY

Due to their ability to simulate non-stationarity in time-series data, machine learning (ML) algorithms have recently become a popular method for speculating on the prices of financial instruments. This is in contrast to earlier methods. However, two errors in the writing were discovered by our research. The most pressing issue is the recent flood and the decline in bitcoin prices. Developed ML-based models are unable to accurately predict future attributes because the cost fluctuates in an undetectable range. Any expectation model developed using acceptable range valuation data and specialized projection computations may be affected by this issue. Consequently, the change point detection (CPD) procedure is presented in this study as a novel approach to addressing the difficulty previously mentioned. In particular, during the preparation process, input data is broken up using CPD to the point where each divided informative collection contains distinct quantifiable highlights. Material is standardized separately according to divisions in order to accurately depict emotional swings. This review's testing indicates that this is a viable solution to the primary issue. When writing about bitcoin value projection, the second issue that this study focuses on is that many newly distributed endeavors just use old-fashioned standards like verifiable expenses and web-based entertainment data.

Disadvantages

1. because of the recent rise and fall in the price of bitcoin.
2. Several current endeavors rely solely on out-of-date components like price history and information about online entertainment.

This study suggests that a variety of blockchain-related limits can be used to increase cost expectation. On-chain data and the proposed system's autonomous forces are the main points of view for determining

bitcoin prices. For the development of effective trading algorithms, precise value forecasting is essential due to the cryptocurrencies' unique volatility and volatility. The researchers propose a cutting-edge method for determining the value of Bitcoin (BTC), a well-known cryptocurrency, in order to accomplish this. The change point detection method is utilized to provide consistent prediction performance across previously unknown price ranges. Time-series data are split specifically so that segmentation-based normalization can be carried out separately. Price forecasting also makes use of on-chain data as an input variable. The various records that are contained in cryptocurrencies and saved on the blockchain are referred to as "on-chain data." Additionally, the consideration instrument and a few LSTM modules for on-chain variable groups are included in the SAM-LSTM expectation model that is recommended in this paper. Self-consideration based various long and short term memory is spelled SAM-LSTM.

Advantages

1. how accurately the proposed framework predicts Bitcoin values.
2. To confirm the efficacy of CPD and SAM-LSTM in Bitcoin cost forecasting, extensive experiments are used.

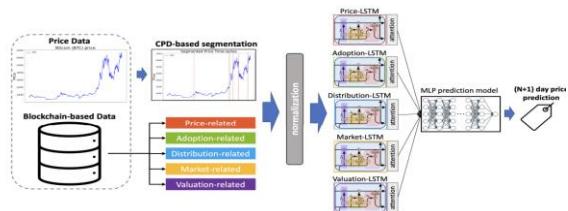


Fig.2: Proposed System architecture

MODULES:

- The modules recorded beneath were intended to achieve the previously mentioned task.
- Investigating information: We will incorporate data into the framework with this module.
- Handling: The module's information will be read and processed by us.
- Division of information: This module will be used to divide the information into train and test.
- The following models are utilized during model development: Linear Regression, Lasso Regression, Ridge Regression, XGBooster Regression, and Voting Regression. LSTM, LSTM + CPD. Attention + CPD + LSTM.
- Client enrollment and login data are collected using this module.
- Using this module will give you the expected input based on what the client has said.
- The run of the mill end outcome was found.

4. IMPLEMENTATION

ALGORITHMS:

LSTM:

Deep learning utilizes long momentary memory associations, or LSTMs. A large number of recurrent neural networks (RNNs), which can simultaneously perform predicting tasks, may learn long-term connections.

Linear Regression:

Controlled learning underpins the ML approach known as linear regression. It concludes a regression technique. Regression models an optimal expectation esteem by employing free variables. Most of the time, it is used to figure out how causes and effects relate to one another.

Lasso Regression:

A measurement and machine learning (ML) relapse examination technique known as Less absolute shrinkage and selection operator (LASSO) is used to improve the consistency and understandability of the resulting factual model. It is also referred to as tether or LASSO.

Ridge Regression:

Using the ridge regression model tuning technique, any multicollinear data can be investigated. This approach does L2 regularization. When multicollinearity is present, least-squares are valid, expected values diverge significantly from actual values, and significant fluctuations occur.

XGBooster Regression:

Gradient boosted trees, a notable methodology, is really executed in the open-source programming language XGBoost. Gradient boosting is a controlled learning method that combines the predictions of several more fragile, simpler models to successfully predict an objective variable.

Voting Regression:

A voting regressor is a type of group meta-assessment that linearly applies multiple base regressors to the entire dataset. The final expectation is produced by averaging the various judgments.

MLP:

An entirely linked feedforward artificial neural network (ANN) is known as a multilayer perceptron (MLP). The term "MLP" is not strictly used; it might allude to any feedforward ANN, yet it additionally alludes to networks worked of many layers of perceptrons (with edge sanctioning); Pay attention to the language. A "vanilla" brain structure is one in which a multi-facet perceptron has only one hidden layer.

RNN:

Recurrent neural networks (RNNs), which are the most remarkable calculation for successive data, are utilized in Google voice search and Apple's Siri. It is excellent for ML challenges like sequential information because its main computation for evaluating feedback is stored in its internal memory.

CNN:

Image identification and pixel information management are two uses for the deep learning network engineering technique known as a CNN. A number of neural networks are used in deep learning, but CNNs are best for identifying and detecting objects.

5. EXPERIMENTAL RESULTS

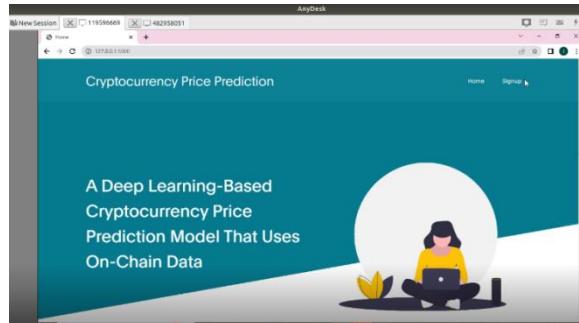


Fig.3: Home page

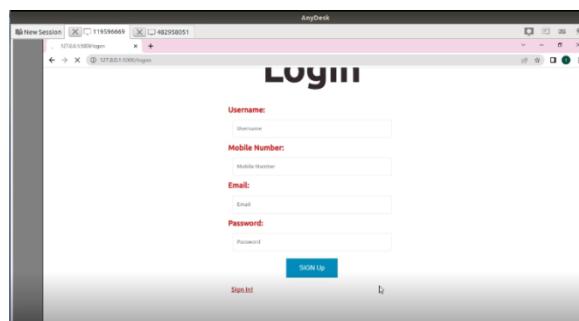


Fig.4: Registration of users



Fig.5: login by user

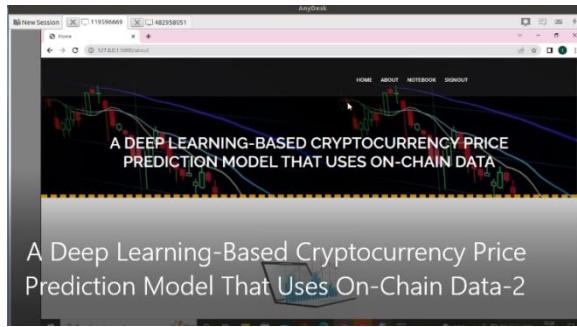


Fig.6: Main display

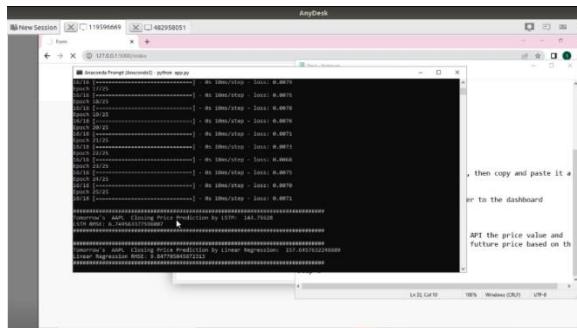


Fig.7: Creation of models

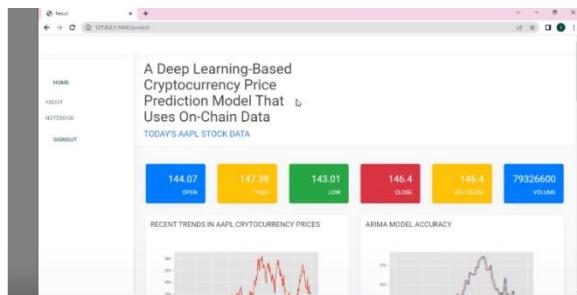


Fig.8: Calculations for predictions

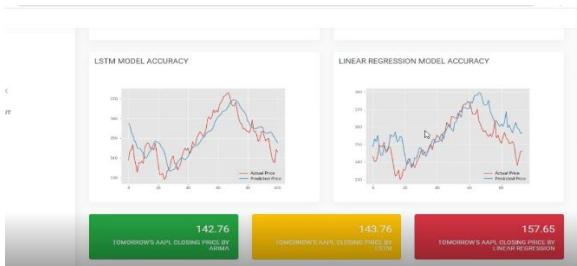


Fig.9: Graph of predictions

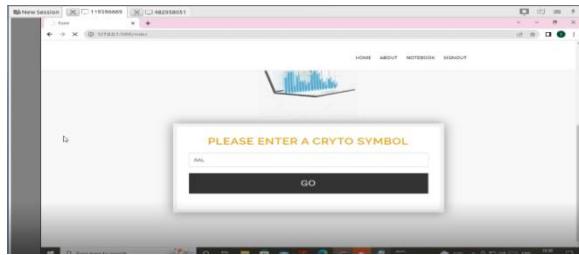


Fig.10: user input

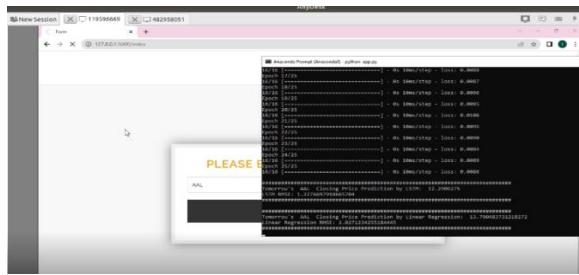


Fig.11: prediction outcome

6. CONCLUSION

Using multivariate on-chain time-series data, the developers present a novel method for forecasting bitcoin costs. Bitcoin cost forecasting is incorporated into the suggested approach. Cost prediction models can estimate unanticipated cost ranges using a CPD-based normalizing method rather than traditional ML-based models. For cost estimation, a selection of on-chain characteristics are ranked according to their inherent characteristics and used as information components. Highlights are isolated from a variety of on-chain data by the suggested cost forecast model (SAMLSTM), which is made up of a few LSTM modules with discrete consideration processes and an MLP-based total module. There are five distinct phases to this work. On-chain data are used to begin a thorough selection of variables. Second, pertinent on-chain components are chosen as data factors and classified in view of CCFs. Finally, the PELT CPD method is used to segment and standardize time series data across all divisions. Fourth, expenses are forecast using SAM-LSTM, an approximated consideration instrument and various LSTM for various on-chain variable collections. Last but not least, extensive research is carried out to demonstrate the accuracy of CPD and SAM-LSTM in predicting BTC costs. The absence of an exhibition evaluation with other bitcoin cost projection estimations is one of the study's flaws. There are many reasons why near testing cannot be accepted. In the first place, every piece of writing makes use of particular information, whether in terms of time spans, information types (such as information about web-based entertainment and Google Patterns), preprocessing procedures, or other aspects. For instance, it is not certain that a previous evaluation conducted prior to a new decline using cost data will yield comparable forecast endpoints. Later on, flow research, which claims to have excellent execution in terms of cost expectation, for

instance, will be used in an investigation. One potential area of study for the future is the development of a comprehensive system for evaluating bitcoin values. A specific collecting model should be developed using a combined system that combines cost-related perspectives like on-chain and web-based entertainment data to replicate the cryptographic money market's value features. A continuous cost expectation computation that uses a variety of data to produce hourly or minutely gauges would also be beneficial.

REFERENCES

- [1] P. Jay, V. Kalariya, P. Parmar, S. Tanwar, N. Kumar, and M. Alazab, "Stochastic neural networks for cryptocurrency price prediction," *IEEE Access*, vol. 8, pp. 82804–82818, 2020, doi: 10.1109/ACCESS.2020.2990659.
- [2] L. Herskind, P. Katsikouli, and N. Dragoni, "Privacy and cryptocurrencies—A systematic literature review," *IEEE Access*, vol. 8, pp. 54044–54059, 2020, doi: 10.1109/ACCESS.2020.2980950.
- [3] M. KubÆt, "Virtual currency bitcoin in the scope of money definition and store of value," *Proc. Econ. Finance*, vol. 30, pp. 409–416, Jan. 2015, doi: 10.1016/S2212-5671(15)01308-8.
- [4] T. Klein, H. P. Thu, and T. Walther, "Bitcoin is not the new gold—A comparison of volatility, correlation, and portfolio performance," *Int. Rev. Financial Anal.*, vol. 59, pp. 105–116, Oct. 2018, doi: 10.1016/j.irfa.2018.07.010.
- [5] S. Hashim, H. Ramlan, N. Razali, and N. Nordin, "Macroeconomic variables affecting the volatility of gold price," *J. Global Bus. Soc. Entrep.*, vol. 3, no. 5, pp. 97–106, 2017.
- [6] N. Jagannath, T. Barbulescu, K. M. Sallam, I. Elgendi, B. McGrath, A. Jamalipour, M. Abdel-Basset, and K. Munasinghe, "An on-chain analysis-based approach to predict ethereum prices," *IEEE Access*, vol. 9, pp. 167972–167989, 2021, doi: 10.1109/ACCESS.2021.3135620.
- [7] S. Nanayakkara, A. Wanniarachchi, and D. Vidanagama, "Adaptive stock market portfolio management and stock prices prediction platform for Colombo stock exchange of sri Lanka," in *Proc. 5th SLAAI Int. Conf. Artif. Intell. (SLAAI-ICAI)*, Dec. 2021, pp. 1–6, doi: 10.1109/SLAAIICAI54477.2021.9664735.
- [8] Preeti, R. Bala, and R. P. Singh, "Financial and non-stationary time series forecasting using LSTM recurrent neural network for short and long horizon," in *Proc. 10th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Jul. 2019, pp. 1–7, doi: 10.1109/ICCCNT45670.2019.8944624.
- [9] S. Nakamoto. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. [Online]. Available: <https://www.debr.io/article/21260.pdf>
- [10] M. Nofer, P. Gomber, O. Hinz, and D. Schiereck, "Blockchain," *Bus. Inf. Syst. Eng.*, vol. 59, no. 3, pp. 183–187, Mar. 2017, doi: 10.1007/s12599- 017-0467-3.