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DEVELOPMENT OF STRATEGY FOR ETHEREUM PRICE ANALYSIS USING DEEP LEARNING BASED ON TIME SERIES DATA

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Abstract
The economic era is changing quickly throughout the world. Looking at the history of the currencies, from the barter system to Bitcoin and now to Ethereum, the core aim is to predict the cost. Ethereum differs from Bitcoin in many aspects, like hashing algorithms and the execution time of blocks. However, as Ethereum is a programmable code taking part in transactions considering smart contracts, it is necessary to predict the Ethereum prize based on historical and live data. Hence, this paper presents the proposed algorithm 'DeepCoinCap,' which can compare the various datasets using deep learning training and validation of time-series datasets. The core aim is to identify the Ethereum price trends and correlated elements which impact the future cost. The aspects like social situations, economic changes, and geographical conditions can affect the Ethereum price trends, which need to be validated.
Keywords: Block chain, deep learning, machine learning, price prediction, Ethereum

1. Introduction

The Ethereum blockchain produces a vital volume of data anticipated to its inbuilt visibility and decentralized characteristics. It is likewise alluded to as on-chain data and is freely reachable globally. Furthermore, the on-chain data is time-stamped, bundled, and authenticated into an open ledger. This essential blockchain characteristic allows us to evaluate the network's fitness and utilization. It provides a substantial data warehouse for cutting-edge auguration algorithms that can successfully discover systemic developments and predict upcoming patterns [1]. Unlike Bitcoin, the Ethereum program targets Smart Contracts to assist financial trades and release distributed functions. Smart contracts are independent system programs that provide predetermined logic in cases where they are induced. Ethereum, hence, gives more versatility to its end users and can accomplish much more detailed results and accomplish various Bitcoin gaps. Irrespective of the rising interest and acceptance of Ethereum, merely a few works look into the dynamic of costs and possible time in its environment. However, most of this analysis has been done in Bitcoin [2].

The breakthrough of the blockchain concept gives new circumstances for exchange data mining. Generally, a blockchain is a distributed ledger of transactions or information recorded chronologically or continuously. Due to its decentralized, traceable, immutable, and apparent nature (in most cases), blockchain is considered essential in the 'trust economy' of the foreseeable future [3]. Analysts from different scientific specialties have substantially analyzed the elements that impact cryptocurrency cost and have leveraged approaches from statistics, machine, and deep learning to forecast it with substantial precision. Nevertheless, most models function as a black box without looking at the impact of every characteristic on the prediction precision [4]. Ethereum is intensely employed for decentralized trading exchanges of crypto tokens. These crypto stablecoins are fulfilled as liquid systems of accounts for exchanging crypto tokens and financing and making interest on crypto tokens. This practice acts as a liquidity/borrowing resource for investors of crypto tokens. On a smaller level, it is also utilized for gamified approaches to generate or trade different crypto tokens [5].

Blockchain technology is a growing discipline critical in nearly every utility area involving education, finance, and health care. Many health issues occur in health care because of the carelessness of appropriate analysis by the health care provider and lack of knowledge of the indication by individuals. The most prevalent disease currently is known as a tumor. A tumor is a kind of disease commonly not heading to be discovered by the sufferer at its initial stage. At the initial level, it produces headaches, which is typical, although as the period of time rises, it produces significant damage to the brain [6]. Cancer is among the most vital causes of death globally, counting for thousands of deaths every year. The death rate of cancer is becoming more prominent. Through the last three decades, deep neural networks have been essential in cancer studies [7].

2. Literature Review

In time series research, the intent is to approximate the probable prospect value with the support of the earlier data. On the other hand, Machine learning methods are also viewed as an enhanced option used to forecast and categorize based on the precision of the time series issue. The presented strategies for time series forecasting are Moving Average, Auto Regression, Autoregressive, Artificial Neural Network (ANN), etc. The author recommended unique Deep Learning models: Multi-Layer Perception (MLP) and Long Short-Term Memory (LSTM) are applied, and the activities are evaluated for the Ethereum price prediction [8].

The author (s) targeted the challenges of the interim forecasting cryptocurrency time series by applying a machine learning (ML) strategy. Focus on understanding the economic time series enables examining the methodological concepts, incorporating the positive aspects and drawbacks of employing ML algorithms. The 90-day time measure of the dynamics of the most capitalized cryptocurrencies was predicted by applying the Binary Autoregressive Tree model, Neural Networks, and an ensemble of Classification and Regression Tree models Random Forest (RF). The benefit of the formulated models is that their application does not enforce rigid limitations on the statistical characteristics of the analyzed cryptocurrencies' time series, with only the previous values of the target variable being employed as predictors [9].

The author applied effective deep learning-based auguration models, pervasive short-term memory (LSTM), and gated recurrent unit (GRU) to manage the price volatility of Bitcoin and so to get high accuracy. This research entails evaluating all these time series techniques and proving their effectiveness in predicting the price of Bitcoin [10]. According to the author(s), cryptocurrency may count not only on historical prices, sentiments, and global stock indices but also on the prices and predicted rates of other cryptocurrencies. C2P2 consequently does not forecast cryptocurrency rates one coin at a time; alternatively, it incorporates likeness metrics in association with collective category to evaluate diverse cryptocurrency aspects to collectively predict the cryptocurrency prices for all 21 coins taken into consideration [11].

A new hybrid forecasting framework has been recommended by the author(s) in digital currency time series to reduce this adverse circumstance and boost forecasting accomplishment. In this research, a new hybrid forecasting model structured on long short-term memory (LSTM) neural network and empirical wavelet transform (EWT) decomposition along with a cuckoo search (CS) algorithm is formulated for digital currency time series [12]. In this paper, the author analyzed and investigated numerous cutting-edge deep learning strategies, just as a deep neural network (DNN), a long short-term memory (LSTM) model, a convolutional neural network, a deep residual network, and their permutations for Bitcoin price prediction. An ordinary earnings analysis demonstrated that classification models were more competent than regression models for algorithmic trading. Overall, the performances of the proposed deep learning-based auguration models were equivalent [13]. In this paper, the author(s) analyzed Twitter signals as a medium for customer sentiment to forecast the price variances of a small-cap option cryptocurrency called ZClassic. According to the author(s), this model is the first instructional proof of strategy that social media systems such as Twitter can serve as effective social signals for forecasting price activities in the extremely risky option cryptocurrency, or "alt-coin," market. [14].

3. Research Methodology

The price prediction of virtual currencies in the monetary sector is of tremendous importance, explicitly following the worldwide financial downturn. Because of the nonlinear characteristics that incorporate the fractality of the virtual currencies, it is comprehended from the analysis carried out by various experts that a solitary model is not adequate in predicting the virtual currencies with significantly superior precision. Data was collected from the coin market repositories. The data set file is in the (CSV) file format. Models were compared on daily, hourly, and minute basis data. Daily data consist of 400 high-price data samples. Daily data collected from April 2020 to April 2021 contain open, closed, high-low prices, and per day.

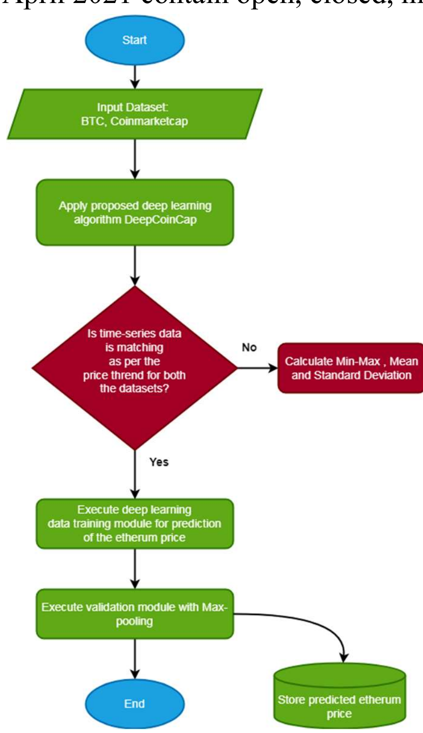

Fig.1: Proposed Methodology

Neural networks can be integrated for price augmentation challenges due to a few unique attributes. Neural Networks tend to be a self-adjusting version structured on training statistics, and they feature the ability to maintain the issues with merely a minimal understanding regarding its pattern and without any compulsion to the auguration model with the extension of any surplus presumption. The proposed algorithm steps are shown below for predicting Ethereum price based on daily and hourly data using time series data training and validation.

Proposed DeepCoinCap Algorithm:

1. Input: BTC dataset, Coinmarketcap dataset
2. String currentPrice, perHourPrice, futurePrice
3. array CP[]
4. array PH[]
5. array FP[]
6. getCP()
7. if (currentPrice!=null)
8. get perHP()
9. update CP[] //current price of Ethereum will be stored
10. go to step-6
11. else
12. update PH[]
13. readCSV(BTC)
14. runTraining(BTC) //training of BTC data will be executed using deep learning framework
15. runValidation(BTC) // validation of BTC data will be executed using deep learning framework
16. runTraining(Coinmarketcap) //training of Coinmarketcap data will be executed using deep learning framework
17. runValidation(Coinmarketcap) //validation of Coinmarketcap data will be executed using deep learning framework
18. Compare both training and validation results for both datasets
19. DrawBTCTrend() //deep learning module for BTC chart representation
20. DrawCoinmarketcapTrend() //deep learning module for Coinmarketcap chart representation
21. getMinPrice()
22. getMaxPrice()
23. getStandardDev()
24. displayForcastPrice()
25. End

Forecasting upcoming occurrences is centered on previous data in many pattern identification difficulties. Due to the substantial unpredictability of cryptocurrency, ANN has been deemed a valuable approach for this kind of issue. Additionally, Neural Networks have generalization potential, which indicates that after training, they can determine the unique structures even if they do not have any training data set.

4. Result and Analysis

As per the previously discussed algorithm and proposed methodology framework, the historical data is shown in Table 1, and the statistical analysis for the time series data set is presented in Table 2.

Table 1: Historical Ethereum Data (Source: Coinmarkaetcap)

Date	Open*	High	Low	Close**	Volume	Market Cap
Apr 01, 2021	$1,919.16	$1,989.06	$1,912.18	$1,977.28	$30,914,259,795	$227,970,125,751
Mar 31, 2021	$1,846.10	$1,947.84	$1,793.00	$1,918.36	$30,226,902,621	$221,151,811,159
Mar 30, 2021	$1,819.47	$1,860.97	$1,793.92	$1,846.03	$22,512,781,703	$212,788,788,571
Mar 29, 2021	$1,691.26	$1,837.19	$1,683.72	$1,819.68	$22,796,570,548	$209,726,738,382
Mar 28, 2021	$1,716.41	$1,728.58	$1,672.66	$1,691.36	$16,599,472,938	$194,913,443,083
Mar 27, 2021	$1,703.04	$1,732.82	$1,674.32	$1,716.49	$18,102,277,710	$197,787,142,643
Mar 26, 2021	$1,595.21	$1,702.92	$1,594.74	$1,702.84	$22,548,516,548	$196,191,139,867

The price trend for period April 2020 to April 2021 is shown in following Fig.2.

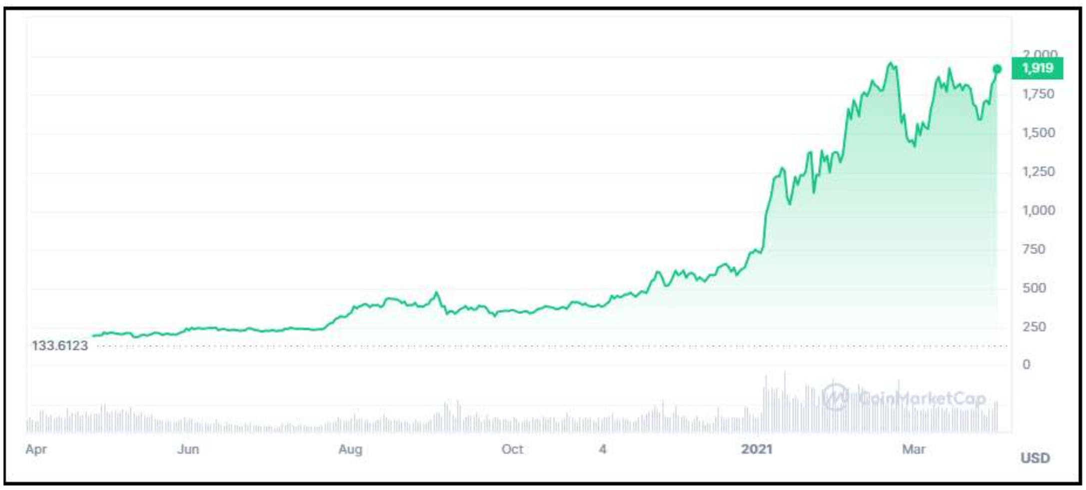

Fig. 2: One year analysis of Ethereum (Source: Coinmarkaetcap)

The proposed algorithm is executed for both datasets, and the min-max, mean, and standard deviation are calculated.

Table 2 Statistical result for Ethereum data sampling

Dataset	Samples	Entries	Min	Max	Mean	Std. Dev.
BTC	All samples	1647	0.20	3542	2541	467
	Training	916	0.20	2867	548	263
	Validation	731	0.2518	3542	1974	644
Coinmarketcap	All samples	2856	0.10	4857	1622	509
	Training	1276	0.10	3411	1543	465
	Validation	1580	0.1609	4857	697	446

From the analysis, it is identified that the prediction of the price of Ethereum is not stable hour-to-hour but can be predicted for a monthly time frame. The covid-19 pandemic pushed the Ethereum price high subsequent incidence-based prediction can be forecasted.

5. Conclusion

As per the discussed existing deep learning, machine learning literature, and historical data analysis for Ethereum price, the proposed algorithm can be helpful for long-time frame forecasting. The proposed methodology can provide the optimum precision for Ethereum price prediction using incidence logging. The proposed research can be used as a base for live data run using a deep learning model, which can be used for a continuous run of datasets. Future studies can be done for fraud detection where scrips can be secured using new methods.

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