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Research article

Prediction of bitcoin stock price using feature subset optimization

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ABSTRACT

In light of recent cryptocurrency value fluctuations, Bitcoin is gradually gaining recognition as an investment vehicle. Given the market's inherent volatility, accurate forecasting becomes crucial for making informed investment decisions. Notably, previous research has utilized machine learning methods to enhance the accuracy of Bitcoin price predictions. However, few studies have explored the potential of employing diverse modeling methods for sampling with varying data formats and dimensional characteristics. This study aims to identify the internal feature subset that yields the highest returns in forecasting Bitcoin's price. Specifically, Bitcoin's internal features were categorized into four groups: currency data, block details, mining information, and network difficulty. Subsequently, a long short-term memory (LSTM) artificial neural network was employed to predict the next day's Bitcoin closing price, utilizing various categorizations of feature subsets. The model underwent training using two and a half years of historical data for each feature. The findings revealed a mean absolute error rate of 6.38% when modeling with the block details category features. This enhanced performance primarily stemmed from the positive relationship between Bitcoin price and this data subset's low ambiguity. Experimental results underscored that, compared to other investigated feature subsets, the categorization of block detail features provided the most accurate Bitcoin price predictions, laying the foundation for future research in this domain.

1. Introduction

Forecasting the price of Bitcoin, whether directly or via statistical models, is generally prone to substantial errors due to the non-linear and non-stationary nature of high-frequency Bitcoin price series. In response to two key research questions, heated discussions have emerged: What precisely makes Bitcoin valuable? What factors influence Bitcoin's value? Interestingly, the value of Bitcoin represents investors' faith in cryptocurrencies regarding financial innovation [1]. Consequently, numerous studies have focused on the factors influencing or shaping Bitcion's price. Moreover, the price fluctuations resulting from Bitcoin's inherent volatility have been a cause for concern among investors since the currency's inception. Predicting Bitcoin price changes is of paramount importance. Meanwhile, stock market forecasting has gained prominence over the past few decades due to the availability of daily and high-frequency data [2]. However, there has been limited research on forecasting the price of Bitcoin. Previous studies employed two methods to predict Bitcoin prices: empirical analysis and evaluation of potent machine-learning algorithms. Specifically, machine learning algorithms have found widespread use in various sectors such as manufacturing [3–6] and finance [7,8]. These algorithms and

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models, generating predictions based on training data, can be developed by analyzing the details of past events. Given that T+0 trading rules enhance liquidity and volatility, similar algorithms may be developed for the Bitcoin market and potentially the entire financial landscape.

Bitcoin, a peer-to-peer digital currency [9], operates on a network of peers. Bitcoin enables secure and transparent transactions without relying on traditional legal entities [10]. Moreover, it operates on a highly secure system, as all transactions are public and validated by network nodes [11]. In April 2021, Bitcoin reached an all-time high, closing at $63,503.46, marking a gain of almost 927% in a single year [12]. The anonymity of Bitcoin, coupled with its rapid increase in a short period, presents opportunities for investors, leading to the prominence of Bitcoin price prediction [13].

Furthermore, developing a method for accurately predicting Bitcoin prices using machine learning algorithms is imperative. Since Bitcoin exhibits no seasonality, machine-learning models remain relevant and valuable. Interestingly, various essential machine learning methods, such as recurrent neural networks (RNNs), long short-term memory (LSTM), support vector machines (SVM), and random forest (RF) models, have been employed in previous studies. However, past research often involved indiscriminate data insertion into models, disregarding data frequency or sample size. Moreover, different frequency data sets exhibit distinct structures, and consequently, unthinkingly applying machine learning methods may result in errors like overfitting.

Meanwhile, the features fed into a neural network constrain its accuracy [10]. Therefore, model accuracy is enhanced by selecting an optimal subset of input characteristics, as superfluous input information may introduce noise into the system [10]. Due to Bitcoin's volatility, determining which features to use during prediction poses a challenge. Furthermore, Bitcoin's value is not influenced by a company's performance in the same way as other stock values; thus, the prediction approach must differ [11,14]. Hence, this study aims to gain insights into identifying which internal Bitcoin features should be utilized to forecast Bitcoin values.

Precisely, the characteristics of Bitcoin are divided into four categories: currency data, block details, mining information, and network difficulty, as shown in Fig. 1. Understanding the connection between the identified features and the daily closing price could be useful for future research [11]. In this study, an LSTM neural network is used to predict the closing price of Bitcoin the next day. Specifically, the model is trained using feature subsets, and the resulting prediction accuracy is compared. This research makes a major contribution by developing a novel predictive modeling technique for time series forecasting, combining optimization and recursion frameworks in a granular setting.

The subsequent sections of this article are structured as follows: Section IIdelves into diverse methods for forecasting Bitcoin prices and the inherent challenges, encompassing the analysis of crucial statistical elements in Bitcoin pricing. Section III explores various approaches to predicting the price of Bitcoin and other cryptocurrencies. Section IV presents a concise overview of data collection and prepossessing methodologies. Moving forward, Section V details the methodology, succeeded by Section VI, which provides a comprehensive analysis of the results obtained from the proposed model. Finally, Section VII presents the concluding remarks.

2. Literature review

Introduced in 2009 by Satoshi Nakamoto, Bitcoins have ascended to prominence in the peer-to-peer currency market [15]. Moreover, They have garnered widespread popularity and curiosity, with experts projecting that the number of Bitcoin users will reach 200 million by 2024. Specifically, the younger demographic is well-acquainted with innovative digital formats, leading to increased adoption. This burgeoning segment engages in online marketplaces to purchase Bitcoins, exchange them for fiat currency, or utilize them for various transactions [16]. These transactions differ substantially from conventional fiat money transactions, rooted in the concept of money. Notably, Bitcoins are mined, not produced, leveraging the globally dispersed computational power of the blockchain.

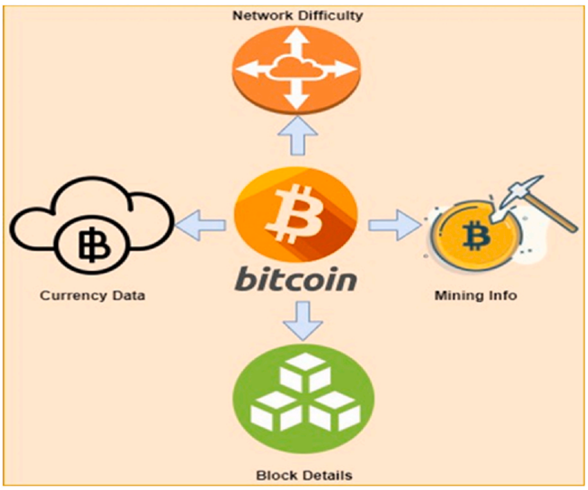

Fig. 1. Characteristics of bitcoin.

Validation of Bitcoin transactions occurs through intricate algorithms and is stored on miners' computers worldwide. Satoshi devised these algorithms to enable direct Bitcoin ownership transfer between users through minner-verified transactions, permanently recorded in the blockchain ledger. Importantly, these transactions are trustless, eliminating the need for a trusted third party, a characteristic absent in conventional banking systems [17].

Interestingly, the concept of time series prediction is not new. Forecasting time series data holds significance in economics, business, and finance. Traditional techniques encompass univariate autoregressive (AR), univariate moving average (MA), simple exponential smoothing (SES), and, notably, autoregressive integrated moving average (ARIMA) and its variations [18]. This method is particularly effective for problems with seasonal influences, such as sales forecasting. However, as computer power has increased and complex machine learning algorithms like deep learning have emerged, new time series data forecasting methods are being developed. Given the Bitcoin market's lack of seasonality and high volatility, these evolving methods may prove more suitable for this unique context.

Meanwhile, RNN and LSTM artificial neural network designs are favored over the traditional multilayer perceptron (MLP) architecture due to the temporal nature of more complex algorithms [19]. For instance, a comparison between the ARIMA time series model and the LSTM deep learning algorithm was conducted [20] to predict the future price of Bitcoin. Specifically, ARIMA yielded a mean absolute percentage error (MAPE) of approximately 11.86%, while LSTM achieved a MAPE of approximately 1.40%. Although artificial neural network prediction can approximate the actual log return distribution, more sophisticated approaches such as RNNs and LSTM techniques may be necessary for improved forecast accuracy [21]. Consequently, this study aims to provide a framework for forecasting Bitcoin prices using LSTM.

Various methods, including machine learning algorithms, have been employed to forecast Bitcoin prices. For example, the study in Ref. [9] predicted the Bitcoin price for the next 100 days using a three-layer LSTM neural network and real-time data. Specifically, with a limited feature set of price data, a mean absolute error rate of less than 0.5 was achieved. Another group of researchers [11] constructed ARIMA and LSTM models for real-time Bitcoin price predictions, incorporating public sentiment analysis on extracted Twitter and Reddit postings. The study found that using the LSTM model with multiple features, as opposed to a single feature or an ARIMA model, reduced the error rate [11].

Moreover, Edwin et al. [10] analyzed historical feature data using a genetic algorithm-based selective neural network ensemble (GASEN) and achieved an accuracy of approximately 58% with 200 Bitcoin features. In another study [22], a deep neural network, LSTM model, convolutional neural network, and deep residual network were utilized to forecast Bitcoin prices. According to the experimental data, LSTM slightly outperformed other models. Saad et al. [23] discovered important network characteristics through a correlation study of Bitcoin and Ethereum market prices relative to other cryptocurrency measures. These characteristics were utilized to train machine learning models, accurately predicting Bitcoin price 99% of the time. In several similar studies on Bitcoin price prediction, the LSTM model consistently outperformed alternative models, with references [9,23], and [10] serving as inspiration for this research. The current research builds upon the proposal reported in Ref. [10], training an LSTM model with various internal feature subsets to identify the optimum subset of input characteristics for the best prediction.

3. Bitcoin price prediction methods and cryptocurrencies

3.1. Bitcoin price prediction methods

Thus far, there has been limited research on estimating or predicting Bitcoin prices.

3.1.1. Traditional prediction approaches

i. Shah et al. [24] employed Bayesian regression to predict Bitcoin prices, developing a latent source model. Their model yielded a remarkable 89% return in 50 days with a Sharpe ratio 4.1 [25].
ii. In 2015, Pavel Ciaian et al. [26] utilized a linear model to investigate Bitcoin price formation, considering crucial information categorized into market dynamics, investor attractiveness, and global macroeconomic factors. They highlighted that the first two factors substantially impact Bitcoin price, albeit varying over time. The authors limited the number of regressors in the linear models to streamline analysis.
iii. Greaves et al. [27] employed SVM and ANN to forecast Bitcoin prices on the Bitcoin blockchain. The study reported that a conventional ANN achieved a 55% accuracy in forecasting price direction.
iv. Kim et al. [28] predicted Bitcoin price fluctuations by analyzing sentiment in online Bitcoin forums.
v. Hegazy and Mumford [29] used the first five left derivatives of Bitcoin prices as features in a decision-tree-based algorithm. This generated an exponentially smooth Bitcoin price every 8 min and predicted the direction of the next bitcoin price movement with 57.11% accuracy.
vi. A previously published study [30] proposed a non-linear autoregressive with exogenous inputs (NARX) bitcoin price forecasting model based on the multi-layer perceptron (MLP).

3.1.2. Prediction based on LSTM

The model demonstrated the capability to forecast Bitcoin values accurately and successfully passed all validation tests. Subsequent publications have employed LSTM in the following instances:

i. Experiments were conducted to assess various statistical and machine learning methods for forecasting near-term Bitcoin market exchange rate changes, measured in terms of volatility [31].
ii. Prior research predicted Bitcoin pricing mechanisms using machine learning techniques such as RNNs and LSTM networks, comparing the results to those obtained using ARIMA models.
iii. Karakoyun et al. [32] compared the ARIMA time series model to the LSTM deep learning technique for Bitcoin price prediction. The study found a MAPE of approximately 11.86% with ARIMA and 1.40% with LSTM.
iv. Since LSTM is still in its early stages, its current inability to predict Bitcoin values necessitates the development of a framework for predicting Bitcoin prices using LSTM.

3.2. Cryptocurrencies

Cryptocurrencies represent novel economic and financial instruments with distinct characteristics. Notably, they are independent assets, not issued by any government or central body, and do not generate interest or dividends. The intriguing aspect is the increasing consumer interest and acceptance by businesses, particularly online merchants, contributing to the expanding market share of Bitcoin [33]. Given Bitcoin's unique features and high volatility, it poses a fascinating subject for exploration, questioning its classification as either a commodity or money and assessing the functionality of the Bitcoin market.

Baur et al. [34] investigated whether Bitcoin qualifies as an asset or a form of money. They analyzed its current usage and speculated on its future dominance, considering its distinctive features. If Bitcoin predominantly serves as a medium for trading goods and services, it could encounter competition with established currencies like the US dollar, influencing its value and potentially impacting monetary policy. Conversely, if it is primarily adopted for investment purposes, it competes with other traditional assets, such as government bonds, equities, and commodities, influencing the broader financial system and stability. Whether categorized as money or assets, the potential impact of Bitcoin or other alternatives to conventional monetary and financial assets on the broader economy hinges on their performance. The subsequent findings shed light on this exploration.

i. According to the conceptual framework of the International Accounting Standards Board (IASB), an asset is "a current economic resource that the business possesses as a consequence of past events." It further clarifies that "an economic resource is a legal right that includes the possibility of financial gain." Entities are required to assess whether any Bitcoin they own qualifies as an asset.
ii. Approximately 70% of all Bitions are reported to be held in dormant accounts, as indicated by Ref. [35]. This statistic indicates that most individuals perceive Bitcoin as a valuable asset.
iii. Bitcoin shares many similarities with gold, as both lack a monopoly on supply from governments and other organizations, contributing to their decentralized nature and intended operation as global currencies.
iv. Bitcoin and gold derive value from scarcity and high mining costs, lacking inherent monetary flow. Despite these similarities, Dyhrberg [36] concludes that Bitcoin is a hybrid of assets and currency due to certain features it shares with fiat money.

To prevent the exploitation of cryptocurrencies by speculators or investors and to maintain fair competition and market opportunities, it is crucial to comprehend how Bitcoins function under effective market theory. The following findings outline key insights from the study:

i. Jakub [33] discovered that the Bitcoin market was slightly efficient, with prices responding promptly to new information.
ii. Wu et al. [37] employed statistical methods to analyze Bitcoin data and found that Bitcoin returns exhibited inefficiency.
iii. A group of researchers [38] demonstrated that the market efficiency assumptions underlying the Bitcoin and Litecoin markets were inconsistent with weak efficiency, as the unit root test revealed stagnation in the Bitcoin model.
iv. Previous research has produced contradictory results, and there are indications that the Bitcoin market may be inefficient [39, 40].

The widespread volatility of Bitcoin has been extensively reported [32,41], as outlined below:

i. Katsiampa and Paraskevi [42] utilized econometric methods, specifically the GARCH model, to estimate Bitcoin volatility.
ii. A sentiment analysis based on user ratings was employed to predict Bitcoin volatility [28].
iii. Wavelet coherence analysis was conducted to examine the primary drivers of Bitcoin price, including Chinese demand [43].
iv. A recent study investigated the predictability of Bitcoin returns and volatility using transaction volume. The study found volume was a significant predictor variable in the quantile range of 0.25–0.75, excluding extreme events [44].

4. Data collection and preprocessing

During the training of the proposed model, the dataset was generated by combining features from finance.yahoo.com, a website that enables users to download historical stock price data, and blockchain.com also data is available at https://www.kaggle.com/datasets/mczielinski/bitcoin-historical-data/data. This cryptocurrency wallet monitors and categorizes crucial internal Bitcoin characteristics. The choice of blockchain.com was deliberate due to its comprehensive maintenance and categorization of diverse Bitcoin features, amounting to 31 unique characteristics. The dataset from blockchain.com underwent preprocessed, excluding only one feature that contained empty sets. While blockchain.com exclusively tracked the average Bitcoin market price, finance.yahoo.com contributed pricing data encompassing daily, closing, and total trading volume. Specifically, six price-related features were derived, with the adjusted closing price excluded from the feature set. The exclusion was based on its consideration of company movements like dividends, which are irrelevant to Bitcoin. Consequently, the adjusted price, always identical to the closing price, was removed to eliminate potential confusion [45].

5. Methodology

Utilizing various classified feature subsets, an LSTM was employed to forecast the Bitcoin closing price for the following day. Specifically, the model underwent training for each feature, incorporating 2.5 years of historical data. During the modeling phase with the block details category features, a mean absolute error rate of 6.38% was identified. This enhanced performance was attributable to the positive correlation between the features and the Bitcoin price and the low ambiguity within the data subset. Moreover, the experimental findings highlighted that, compared to the other examined feature subsets, the classified block detail characteristics of Bitcoin made the most substantial contribution to accurate price prediction. These results provide a solid foundation for future research in this domain.

5.1. LSTM networks

RNNs serve as information-retaining-retaining networks, particularly beneficial for tasks involving sequences such as speech recognition and music production. However, RNNs face a challenge of limited short-term memory, known as the vanishing gradient problem. This issue arises when sequences become lengthy, making it difficult to transfer information from earlier to later time steps. This study explores potential solutions to the vanishing gradient problem, focusing on the gated recurrent unit (GRU) and LSTM networks.

LSTM networks, a subset of RNNs, are specifically designed to remember and predict data by capturing long-term dependencies inherent in time series data. The LSTM repeating module comprises four interconnected components, as depicted in Fig. 2 [46]. In a more detailed explanation, the LSTM is trained by modifying parameters using a window of previous data as input, aiming to minimize the difference between predicted and measured values in subsequent steps. Sequential algorithms based on preceding data frames predict a single subsequent value. In the presence of contextual data, CNNs played a crucial role in enhancing performance while demanding less training and resource deployment. This improvement was observed both before and after the goal prediction point.

5.2. Determination of time series integration

To determine the order of integration for each time series, three unit root tests were employed: the augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979), the Phillips Perron (PP) unit root test (Phillips & Perron, 1988), and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (Kwiatkowski et al., 1992b). For each test, two alternative models were utilized to ensure the robustness of the findings. These tests determined stationarity, indicating that a time series's mean, variance, and covariance remained constant over time. An external shock to a stationary time series gradually fades away, while a shock to a non-stationary or unit root time series is

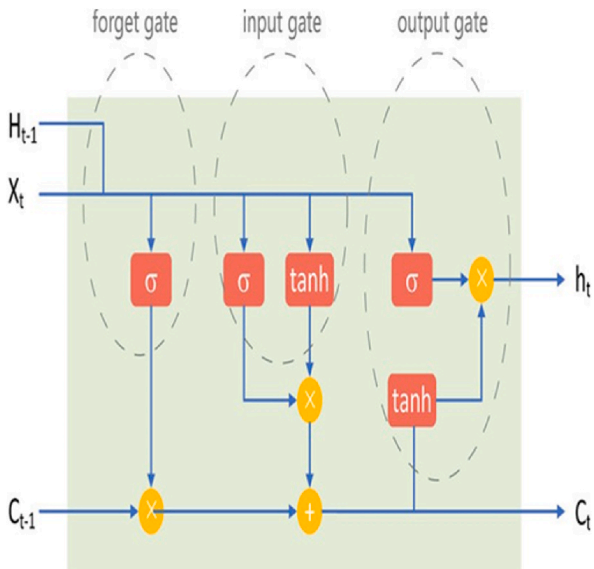

Fig. 2. Basic unit of a repeating LSTM cell.

permanent. This concept implies that when a time series is shocked, the impact does not diminish gradually over subsequent time steps (t + 1; t + 2; t + 3; t + 4; t + 5; t + 6; t + 7; t + 8; t + 9; t + 10; t + 11; t + 12; t + 13; t + 14; t + 15; t + 16; t + 17; t + 18; and t+19). Brooks (2014) identified structured, codified, formalized, expressed, or spurious regression as a significant problem in time series analysis. This occurs when F- and t-statistics appear significant, indicating a connection between time series even when none exists in reality (Granger & Newbold, 1974). To avoid false regressions and obtain relevant findings, screening for potential unit roots is crucial before initiating a time series analysis (Harris & Sollis 2003). Unit root tests, including ADF, PP, and KPSS, were employed to investigate the presence of unit roots, both with and without a linear time trend (constant only). These tests verify findings, with the first two (ADF and PP) testing for the unit root and the third (KPSS) testing for stationarity.

Fig. 3 illustrates the co-movements of cryptocurrencies from November 2020 to July 2021. The y-axis represents the predicted values of cryptocurrencies, and the x-axis displays the time in months. In February 2021, a vertical line denotes a high-volume prediction rate of 42.894 M using the LSTM module. The graph reveals that the prices of each cryptocurrency dropped after the announcement but quickly rebounded to their previous values. The unit root test, conducted using the ADF method, analyzed the original Bitcoin close price sequence data. The results did not support the null hypothesis, indicating that the Bitcoin close price sequence was non-stationary with unit roots (t-statistic: −2.209; p-value: 0.204). Consequently, the ADF test was employed to evaluate the data concerning the Bitcoin price difference (Fig. 4). The test results rejected the null hypothesis that the Bitcoin price difference was random, affirming the data's stationary (t-statistic: 14.999; p-value: 0.000**** at the 1% level of significance), as depicted in Figs. 5 and 6.

6. Results

The performance of the proposed technique was assessed using the original Bitcoin price series and an 8-month (November 2020 to July 2021) surrogate time series created randomly from the original data through the Monte Carlo method. Notably, the surrogate series exhibited more unpredictability and chaos. This evaluation using surrogate series was crucial to establish the robustness and efficacy of the proposed forecasting technique, with the parameter settings maintained consistently in both cases.

The model comprised three layers and a linear activation function, following the recommendation in Refs. [47,48], proving to be the optimal configuration considering all characteristics. A 0.2-layer dropout in the model accompanied each LSTM layer to prevent overfitting by reducing sensitivity to specific neuron weights [37]. The adaptive moment estimation (Adam) optimizer was employed with the mean squared error (MSE) loss function.

The number of epochs was limited to 50 to manage computational costs, and the batch size was set to 10. The model was tested for each feature category set, with the number of nodes set to 32 and 64 and the look-back value set at 30 and 60 days. The look-back value represents the number of previous days' worth of features used to predict the following day's Bitcoin price [49].

Additionally, evaluating the model's performance without data is crucial, especially when relying on historical predictions to anticipate future results. This assessment is necessary for applications like model predictive control, where the model is projected forward over the control horizon to determine the optimal sequence of controlled variable movements and potential future constraint violation, thus highlighting the importance of forecasting without relying on measurement data.

During our research sample period, the Bitcoin price exhibited characteristics of a non-stationary time series, and the difference sequence failed to identify a specific type. Consequently, the appropriate ARIMA model was not applicable. We introduced an innovative forecasting framework centered around the LSTM model in response to these challenges. This framework aimed to predict the daily price of Bitcoin by combining two distinct LSTM models.

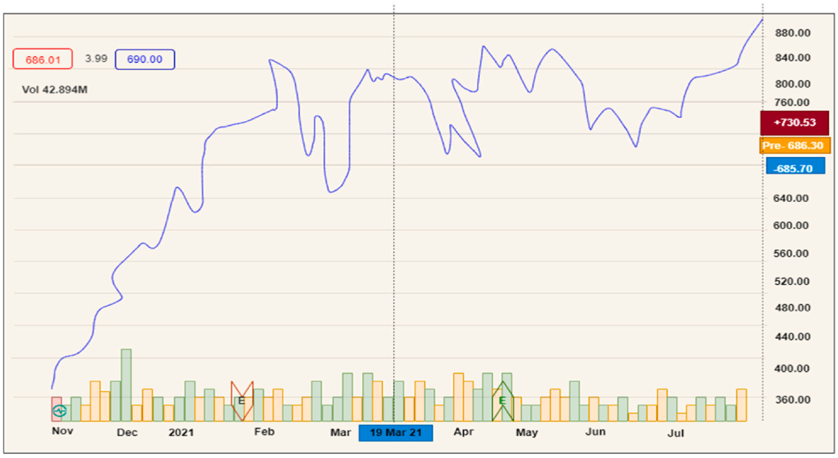

Fig. 3. Actual and predicted bitcoin price visualization.

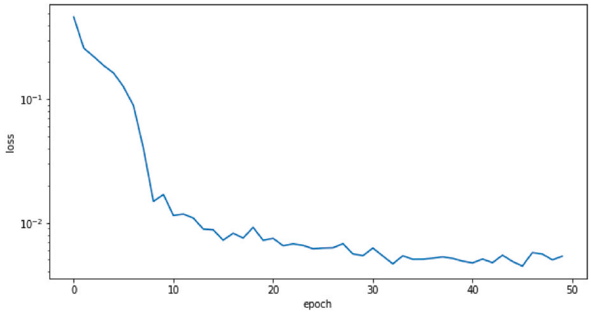

Fig. 4. Basic unit loss with training samples.

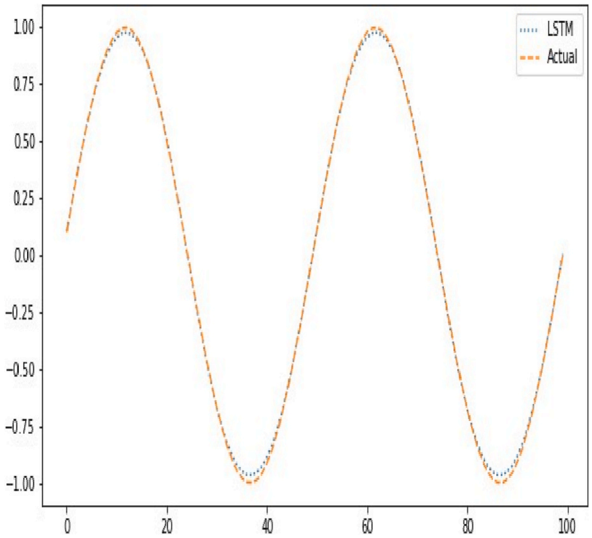

Fig. 5. Comparative analysis of repeating LSTM cell predictions.

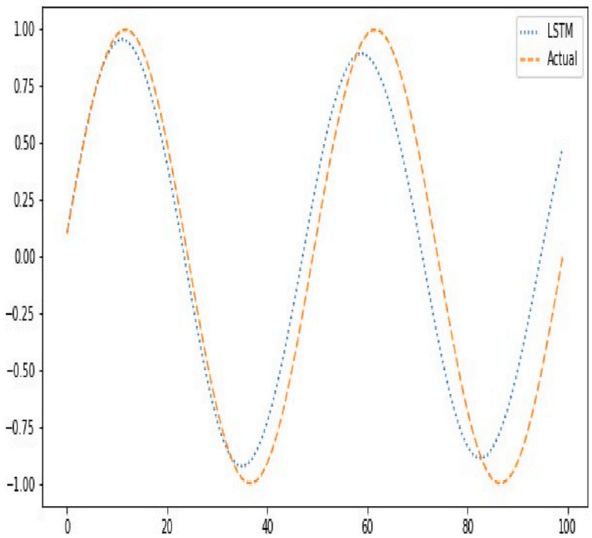

Fig. 6. Test Price Prediction using LSTM.

7. Conclusion and future work

Bitcoin is widely acknowledged for its diversification benefits, offering potential stability to investors during challenging periods. The distinctive characteristics of Bitcoin make it conducive to accurately assessing its volatility over both short and long durations. The proposed design proves highly effective, contributing to the precise prediction of Bitcoin's future prices and aiding investors in risk reduction. The demonstrated efficacy of the indicated framework on the surrogate series highlights its potential to yield substantial returns even in crisis scenarios. This study aims to analyze the predictability of the cryptocurrency with the largest market capitalization. The proposed method can serve as a tool for evaluating the predictability and effectiveness of various cryptocurrencies, contributing to a broader understanding of market behavior. This research opens avenues for developing new forecasting frameworks by incorporating relevant alternative components.

Data availability statement

The raw data required to reproduce the above findings is available to download from [https://www.kaggle.com/code/someadityamandal/bitcoin-time-series-forecasting/input?select=bitstampUSD_1-min_data_2012-01-01_to_2018-11-11.csv].

CRediT authorship contribution statement

Saurabh Singh: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing. **Anil Pise:** Conceptualization, Data curation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Byungun Yoon:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Byungun Yoon reports financial support was provided by Dongguk University. Byungun Yoon reports a relationship with National Research Foundation of Korea that includes: funding grants.

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