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Forecasting returns volatility of cryptocurrency by applying various deep learning algorithms

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Abstract

The study aims at forecasting the return volatility of the cryptocurrencies using several machine learning algorithms, like neural network autoregressive (NNETAR), cubic smoothing spline (CSS), and group method of data handling neural network (GMDH-NN) algorithm. The data used in this study is spanning from April 14, 2017, to October 30, 2020, covering 1296 observations. We predict the volatility of four cryptocurrencies, namely Bitcoin, Ethereum, XRP, and Tether, and compare their predictive power in terms of forecasting accuracy. The predictive capabilities of CSS, NNETAR, and GMDH-NN are compared and evaluated by mean absolute error (MAE) and root-mean-square error (RMSE). Regarding the return volatility of Bitcoin and XRP markets, the forecasted results remarkably suggest that in contrast to rival approaches, the CSS can be an effective model to boost the predicting accuracy in the sense that it has the lowest forecast errors. Considering the Ethereum markets' volatility, the MAE and RMSE associated with NNETAR are smaller than the MAE and RMSE of CSS and GMDH-NN algorithm, which ensures the effectiveness of NNETAR as compared to competing approaches. Similarly, in case of Tether markets' volatility, the corresponding MAE and RMSE reveal that the GMDH-NN algorithm is an efficient technique to enhance the forecasting performance. We notice that no single tool performed uniformly for all cryptocurrency markets. The policymakers can adopt the model for forecasting cryptocurrency volatility accordingly.

Keywords Cryptocurrency, Cubic smoothing spline, Machine learning, Nonlinear models, Forecasting

Introduction

The financial markets have introduced many new technologies over time, but the majority of these have not survived or succeeded over time. But the emergence of cryptocurrencies has got the attention of many researchers across the globe, and some of the researchers have expected that these digital currencies would have a disruptive impact on the financial system [53]. Cryptocurrencies are technologies with unexpected behavior that are difficult to predict in terms of their future adoption in the global financial system [48]. Cryptocurrencies have attracted the interest of many investors, and it has got an alternative form of a coin due to their digital characteristics. The digital attributes have made cryptocurrencies more dynamic than traditional currencies in the case of payments because these are based on cryptographic proof [25].

Furthermore, cryptocurrencies are considered more volatile on account of their digital nature, which is why investors need to be very smart when trading in any kind of cryptocurrency [7]. Since cryptocurrencies were introduced and emerged in the financial markets as a transaction vehicle, enormous researchers and scholars have attempted to explore their behavior. A secured electronic

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cash system is made by cryptocurrencies to give people a facility for the transfer of online payments and does not have any intrinsic value, and the same time, future payments are not certain [15]. Some scholars consider them just speculative assets rather than to be called currencies at all [60]. No legal and regulatory body exists to control cryptocurrency transactions, and this is one of its unique features, which makes cryptocurrencies riskier than other assets. The cryptocurrency market is considered extremely volatile on account of the mentioned features, and based on this, cryptocurrencies have more average volatility than gold or any other set of currencies [18]. Despite its high volatility, few scholars found this market to offer more diversification and present advantages for investors with short investment plans [9, 23]

A very limited number of studies maintain persistency in the cryptocurrencies that can be used as a base for trading strategies that will give abnormal profits [14, 50] Similar studies in this area have been conducted exploring the dynamics of cryptocurrencies, and their empirical evidence shows that their returns are more volatile and exhibit long-memory features. Hence, predicting and estimating the volatility of cryptocurrency markets is very important [6, 56]. Forecasting volatility in finance is a complex task, and capturing the sensitive nature of cryptocurrencies is hard in both finance and economics. There are many types of cryptocurrencies, including 'Bitcoin, Ethereum, Tether, and XRP (Ripple), etc. Bitcoin is a dominant figure and the most famous digital currency which is traded in more than 16,000 markets around the globe [44]. The market capitalization of Bitcoin drastically increased from 101 million US dollars to 79 billion dollars in the years 2016 to 2017. Prediction, especially about the future, is very hard and unexpected, but various performance techniques have made it easier to deal with this challenge. To discuss the same pattern, one of the most important dimensions of analysis has always been the forecasting of the dynamics of technology and its consequences for financial asset markets and their returns. Hence, it is imperative to make the application of such predictions in new developing markets, because of the complex and nonlinear nature of high-frequency financial data, the modeling of prediction systems is a challenging task [1]. Furthermore, cryptocurrency-related machine learning algorithms are viewed as a nascent area and rarely found in academic studies. Although many models of predictions were developed to predict the behavior of different financial systems based on various econometric methods, most of them failed to catch nonlinear patterns in financial data and have shown less accurate results [2]. In recent decades, various time series nonlinear models, such as the threshold autoregressive model [39], the bilinear model [28], and the autoregressive conditionally heteroscedastic model [24], have been developed over the years. However, these nonlinear techniques are still limited due to their clear association with the data series at hand and have to be assumed with a slight knowledge of the underlying law. The application of a nonlinear technique to specific data sets is a more complicated job, since having so many possible nonlinear patterns and a pre-specified nonlinear technique that may not be generalized sufficiently to hold all the significant characteristics.

Neural network algorithms and machine learning techniques are more nonlinear data-driven tools compared to the aforementioned models. These algorithms are proficient in conducting nonlinear estimation without a piece of prior information about the association between independent and dependent variables and are ranked as more flexible modeling tools for prediction [61]. Many famous models are not so powerful to predict the volatility of financial data, like ARIMA, ARCH, and GARCH family models, and VAR models. But machine learning techniques are more powerful in predicting and forecasting complex financial data, and such techniques capture many econometric issues like non-stationarity, nonlinearity, autocorrelation, etc. In current times, machine learning techniques have become famous methods in time series modelling because of their ability to detect complex relationships in non-stationary data and their successful performance in prediction tasks. In high-frequency data of finance, there is a high likelihood of conditional volatility in financial data. In the case of cryptocurrency markets, most of the series is not stationary at levels, and whenever the returns are differentiated, the mean becomes zero but the variance remains non-constant, which causes an arch effect. Since 2017, the growing interest in the cryptocurrency market has brought a huge number of relevant academic research, such as [16, 37].

In addition to the above literature, many ensemble techniques have been developed to further enhance forecasting. Mehta et al. [43] developed a new ensemble approach in order to increase forecasting accuracy by giving different weights to existing techniques. As a result, the novel ensemble method outperformed the previous approaches.

A stacking ensemble can improve performance with fewer training resources, and social media sentiment analysis contributes more to extra-short-term price prediction than to short-term price prediction [59]. Buyrukoğlu and Savaş [13] proposed a new method that is based on the ensemble learning of numerous weak LSTM learners (RQ2). They showed that the new ensemble learning method outperforms the existing methods. Gyamerah [30] performed a study in which the

VMD-GAM model beat the EMD-GAM ensemble model by utilizing three assessment metrics (RMSE, MAPE, and Bias). The developed model will aid market participants and investors in the cryptocurrency market in making sound financial choices. Using cryptomarket data, [11] stated that ensemble LTSM networks are not always better than single-based LSTM networks. Doğru et al. [21] built a novel ensemble technique and imply in the field of medicine. They concluded that in classification of diabetes mellitus, the super learner ensemble model outperforms single base, bagging, and boosting machine learning algorithms. Buyrukoğlu and Savaş [13] followed two-stage application procedure in the field of sports and found that the best accuracy is obtained by combining the Chi-square feature selection technique and the stacked-based ensemble learning model. Similarly, on the basis of prediction accuracy (94.9%) and area under the ROC curve (0.98), Buyrukoğlu [12] showed that the ensemble RF and ANN models gained higher accuracy than all separate and ensemble models, in the field of agriculture. While comparing with the tested regression models using count data, the ensemble models demonstrated more impressive results. In comparison with single-based models, stacked ensemble models provided the most accurate wireless sensor network parameter prediction [10].

One of the first research studies exploring volatility in digital currencies was employed by [34], and it explores cryptocurrency volatility by making comparisons of numerous GARCH models and concludes that AR-CGARCH is the model best estimating bitcoin's volatility. These models are used to compute the volatility of cryptocurrencies. The foremost step of time series data is to check the order of integration of each series or to check the existence of unit-roots. For checking stationarity, a KPSS test is performed, and the reason to apply the KPSS test instead of the ADF test in such a study is due to the hourly nature of the data and its high frequency. For this purpose, applying the KPSS test is an appropriate and suitable choice.

Furthermore, after estimating the volatility of cryptocurrencies, dual machine learning algorithms like GMDH-NN and NNETAR along with traditional approach are to be performed, to forecast the volatility. This work provides an evaluation of the predictive performance of the volatility of four cryptocurrencies' returns using daily frequency data. In this paper, we attempt to examine various relevant objectives. First, to estimate the volatility of cryptocurrency returns, and second, to establish more accurate volatility forecasting of cryptocurrency returns through machine learning techniques, Thirdly, to compare the CSS, GMDH-NN, and NNETAR algorithms in terms of forecasting cryptocurrency returns; fourth, to forecast the direction of cryptocurrency returns in the future; and finally, to examine whether the cryptocurrency market is more volatile or not.

This study seeks to assess the dual research questions:

- Which technique is more robust in terms of forecasting cryptocurrency returns: CSS, GMDH-NN or NNETAR?
- Whether the cryptocurrency market is more volatile?

This research work has certain contributions. This study is comprehensive and different in several ways from previous ones. We explain that machine learning tools have a great capability for forecasting uncertainty in the cryptocurrency markets. First and foremost, they can account for the stylized facts about the return volatility of cryptocurrency. They give understandable outcomes for the volatility as well as the asymmetric impact of returns on volatility. This research makes a contribution to the return volatility of cryptocurrency analysis literature in four ways. This is the first study that employs the CSS along with the NNETAR and GMDH-NN models for cryptocurrency return volatility forecasting. Second, the NNETAR and the GMDH-NN are the most famous techniques in their field. However, no study provides detailed explanations of how they perform differently in the cryptocurrency market. Firstly, this study attempts to check the predictive capabilities of the CSS, NNETAR, and GMDH-NN models together in the case of the cryptocurrency markets. Secondly, in most cases, neither the real phenomena are pure linear nor nonlinear, but the combination of these two. Thirdly, usually, the researchers are interested in predicting the prices or returns of the cryptocurrency market, but in our case, the study focuses on the return volatility of cryptocurrency using machine learning techniques. Four, this study is not the first one to investigate whether the machine learning method is more advanced in financial time series forecasting. However, it contributes to the existing literature by providing more evidence on the limitations of applying machine learning approaches to solve economic issues. The root-mean-squared error (RMSE) and mean absolute error (MAE) are used to evaluate their forecasting accuracy performances.

The remainder of the paper is synthesized in Part 2, which presents a review of the literature. Section "Research methodology" presents the data and research methodology. Section "Results and discussion" describes the estimation, algorithms, parameter settings, and model configuration. Conclusions are mentioned in Part 5.

Review of literature

In this section, first, we focus on the background of models in traditional stock market forecasting, then we review the literature on the prediction of volatility in cryptocurrency markets. In the forecasting literature, a variety of models have been used in the past decade, but there is still a lack of consensus on the best appropriate model for predicting stock exchange performance. Kamruzzaman et al. [33] argue in this regard that neural networks play a significant role in predicting and analyzing stock prices. While forecasting stock prices, ANN embodied two models, i.e., a soft computing model and a statistical model [42]. Using soft computing models, pure ANN and a combination of other models are considered. For the effectiveness of NN models, MLP, DAN (dynamic artificial neural network), and GARCH are used to deal with the input and predict the future behaviors of stocks [29], while in neuro-fuzzy models, an adaptive neuro-fuzzy inference system (ANFIS) seems to be an appropriate choice to predict the stock market, and it is termed a viable approach for the economists who deal with forecasting stock prices and returns (KARUL, AVCI, DEVECİ, & KARKINER, 2010), while in the paradigm of soft computing models, researchers apply HANN (hybrid artificial neural network) models along with fuzzy set models and metaheuristic algorithms [49].

Metaheuristic approaches are being used by researchers as these are efficient in solving real-world complex problems. In this regard, Holland [31] considers the genetic algorithm as a vital tool for predication, Kuo et al. [36] consider it as an efficient tool GFNN (genetic algorithm-based fuzzy-NN) which build knowledge-based fuzzy inference rules that can be used to compute the qualitative impact on the equity market, while a new hybrid evolutionary learning algorithm purely suggested by Lin et al. [40] is based on NN and GA, whereas [27] suggest the HANN model that can be used in stock market forecasting, which identifies the most suitable indicators using harmony search and a genetic algorithm. Similarly, Majhi et al. [42] suggest developing an efficient model that can better predict stock indices. Likewise, Zhang and [41] developed an upgraded version of IBCO that is formally mixed into BPN to establish an effective model for forecasting numerous stock indices. However, the literature related to forecasting cryptocurrency volatility using machine learning techniques is limited. The related literature that is considered most important in the context of volatility forecasting of cryptocurrency contains the papers of Katsiampa, [34] tested the Bitcoin volatility by performing a multiple GARCH-type tool, while errors are assumed as normally distributed and indicates that AR (1)-CGARCH (1, 1) is considered to be the best model to predict Bitcoin returns volatility.

Another study conducted by Chu et al. [16] analyzed the volatility of seven cryptocurrencies employing GARCH-type techniques with different innovation distributions, and the study announces the IGARCH (1, 1) to be the most suitable and reasonable model for estimating Bitcoin volatility. A study performed by Hultman [32] analyzed the comparison among three types of volatility models regarding their capability to forecast the one-day-ahead volatility in Bitcoin. The study employed a GARCH (1, 1), a bivariate-BEKK (1, 1), and a stochastic volatility model using MAE, MSE, and RMSE for evaluating the forecast accuracy and concludes that the GARCH model seems to outperform the other model and that the SV model is inferior to the other two models. Likewise, a study was carried and explored the valuation of the instability of three standard currencies against three "cryptocurrencies" by combining an old-style “Generalized Autoregressive Conditional Heteroskedasticity” (GARCH) model with the “machine learning” SVR. The study evaluated the support vector regression GARCH against GARCH, EGARCH, and GJR models based on volatility forecast and indicated that SVR-GARCH provides forecast volatility with better accuracy. Conrad et al. [19] employed the GARCH-MIDAS model for the better prediction of Bitcoin’s long-term volatility. However, there are some limitations with GARCH models that make it difficult to capture the complex fluctuations of nonlinear correlation that exist in time series data. Many researchers have proposed to overcome these limitations by nonparametric forecasting methods that are based on approaches of machine learning such as, for better forecasting ANN for Bitcoin volatility. In this regard, Giudici and Abu-Hashish [26] confirmed cryptocurrency markets as more volatile than traditional foreign exchange markets.

Chu et al. [17] also reported considerable volatility in the price of cryptocurrencies. Likewise, Bouri et al. [8] validated the footprints of greater volatility in cryptocurrencies than their counterparts, i.e., the traditional foreign exchange market. Moreover, in similar studies, Badenhorst [4] analyzed the bitcoin returns and reported more profitability in the tails than foreign exchange and the stock market, testing the regime-switching and structural breaks in the volatility of bitcoin, but many researchers have documented regime-switching behavior in bitcoin [5, 45] While some of the researchers predicted a structural break in bitcoin’s return [55]. Likewise, Seo et al. [47] explored the Bitcoin market for examining volatility and developed hybrid forecasting models combining ANN (artificial neural network) and HONN (higher-order neural network) for the approach of the ML and models of hybrid by using the GARCH models output and many relevant as input variables. The study found that based on HONN the hybrid models show more accurate forecasts than the rest of the models. The recent portfolio of studies that predict cryptocurrency volatility argue that bitcoin markets have the characteristics of multifractality and long memory pattern over the period [3]. There are footprints of some key stylized facts exhibited by the cryptocurrency market that are also present in traditional foreign exchange and stock markets. Due to these characteristics, many empirical studies applied GARCH in predicting the volatility of digital currency [16]. Some of the volatility helped determine cryptocurrency volatility [52]. Kyriazis et al. [38], in their study, estimated the volatility of cryptocurrencies in bearish market situations, using the GARCH family and revealed that numerous cryptocurrencies are complimentary with Bitcoins and Ethereum, and these are having the ability to hedge in a most distressing time. Similarly, Symitsi and Chalvatzis [51] analyzed the spillovers of bitcoin with technologies companies and energy, the results demonstrate short-run volatility from technology firms to Bitcoin and long-run from energy was detected. Particularly in the cryptocurrency market, Bitcoin is found to be largely inefficient, for example, immense volatility in its value over the period was confirmed [57]. Similarly, Vidal-Tomás and Ibañez [58] also validated the inefficiency of cryptocurrency and predicted its performance as very uncertain. In the recent literature, some of the emerging newest studies confirmed the movement volatility is a spillover, lead-lag effect, and market movement in digital currencies [3, 35]. Systematic risk is also associated with the digital currency market, which reflects the volatility in its prices [20]. One obvious reason for the prevailing risk and mounting inefficiencies can be attributed to the fact that these markets are perhaps difficult to trade due to their lack of liquidity characteristics as compared to other traditional markets. The liquidity in different cryptocurrencies varies substantially at the ease of one currency over another cryptocurrency [46].

Research methodology

This paper estimates and predicts the return volatility of cryptocurrencies using different algorithms like NNETAR, CSS, and GMDH-NN. The data used in this study encompasses the returns of four cryptocurrencies, such as Bitcoin, Ethereum, Tether, and XRP (Ripple). These cryptocurrencies are chosen based on their market capitalizations. The data range spans from April 14, 2017, to October 30, 2020, i.e., the data consists of 1296 observations. The data was divided into two sections, i.e., 80% of the data was used as training data and 20% was used as testing data to assess the performance of the model by predicting test data. We predicted the return volatility of four cryptocurrencies, namely Bitcoin, Ethereum, XRP, and Tether, and compared the predictive models in terms of forecasting accuracy. The study also compared the NNETAR, CSS, and GMDH-NN algorithms in terms of forecasting. To derive more accurate and reliable results, returns in the form of logarithmic differences of variables were employed for estimation. All raw data of the prices have been collected from reliable source of coinmarketcap.com and investing.com, etc. One way to evaluate four cryptocurrency markets predicting the performance of the CSS, the NNETAR, and the GMDH-NN tools on historical data is to divide the sample data into two sets. The data that is used as testing data is commonly called "out-of-sample testing," while the data used as training is called an 'in-sample set." The first part of the data set, the so-called in-sample set, is used to train the various model parameters. The estimated models are then used to make predictions of the cryptocurrency's volatility for the period that is left out. The period that is left out is simply the second part of the data set, the so-called out-of-sample set. The root-mean-square error (Gormsen & Koijen) and mean absolute error (MAE) have been used to evaluate the accuracy of forecasting models in terms of cryptocurrencies. The flowchart of the modeling is given in Fig. 1.

Modeling cryptocurrency returns requires time series data to be stationary, i.e., it must not have a unit root. The first step in analyzing time series data is to check the order of integration of each series or to determine the existence of a unit root. For checking the unit root, a KPSS test is performed. The reason to apply the KPSS test instead of the ADF test in such a study is that the data is hourly and of high frequency.

For that purpose, applying the KPSS test is suitable. The hypothesis isH_0: $x = 0$ (series contains stationary) and H_1: $x \neq 0$ (series does not contain unit root). The general equation of the KPSS test is written as follows:

$$x_t = r_t + \beta_t + \varepsilon_t \quad (1)$$

This breaks up a series into three parts, i.e., a random walk r_t, a deterministic trend β, and a stationary error ε_t, with the regression equation.

Forecasting methods

After estimating the volatility of cryptocurrency returns, the next step is to forecast the volatility of Bitcoin, Ethereum, Tether, and XRP (Ripple) with the help of the CSS, NNETAR, and GMDH-NN algorithms. Many famous models are not so powerful to predict the volatility of financial data, like the ARCH and GARCH family models, ARIMA, and VAR models. Machine learning techniques are more powerful techniques for predicting and forecasting complex financial data. Such techniques capture many econometric issues like non-stationarity,

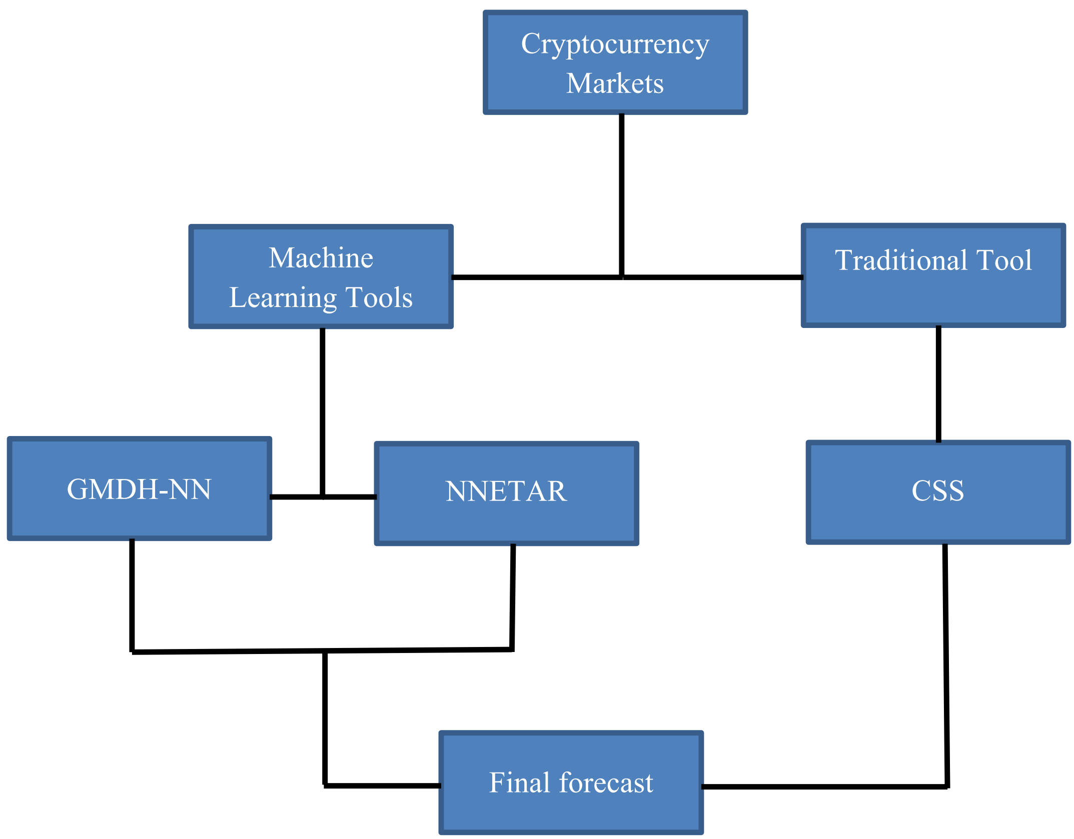

Fig. 1 Flowchart of the algorithms that are used for cryptocurrency markets

nonlinearity, autocorrelation, etc. The study employed the aforementioned algorithms for forecasting.

Group method data handling algorithm

The GMDH-NN algorithm is considered a self-organized model, in which the model structure converges itself following the data inputs. The key objective of this algorithm is to build a function in feedforward that is based on a second-degree transfer function. The nexus between output and input is done via the GMDH-NN algorithm. In our study, the general form of the equation can be described as follows:

$$x_t = \varphi_0 + \sum_{j=1}^{r} \varphi_i x_i + \sum_{j=1}^{r}\sum_{k=0}^{r} \varphi_{jk} x_j x_k + \sum_{j=1}^{r}\sum_{k=1}^{r}\sum_{l=0}^{r} \varphi_{jkl} x_j x_k x_l + \dots \quad (2)$$

In case of two variables, second degree polynomial can be defined as:

$$M(x) = \varphi_0 + \varphi_1 x_j + \varphi_2 x_k + \varphi_3 x_j^2 + \varphi_4 x_k^2 + \varphi_5 x_j x_k \quad (3)$$

The above-mentioned equations are basically referred to as the Volterra series. The GMDH algorithm attempts to determine the unknown parameters in the Volterra series by using regression methods [22]. Forecasting the future of financial interest variables is not only a basic factor for models in economics, but also for business decisions. However, it is not easy to predict things in economic crises, and this causes nonlinear influences in data. Various linear models, such as AR (autoregressive) and ARMA (autoregressive moving average) processes, have been discovered to predict the values of future economic and financial variables). However, empirical results showed that linear models are not always the best for process identification and do not always deliver the best prediction results. In this regard, Teräsvirta et al. [54] speaks of hidden nonlinearity that needs the adoption of nonlinear methods. The best method for capturing nonlinearity and non-stationarity problems in time series analysis is argued in this study are cubic smoothing spline Algorithm, NNETAR, and GMDH-NN algorithm.

Cubic smoothing spline

A smoothing spline can do everything for one input variable and one output variable. The benefits of splines are their computational simplicity, speedy, and the clarity of controlling curvature directly. Smoothing splines produce a flexible way of fitting the regression function. Our study merely considers a univariate time series. For $t = 1, \ldots, r$, the cubic spline is a function that minimizes

$$\sum_{t=1}^{r} \left(x_t - g(t)\right) + \theta \int_h \left(g''(v)\right)^2 dv \tag{4}$$

Over dual differencing of the function g on h where $[1, r] \subseteq h \subseteq R$. θ controls the exchange rate between the local variation and sum of squared residuals, which is measured by the second derivative of g in the square form.

Neural network autoregression (NNETAR)

In a neural network, the lagged values are included as input variables, and therefore the model refers to NNETAR. To be more specific, we simply use the available historical data as inputs for forecasting. This process proceeds until we achieve the required forecasts. The equation can be written as

$$x_t = f(x_{t-1}, x_{t-2}, \ldots, x_{t-r}) + \varepsilon_t \tag{5}$$

where $f(.)$ is the unknown function for next month, hence neural attempts to approximate it through optimizing the neural bias and network weights. Resultantly, the NNAR can be specified precisely by the following equation as

$$x_t = \omega_0 + \sum_{v=1}^{r} \omega_v \aleph \left(\omega_{0u} + \sum_{u=1}^{p} \omega_{uv} x_{t-i}\right) + \varepsilon_t \tag{6}$$

where r indicates the number of hidden layers along with the activation function, p indicates the entries, and these are typically the weights. ω_0 is the constant term in the model.

Error metrics

Among many forecast evaluation metrics, our study considers root-mean-squared error (RMSE) and mean absolute error (MAE) because we believe both are appropriate methods for measuring the accuracy of forecasting using obtained data on the same scale. Further, several previous studies employed this criterion. From a statistical point of view, the forecast error is a more credible criterion to choose the best method. Mathematically, the following equations can be written as

$$\mathrm{RMSE} = \sqrt{\frac{1}{r} \sum_{t=1}^{r} \left(x_t - \hat{x}_t\right)^2} \tag{7}$$

$$\mathrm{MAE} = \frac{1}{r} \sum_{t=1}^{r} \left|x_t - \hat{x}_t\right| \tag{8}$$

where in the RMSE and MAE formulae and indicate the actual and forecast values, respectively, and r shows the forecast horizon.

Results and discussion

The descriptive statistics of four cryptocurrencies' returns are presented in Table 1. The mean of the XRP, Tether, Ethereum, and Bitcoin returns are positive, demonstrating the fact that all four cryptocurrencies have performed well over time, showing the markets are favorable for investors. The descriptive statistics of XRP (Ripple) and Tether display that the returns are positively skewed, indicating that there is a high probability of earning returns, while the returns of Ethereum and Bitcoin are negatively skewed. The kurtosis of the return series of XRP (Ripple), Tether, Ethereum, and Bitcoin returns is > 3, which implies that the volatility series are fat-tailed and do not follow a normal distribution. This is further confirmed by Jarque–Bera test statistics, which are significant at the 5% level, and hence the null hypothesis of normality is rejected.

KPSS unit test result

Table 2 depicts the results of the unit root. The KPSS unit root test was employed on two sets simultaneously: constant and constant along with time trend. The t statistics values of Bitcoin, XRP (Ripple), and Ethereum are greater than critical values at 5%, which means that they are not stationary at that level. Taking the first difference of Bitcoin, XRP (Ripple) and Ethereum become stationary at first difference because their t statistics values are less than critical values now. The stationarity of Tether was tested, and the t statistics value of Tether is less than the critical value at a level, indicating that it is stationary at that level. The results revealed that all the variables are non-stationary at all levels except for a single series which is Tether. While all the series have unit root, converting them into first difference becomes stationary. In other words, Bitcoin, XRP (Ripple), and Ethereum are all

Table 1 Descriptive statistics

	XRP	Tether	Ethereum	Bitcoin
Mean	0.0015	0.0001	0.0015	0.0016
Median	− 0.0005	0.0001	0.0004	0.0001
Maximum	0.6183	0.0453	0.2324	0.2300
Minimum	− 0.4251	− 0.0574	− 0.5896	− 0.5000
Std. Dev	0.0654	0.0056	0.0565	0.0435
Skewness	1.4572	0.0341	− 0.8576	− 1.0967
Kurtosis	17.109	23.125	13.880	18.791
Jarque–Bera	(0.001)	(0.001)	(0.001)	(0.001)

Values in parentheses for Jarque–Bera test are p-values

Table 2 Kwiatkowski–Phillips–Schmidt–Shin (KPSS)

Variables	At level		At first difference		Conclusion
	Constant	Constant with trend	Constant	Constant with trend	
Bitcoin	0.985 (0.463)	0.221 (0.146)	0.070 (0.463)	0.070 (0.146)	I (1)
XRP	0.767 (0.463)	0.226 (0.146)	0.040 (0.463)	0.025 0.146	I (1)
Ethereum	0.924 (0.463)	0.318 (0.146)	0.104331 (0.463)	0.096 (0.146)	I (1)
Tether	0.235 (0.463)	0.080 (0.146)			I (0)

Values in parentheses are Asymptotic critical values

non-stationary at level except Tether which is stationary on the level. The volatility of each series is visually represented by Fig. 2.

Discussion

To compare the performance of the different models, it is necessary to evaluate them on unseen data, i.e., test data. The prediction performance is evaluated using two statistical metrics: the mean absolute error (MAE) and root-mean-square error. The smaller the values of MAE and RMSE are, the closer the predicted time series values are to the actual values. In this section, the predictive capabilities of four algorithms, i.e., NNETAR, CSS, and GMDH-NN, are compared together in the four abovementioned data sets of cryptocurrencies, namely Bitcoin, Ethereum, Tether, and XRP. Two statistical error metrics, including mean absolute error (MAE) and root-mean-square error (RMSE), which are computed from the following equations, are employed

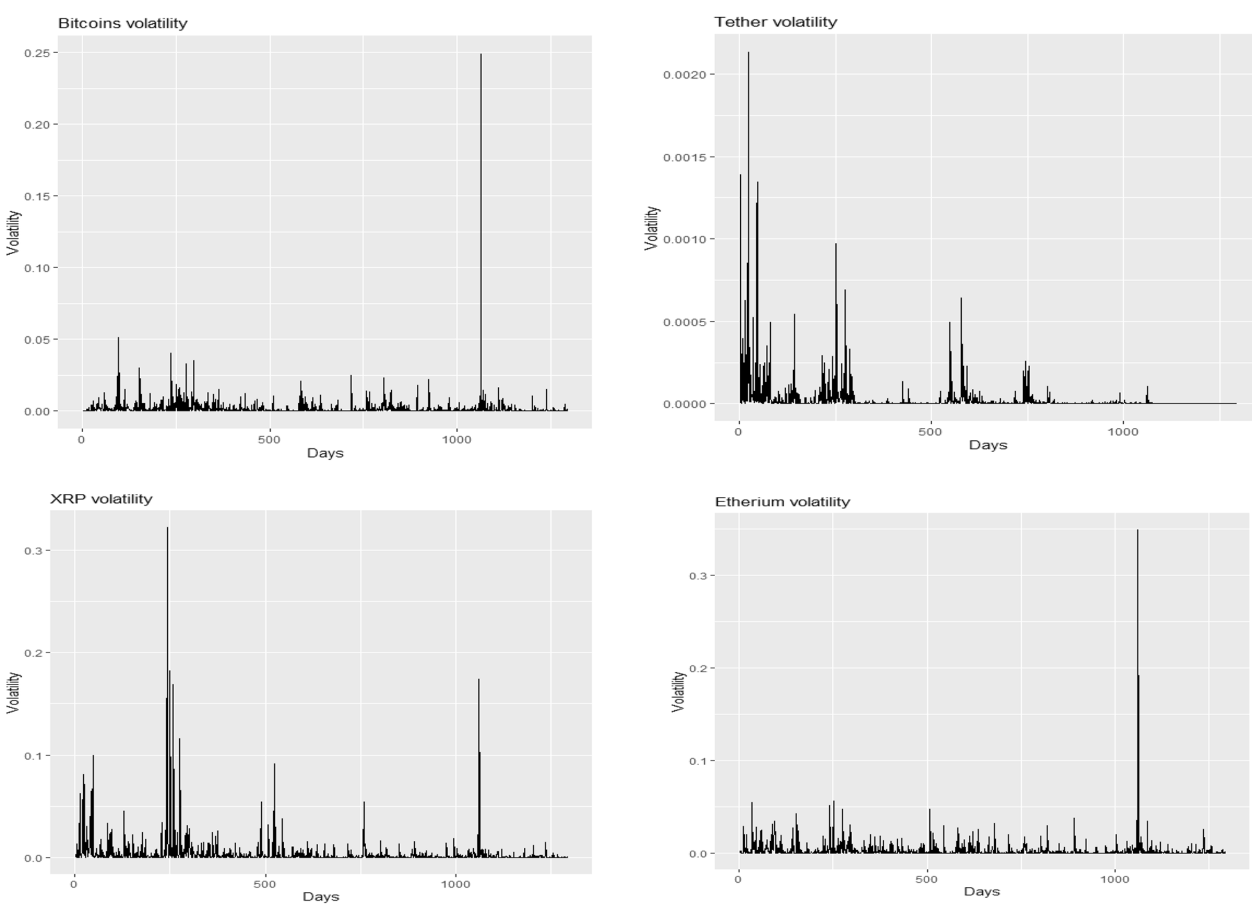

Fig. 2 Volatility of cryptocurrency markets

Table 3 Forecast comparison using bitcoin return volatility

	RMSE		MAE	
	Testing	Training	Testing	Training
NNETAR	0.015	0.003	0.002	0.002
CSS	**0.014**	0.004	**0.001**	0.002
GMDH-NN	0.019	0.004	0.003	0.002

Bold indicates minimum the RMSE and MAE of the model, more efficient the model is

Table 4 Forecast comparison using Tether return volatility

	RMSE		MAE	
	Testing	Training	Testing	Training
NNETAR	0.0001	0.0005	0.0002	0.0003
CSS	0.0002	0.0001	0.0002	0.0004
GMDH-NN	**0.0001**	0.0009	**0.0001**	0.0004

Bold indicates minimum the RMSE and MAE of the model, more efficient the model is

Table 5 Forecast comparison using XRP return volatility

	RMSE		MAE	
	Testing	Training	Testing	Training
NNETAR	0.0101	0.0093	0.0219	0.0045
CSS	**0.0002**	0.0164	**0.0171**	0.0058
GMDH-NN	0.0105	0.0178	0.0319	0.0057

Bold indicates minimum the RMSE and MAE of the model, more efficient the model is

Table 6 Forecast comparison using Ethereum return volatility

	RMSE		MAE	
	Testing	Training	Testing	Training
NNETAR	**0.0101**	0.0057	**0.0029**	0.0033
CSS	0.0210	0.0164	0.0069	0.0058
GMDH-NN	0.0290	0.0065	0.0053	0.0037

Bold indicates minimum the RMSE and MAE of the model, more efficient the model is

to compare the forecasting performances of the NNETAR, CSS, and GMDH-NN models.

The forecasting results in the case of Bitcoin return volatility for training as well as test data sets are summarized in Table 3. Empirical results showed that the CSS beat the other three models because the MAE and RMSE related to the CSS model are significantly lower than the NNETAR and GMDH-NN in the case of bitcoin. The CSS algorithm is appropriate for the bitcoin market, while the NNETAR and GMDH-NN models are not suitable for any bitcoin market in this study. Out of four cryptocurrency markets, the CSS model produced optimal forecasts for two markets. This may recommend that neither GMDH-NN nor NNETAR capture all of the patterns in the data.

Forecasting performance based on Tether return volatility is presented in Table 4. Based on MAE and RMSE, the forecast results remarkably conclude that the GMDH-NN model can be an efficient technique to improve the forecasting accuracy obtained by either of the models used separately, in the sense that it has the lowest forecast errors. So, the GMDH-NN model produced optimal forecasts in the case of Tether cryptocurrency. This may suggest that neither the CSS nor the NNETAR models capture all of the patterns in the data.

The predictive capabilities of the CSS, NNETAR and GMDH-NN models are compared collectively in the context of XRP and tabulated in Table 5. Regarding the XRP market, CSS is more suitable based on MAE and RMSE. The forecast results remarkably suggest that the CSS model can be an effective model to improve the predicting accuracy obtained by either of the models used separately, in the sense that it has the lowest forecast errors. The NNETAR and GMDH-NN models are not appropriate for any XRP market.

The predictive capabilities of the CSS, NNAR, and GMDH-NN models are compared together in the context of Ethereum in Table 6. The lowest values of MAE and RMSE are provided by the NNETAR model, which confirms that this model is an effective tool to improve the forecasting accuracy obtained by either of the models used separately.

Conclusions

This study predicts the return volatility of four cryptocurrencies, namely Bitcoin, Ethereum, XRP, and Tether, by comparing the GMDH-NN algorithm, CSS, and NNETAR to determine the prediction accuracy. The statistical properties of the models used in this study are briefly discussed, evaluated, and compared in terms of forecasting. Daily data are used to forecast return volatility in this paper to examine the comparison of different algorithms in terms of prediction accuracy. The prediction performance is evaluated using two statistical metrics: the mean absolute error (MAE) and root-mean-square error (RMSE). The predictive capabilities of the CSS, NNETAR, and GMDH-NN models are compared collectively in the context of XRP. Regarding the XRP and bitcoin markets, CSS method is suitable based on MAE and RMSE. In other words, the forecasted results remarkably suggest that the CSS model can be an effective way to improve prediction accuracy in the sense that it has the lowest forecast errors. Furthermore, based on the lowest values of MAE and RMSE, the forecasted results remarkably suggest that compared to the other three algorithms, the NNETAR model is a more robust tool in predicting the Ethereum market, while in the case of Tether markets, it can be concluded that the GMDH-NN model can be an efficient technique to improve the forecasting accuracy in the sense of having the lowest forecast errors. The CSS model which can capture higher-order correlations in input variables showed an improved performance for forecasting XRP and Bitcoin volatility. Conclusively, we may infer that no single approach performs uniformly for all cryptocurrency markets, although the findings of the study reveal that the CSS algorithm provides more accurate forecasts than the competing counterparts, especially for forecasting returns' volatility in the Bitcoin and XRP markets.

This study concludes that the volatility of cryptocurrency returns in the market is one of the key issues for the participants. However, investors have lower confidence due to the unpredictability of the highly volatile market, which affects the total market. On the other side, fewer cryptocurrency markets are found to be stable and increase investor confidence, which ultimately results in their propensity to invest their funds. The behavior of volatility in cryptocurrency returns is a challenging aspect for researchers and experts who need to better understand and address the arising issues through better forecasting and modeling, which will assist in decision-making. The greater volatility in cryptocurrency returns is due to a lack of regulatory frameworks; in this regard, strong policy formulation and law promulgation should be made to boost investors' confidence. International monetary fund (IMF) and other key international institutions should take the initiative and take an interest to give repute to the version of digital currencies in the world. In the future, researchers with the same mindset in the same area should compare the volatility of cryptocurrency returns with traditional currency using the same portfolio of machine learning techniques. Besides, researchers can also test the volatility of all types of cryptocurrency returns over an extended period. The regional block currencies' volatility can also be compared with digital currencies.

The findings of this study can ensure the robustness and usefulness of the best tool for predicting the cryptocurrency market. In other words, we believe that these results are beneficial to policymakers and investors because they provide a new outlook on cryptocurrency investment strategies and regulatory frameworks in an effort to enhance financial stability. In contrast, this study is only limited to three tools. In addition, our study has only modeled the volatility.

Author contributions
FUK made a significant contribution to the draft by gathering information from various websites, performing data curation, formal analysis, interpretation of the results, and methodology writing. In a similar way, FK successfully led the group and helped while writing the original draft. PAS assisted in conceptualization and investigation. All authors reviewed the results and approved the final version of the manuscript.

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Availability of data and materials
The corresponding author will provide the datasets used and/or analyzed during the current study upon reasonable request.

Declarations

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Not applicable.

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Competing interests
The authors declare no competing interest.

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References

1. Abu-Mostafa YS, Atiya AF (1996) Introduction to financial forecasting. Appl Intell 6:205–213
2. Adebiyi, AA, Adewumi AO, Ayo CK (2014) Comparison of ARIMA and artificial neural networks models for stock price prediction. J Appl Math 2014
3. Antonakakis N, Chatziantoniou I, Gabauer D (2019) Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. J Int Finan Markets Inst Money 61:37–51
4. Badenhorst JJ (2018) Effect of bitcoin spot and derivative trading volumes on price volatility. University of Pretoria
5. Balcombe K, Fraser I, Williams L, McSorley E (2017) Examining the relationship between visual attention and stated preferences: a discrete choice experiment using eye-tracking. J Econ Behav Organ 144:238–257
6. Bariviera AF (2017) The inefficiency of Bitcoin revisited: a dynamic approach. Econ Lett 161:1–4
7. Bouoiyour J, Selmi R, Tiwari AK, Olayeni OR (2016) What drives Bitcoin price. Econ Bull 36(2):843–850
8. Bouri E, Gupta R, Tiwari AK, Roubaud D (2017) Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Financ Res Lett 23:87–95
9. Briere M, Oosterlinck K, Szafarz A (2015) Virtual currency, tangible return: portfolio diversification with bitcoin. J Asset Manag 16:365–373
10. Buyrukoğlu G, Buyrukoğlu S, Topalcengiz Z (2021) Comparing regression models with count data to artificial neural network and ensemble models for prediction of generic Escherichia coli population in agricultural ponds based on weather station measurements. Microb Risk Anal 19:100171
11. Buyrukoğlu S (2021) New hybrid data mining model for prediction of Salmonella presence in agricultural waters based on ensemble feature selection and machine learning algorithms. J Food Saf 41(4):e12903
12. Buyrukoğlu S (2021b) Promising cryptocurrency analysis using deep learning. In: 2021 5th international symposium on multidisciplinary studies and innovative technologies (ISMSIT), pp 372–376
13. Buyrukoğlu S, Savaş S (2022) Stacked-based ensemble machine learning model for positioning footballer. Arab J Sci Eng 1–13

14. Charfeddine L, Benlagha N, Maouchi Y (2020) Investigating the dynamic relationship between cryptocurrencies and conventional assets: Implications for financial investors. Econ Model 85:198–217
15. Cheah E-T, Fry J (2015) Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Econ Lett 130:32–36
16. Chu J, Chan S, Nadarajah S, Osterrieder J (2017) GARCH modelling of cryptocurrencies. J Risk Financ Manag 10(4):17
17. Chu J, Zhang Y, Chan S (2019) The adaptive market hypothesis in the high frequency cryptocurrency market. Int Rev Financ Anal 64:221–231
18. Ciaian P, Rajcaniova M, Kancs D (2016) The economics of BitCoin price formation. Appl Econ 48(19):1799–1815
19. Conrad C, Custovic A, Ghysels E (2018) Long-and short-term cryptocurrency volatility components: a GARCH-MIDAS analysis. J Risk Financ Manag 11(2):23
20. Corbet S, Lucey B, Urquhart A, Yarovaya L (2019) Cryptocurrencies as a financial asset: a systematic analysis. Int Rev Financ Anal 62:182–199
21. Doğru A, Buyrukoğlu S, Arı M (2023) A hybrid super ensemble learning model for the early-stage prediction of diabetes risk. Med Biol Eng Comput 1–13
22. Ebtehaj I, Bonakdari H, Zaji AH, Azimi H, Khoshbin F (2015) GMDH-type neural network approach for modeling the discharge coefficient of rectangular sharp-crested side weirs. Eng Sci Technol Int J 18(4):746–757
23. Eisl A, Gasser SM, Weinmayer K (2015) Caveat emptor: Does Bitcoin improve portfolio diversification? Available at SSRN 2408997
24. Engle RF (1982) Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econom J Econom Soc 987–1007
25. Fantazzini D, Ivliev S, Sukhanovskaya V (2017) Everything you always wanted to know about bitcoin modelling but were afraid to ask. Part 2. Appl Econom 45:5–28
26. Giudici P, Abu-Hashish I (2019) What determines bitcoin exchange prices? A network VAR approach. Financ Res Lett 28:309–318
27. Gökçen E, Frederickson N, Petrides KV (2016) Theory of mind and executive control deficits in typically developing adults and adolescents with high levels of autism traits. J Autism Dev Disord 46:2072–2087
28. Granger CWJ, Andersen A (1978) Non-linear time series modelling. Applied time series analysis. Academic Press, New York
29. Guresen E, Kayakutlu G, Daim TU (2011) Using artificial neural network models in stock market index prediction. Expert Syst Appl 38(8):10389–10397
30. Gyamerah SA (2022) On forecasting the intraday Bitcoin price using ensemble of variational mode decomposition and generalized additive model. J King Saud Univ-Comput Inf Sci 34(3):1003–1009
31. Holland JH (1992) Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. MIT press
32. Hultman H (2018) Volatility forecasting an empirical study on bitcoin using garch and stochastic volatility models
33. Kamruzzaman J, Begg R, Sarker R (2006) Artificial neural networks in finance and manufacturing. IGI Global
34. Katsiampa P (2017) Volatility estimation for Bitcoin: a comparison of GARCH models. Econ Lett 158:3–6
35. Katsiampa P (2019) Volatility co-movement between Bitcoin and Ether. Financ Res Lett 30:221–227
36. Kuo RJ, Chen CH, Hwang YC (2001) An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network. Fuzzy Sets Syst 118(1):21–45
37. Kyriazis NA (2019) A survey on efficiency and profitable trading opportunities in cryptocurrency markets. J Risk Financ Manag 12(2):67
38. Kyriazis NA, Daskalou K, Arampatzis M, Prassa P, Papaioannou E (2019) Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models. Heliyon 5(8):e02239
39. Lim T-K, Rohrbach KG (1980) Role of *Penicillium funiculosum* strains in the development of pineapple fruit diseases. Phytopathology 70(7):663–665
40. Lin Y, Tang P, Zhang WJ, Yu Q (2005) Artificial neural network modelling of driver handling behaviour in a driver-vehicle-environment system. Int J Veh Des 37(1):24–45
41. Liu Y, Tsyvinski A, Wu X (2022) Common risk factors in cryptocurrency. J Financ 77(2):1133–1177
42. Majhi R, Panda G, Sahoo G (2009) Development and performance evaluation of FLANN based model for forecasting of stock markets. Expert Syst Appl 36(3):6800–6808
43. Mehta S, Rana P, Singh S, Sharma A, Agarwal P (2019) Ensemble learning approach for enhanced stock prediction. In: 2019 twelfth international conference on contemporary computing (IC3), 1–5
44. Narayanan A, Clark J (2017) Bitcoin's academic pedigree. Commun ACM 60(12):36–45
45. Nekhili R, Sultan J (2020) Jump driven risk model performance in cryptocurrency market. Int J Financ Stud 8(2):19
46. Phillip A, Chan JSK, Peiris S (2018) A new look at cryptocurrencies. Econ Lett 163:6–9
47. Seo G, Lee G, Kim MJ, Baek S-H, Choi M, Ku KB, Lee C-S, Jun S, Park D, Kim HG (2020) Rapid detection of COVID-19 causative virus (SARS-CoV-2) in human nasopharyngeal swab specimens using field-effect transistor-based biosensor. ACS Nano 14(4):5135–5142
48. Shahzad F, Xiu G, Wang J, Shahbaz M (2018) An empirical investigation on the adoption of cryptocurrencies among the people of mainland China. Technol Soc 55:33–40
49. Soleimani Motlagh M, Ghasemieh H, Talebi A, Abdollahi K (2017) Identification and analysis of drought propagation of groundwater during past and future periods. Water Resour Manag 31:109–125
50. Sun X, Liu M, Sima Z (2020) A novel cryptocurrency price trend forecasting model based on LightGBM. Financ Res Lett 32:101084
51. Symitsi E, Chalvatzis KJ (2018) Return, volatility and shock spillovers of Bitcoin with energy and technology companies. Econ Lett 170:127–130
52. Tan C-Y, Koh Y-B, Ng K-H (2019) Structural change analysis of active cryptocurrency market. ArXiv Preprint http://arxiv.org/abs/1909.10679
53. Tapscott D, Tapscott A (2016) Blockchain revolution: how the technology behind bitcoin is changing money, business, and the world. Penguin
54. Teräsvirta T, Lin C, Granger CWJ (1993) Power of the neural network linearity test. J Time Ser Anal 14(2):209–220
55. Thies S, Molnár P (2018) Bayesian change point analysis of Bitcoin returns. Financ Res Lett 27:223–227
56. Tiwari AK, Jana RK, Das D, Roubaud D (2018) Informational efficiency of Bitcoin—an extension. Econ Lett 163:106–109
57. Urquhart A, McGroarty F (2016) Are stock markets really efficient? Evidence of the adaptive market hypothesis. Int Rev Financ Anal 47:39–49
58. Vidal-Tomás D, Ibañez A (2018) Semi-strong efficiency of Bitcoin. Financ Res Lett 27:259–265
59. Ye Z, Wu Y, Chen H, Pan Y, Jiang Q (2022) A stacking ensemble deep learning model for bitcoin price prediction using Twitter comments on bitcoin. Mathematics 10(8):1307
60. Yermack D (2015) Is Bitcoin a real currency? An economic appraisal. In: Handbook of digital currency. Elsevier, pp 31–43
61. Zhang G, Patuwo BE, Hu MY (1998) Forecasting with artificial neural networks: the state of the art. Int J Forecast 14(1):35–62

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