Technological Forecasting & Social Change 198 (2024) 122938

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Forecasting Bitcoin prices using artificial intelligence: Combination of ML, SARIMA, and Facebook Prophet models

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ARTICLE INFO

Keywords:
Bitcoin
ML
Fb-Prophet
SARIMA
Volatility
Forecasting

ABSTRACT

In recent years, investors, corporations, and enterprises have shown great interest in the Bitcoin network; thus, promoting its products and services is crucial. This study utilizes an empirical analysis for financial time series and machine learning to perform prediction of bitcoin price and Garman-Klass (GK) volatility using Long Short-Term Memory (LSTM), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Facebook prophet models. The performance findings show that the LTSM boost has a noticeable improvement compared to SARIMA and Facebook Prophet in terms of MSE (Mean Squared Error) and MAE (Mean Average Error). Unlike Long Short-Term Memory (LSTM), a component of Deep Learning (DL), the finding explains why the bitcoin and its volatility forecasting difficulty has been partially met by traditional time series forecasting (SARIMA) and auto-machine-learning technique (Fb-Prophet). Furthermore, the finding confirmed that Bitcoin values are extremely seasonally volatile and random and are frequently influenced by external variables (or news) such as cryptocurrency laws, investments, or social media rumors. Additionally, results show a robust optimistic trend, and the days when most people commute are Monday and Saturday and an annual seasonality. The trend of the price and volatility of bitcoin using SARIMA and FB-Prophet is more predictable. The Fb-Prophet cannot easily fit within the Russian-Ukrainian conflict period, and in some COVID-19 periods, its performance will suffer during the turbulent era. Moreover, Garman-Klass (GK) forecasting seems more effective than the squared returns price measure, which has implications for investors and fund managers. The research presents innovative insights pertaining to forthcoming cryptocurrency regulations, stock market dynamics, and global resource allocation.

1. Introduction

Since its invention as a peer-to-peer digital cash system that enables online payment to any individual from any location in the world, Bitcoin (₿) emerged as a method to bypass the conventional banking system just after the financial crisis 2008. It has been witnessing increased investor and academic interest ever since its inception. The hot streaks of 2017–2018 and 2021–2022 helped cement Bitcoin's place in the media limelight (Li et al., 2022b). Governments, economists, and investors made mention of and started creating digital currencies. Bitcoin is the first cryptocurrency that provides a medium for exchanging digital assets, secures transactions, and controls the creation of new coins with the help of cryptography. Indeed, Bitcoin has become the third currency by market capitalization behind only USD and EUR in the international monetary systems. Indeed, bitcoin is an attractive asset investment (Basher and Sadorsky, 2022a; Choithani et al., 2022; S. Gupta et al., 2020; Ma and Luan, 2022). Bitcoin's price changes alternately reflect investor optimism and disappointment with its pledge.

Recently, the number of factors affecting Bitcoin's price has changed dramatically. Regulatory innovations have had an increasingly significant impact on their cost since 2017, when Bitcoin gained media attention, as it expanded the reach of the cryptocurrency (Truby, 2018; Yadav et al., 2020). Every legislative statement raises and lowers Bitcoin prices, whether suitable or not. Institutional investors' interest also has

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https://doi.org/10.1016/j.techfore.2023.122938
Received 3 May 2023; Received in revised form 1 October 2023; Accepted 17 October 2023
Available online 14 November 2023

set an ever-longer shadow on the workings of Bitcoin prices. Bitcoin has been pivoting further from individual investors over the last ten years and has become a desirable investment strategy for institutional investors (Bedi and Nashier, 2020; Su et al., 2020). This is desirable growth as it introduces greater liquidity into the environment and reduces uncertainty. The most recent rally of the cryptocurrency in 2020 happened after many respected financial names accepted its ability to grow into a value store to beat inflation from increased spending during the global epidemic and Russia-Ukrainian conflict (Al-Amri et al., 2019; Ayed et al., 2022; Patel et al., 2019).

While cryptocurrency as a currency has still yet to gain massive success as a unit of account and a buffer against inflation, it has started to gain momentum through a different narrative (Choi and Shin, 2022; Conlon et al., 2021). Bitcoin has the most volatile shifting exchange rates with additional disturbance, making it more difficult for analytical research than any other time series analysis independent of bank and government influence. In recent years, the interest in incorporating Bitcoin into everyday business practices and offering innovative features inside the Bitcoin domain has grown vertically or horizontally. Likewise, venture capitalists are interested in investing capital into that growing sector. The research goal is to prove that despite the high variance, bitcoin prices can be forecasted using time series analysis and machine learning statistical techniques. We seek to include more profound insights into the price changes. The prediction of Bitcoin prices holds great importance due to its considerable impact on multiple facets of the cryptocurrency ecosystem, financial markets, and other domains. Bitcoin is a popular investment option among various individuals and institutions. Precise price predictions enable investors to make well-informed judgments regarding the acquisition, divestment, or retention of Bitcoin assets. Price forecasts are utilized by traders in order to develop trading strategies, effectively manage risk, and perhaps capitalize on price variations. Bitcoin is renowned for its tendency to exhibit significant fluctuations in price. Enterprises that want to accept Bitcoin as a form of payment or include it in their portfolio of treasury assets must effectively handle the risks that come with it. Price projections can play a crucial role in formulating risk management strategies to reduce future financial losses. Acknowledging that the task of predicting Bitcoin prices is intrinsically complex because of its high volatility, speculative characteristics, and susceptibility to several influences is imperative. The sophistication of forecasting models and methodologies can vary, ranging from basic moving averages to sophisticated machine learning algorithms. Although forecasts can provide valuable insights, viewing them within a comprehensive risk management and decision-making approach is essential, as they inherently entail a certain degree of uncertainty and risk.

It is widely argued that compared to different currencies, Bitcoin must be regarded as a speculative commodity (Baek and Elbeck, 2015). Moreover, Bitcoin could be an asset that follows the efficient market hypothesis proposed by several existing studies (Jakub, 2015). The COVID-19 outbreak and the Russian-Ukrain conflict significantly affected the efficiency of cryptocurrencies, particularly Ethereum and Bitcoin. It recovered faster at the end of March 2020 after the pandemic (Naeem et al., 2021), then again affected by a conflict between Russia and Ukraine. However, the average monthly volatility of Bitcoin was higher than gold volatility, and the lowest monthly volatility of gold was higher than that of Bitcoin (O'Dwyer, 2015).

Furthermore, Bitcoin volatility is volatile, as empirically evidenced by EGARCH (Exponential generalized autoregressive conditional heteroscedastic) and GARCH (Generalized Auto Regressive Conditional Heteroskedasticity) models during the speculative periods. In contrast, the fear index (VIX) and S&P500 influence the volatility of Bitcoin in the stable periods (López-Cabarcos et al., 2021). The safe-haven effect of cryptocurrencies triggered the bullish volatility of Bitcoin during uncertain times, such as the COVID-19 pandemic and the Russian-Ukainine conflict (Bouoiyour and Selmi, 2020). Therefore, investors can use cryptocurrencies to diversify their portfolios of different assets (Briere et al., 2015). The existing literature on Bitcoin is mainly related to legality, technical aspects, and security (Barber et al., 2012; Reid and Harrigan, 2013). Amid the speculations in the financial market, bitcoin surged by 300 % in 2020 during the COVID-19 pandemic (Bloomberg, 2021). Moreover, bitcoin has significant scope and use in management and marketing practices and principles (Rahman et al., 2022).

This study makes many distinguished contributions to the literature compared to the most current state of the field. In this regard, prior studies have adequately predicted bitcoin price, although forecasting volatility is still under-discussed. Previously, minimal studies were conducted on Bitcoin price prediction by using the machine learning (ML) and Autoregressive integrated moving average (ARIMA) models. But this is the first study using a combination of ML (Machine Learning), SARIMA (Seasonal Autoregressive Integrated Moving Average), and Facebook Prophet Models for the Bitcoin price prediction. Bitcoin is characterized by significant price fluctuations, rendering it a highly volatile asset attracting investment from individuals and institutions. Price forecasting enables investors to make well-informed decisions regarding the optimal timing for buying, selling, or holding Bitcoin (Jia et al., 2023). Traders employ projections to develop trading strategies, effectively manage risk, and perhaps capitalize on market variations. Organizations that possess Bitcoin as a financial asset or include it as a form of payment must effectively mitigate the inherent price volatility. Price projections play a crucial role in the formulation of risk management strategies, such as the implementation of hedging techniques or the establishment of price limitations. Both price forecasts and sentiment analyses influence market sentiment. Optimistic predictions have the potential to generate increased interest and investments, but pessimistic forecasts may result in sell-offs. The comprehension of market mood holds significant importance for both investors and traders. Regulatory bodies and policymakers frequently consider price estimates and market data when formulating cryptocurrency regulations and policies. Precise predictions can aid regulators in comprehending the intricacies of the market and identifying potential hazards. The assessment of Bitcoin price predictions holds significance for multiple stakeholders. Yet, it is crucial to acknowledge the inherent difficulties associated with this endeavor, such as the considerable volatility and speculative characteristics of Bitcoin.

The assurance of predictions is inherently uncertain, necessitating the use of risk management strategies in the context of cryptocurrency transactions. Forecasting models exhibit a range of complexities, from rudimentary technical analysis to sophisticated machine learning algorithms, each with distinct levels of precision and associated risks. This study aims to perform prediction of bitcoin price and Garman-Klass (GK) volatility using Long Short-Term Memory (LSTM), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Facebook prophet models. The forecast of the close price and GK volatility of Bitcoin based on high, low, opening, and closing values while also comparing the outcome trend. In addition, we conducted our research from 01 January 2017 to 30 October 2022, investigating the Russia-Ukraine conflict, the COVID-19 pandemic, and the bitcoin crash period to demonstrate how the models used can predict bitcoin price and volatility under various market conditions, including financial instability. Our empirical analysis reveals the first evidence of collective and comprehensive predation throughout these historical crises. A rare study investigates bitcoin prediction performance during the Russia-Ukraine crisis, the COVID-19 pandemic, and in any such crisis.

Moreover, This work fills in the gaps between the papers conducted in this research field and makes a comprehensive determination using time series forecasting and machine learning models. Besides the First Section, the remainder of the paper is organized as follows: Section 2 summarizes the literature review. Section 3 provides the user data in this study. Section 4 describes the model and the methodology. Section 5 discusses the findings. Finally, Section 6 offers concluding remarks, policy implications, and prospects for future research.

2. Literature review

As known in several essential fields, behavioral finance investment management and risk assessment volatility play a crucial part. The study of financial stock markets has reached new directions with the application of high data Since the pioneering work of (Andersen et al., 1998) financial quantitative. Researchers have contributed significantly by using high-recurrence information to model and figure instability. Moreover, Table 1 presents relevant literature investigating the different aspects of Bitcoin specifically related to its price and volatility. Additionally, while doing the review analysis, this study followed the guidelines and process suggested by the Lim et al. (2022) for conducting a practical literature review.

Due to its unpredictable and changeable nature, stock market forecasting is difficult, according to (Kou et al., 2019). Some specialists, such as (Ciaian et al., 2016; Yermack, 2013), have attempted to investigate Bitcoin's price development, claiming that the currency should not be described as genuine cash but mainly as a floating exchange rate speculation vehicle. The basis of the opinions is focused on the volatile markets that contain unstable Bitcoin prices. On the other side, several recent researchers have adopted different views, assuming that the price of Bitcoin is regarded as an attractive financial asset (Basher and Sadorsky, 2022a; Choithani et al., 2022; S. Gupta et al., 2020; Ma and Luan, 2022). In this respect, Dyhrberg (2016) documented that Bitcoin

Table 1
Related literature.

Study	Period	Variables	Methodology/models used	Relationship
Acereda et al. (2020)	2010–2018	ES, Bitcoin returns, AST distribution,	GARCH/NGARCH/CGARCH/TGARCH	ES ↔ AST (BR)
Aras (2021)	2013–2020	GDP, Bitfinex exchange API,	ANN/SVM/KNN/GARCH (2,2)/LASSO	GDP → API
Baur and Dimpfl (2018)	2013–2018	Bitcoin, Gold & USD	T-GARCH	Bitcoin; Gold↔ USD
Caporale and Zekokh (2019)	2010–2018	Value-at-Risk (VaR), ES,	MS-GRACH/SGARCH/EGARCH/GJRGARCH/TGARCH	VaR↔ ES,
Chan et al. (2019)	2010–2017	BTC, Euro STOXX, Nikkei, Shanghai A-Share, S&P 500, and TSX Index,	GARCH/CCC/Frequency dependence model	BTC; GSPC- N225 → SSE; GSPTSE & STOXX
Cheikh et al. (2020)	2013–2018	Bitcoin, Ethereum, Ripple, and Litecoin	ST-GARCH/GARCH/EGARCH/GJRGARCH/ZARCH	BTC → ETH, XRP, LIT
Ftiti et al. (2021)	2018–2020	BTC, ETC, ETH, and XRP	HAR-RV/HAR-CV-J/HAR-SRV/HARRV-ΔJ2 /HAR-RV-ΔJ2 + -ΔJ2-	BTC; ETC → ETH↔ XRP
Garcia-Jorcano and Benito (2020)	2011–2019	S&P500 (US), STOXX50 (EU), NIKKEI (Japan), CSI300 (Shanghai), and HS (Hong Kong)	Copula models such as Gaussian, Student-t, Clayton, Gumbel, and Frank	S&P500 → STOXX50,NIKKEI, CSI300, and HS
Hattori (2020)	2016–2018	RBTC &, RBTC	GARCH/GJRGARCH/EGARCH/APARCH/IGARCH	RBTC ↔ RBTC
Hoang and Baur (2020)	2015–2020	BTC & OED	Black–Scholes–IV/GARCH/TGARCH/HARQ-FJ/ARMA/AFIRMA	BTC → OED
Jalan et al. (2021)	2018–2020	OBOP & COV	Black–Scholes–Merton/two-regime Heston–Nandi GARCH	OBOP - COV
Katsiampa et al. (2019)	2015–2018	CVD & CC	Unrestricted BEKK-MGRACH	CVD ↔ CC (Bitcoin-Ether, Bitcoin-Litecoin, and Ether-Litecoin)
Klein et al. (2018)	2011–2017	BTC & Gold	APARCH/FIAPARCH/BEKK-GARCH	BTC ↔ Gold
Köchling et al. (2020)	2015–2018	VF& BTC	ARCH/IGARCH(1,2)	VF ↔BTC
Ma et al. (2020)	2013–2018	BTC, PA & RV	MIDAS-RV/MIDAS-CJ MRS-MIDAS/MIDAS-CJL/HAR-CJ/FTPMRS-MIDAS-RV/FTP-MRS-MIDASCJL/TVTP-MRS-MIDAS-CJL	BTC; PA↔ RV
Maciel (2021)	2013–2018	PP, VF, VaR, & ES	MSGARCH/GARCH/EGARCH/TGARCH	VaR, & ES → PP, VF
Mba and Mwambi (2020)	2017–2019	VO, ES,	MS-COGARCH/COGARCH	ES↔ VO
Mba et al. (2018)	2014–2018	HR, RC, Risk,	GARCH-DE/DE/GARCH-DE-t-copula	Risk; HR → RC,
Miglietti et al. (2019)	2014–2017	VO (BTC, LIT, EUR)	GARCH/ARCH	VO; BTC > EUR > LIT
Omane-Adjepong and Alagidede (2019)	2014–2018	URV, CRV	WMCC/VAR/GJR-GARCH/GARCH	URV ↔CRV
Peng et al. (2018)	2016–2017	PP, CC, TC	GARCH/EGARCH/GJR-GARCH/SVRGARCH	PP; CC > TC
Phillip et al. (2019)	Varry-2017	VO, CC	JBAR-SV-GLR	VO↔ CC
Sabah (2020)	2013–2018	CAV, CV	VAR	CAV → + CV
Sapuric et al. (2022)	2010–2017	BR, VO, VOL	EGARCH	BR → +VO → +VOL
Siu (2021)	2013–2019	CV, CN, VaR, ES,	GRACH/FIGARCH/AR-GARCH/ARFIGARCH/MS-GRACH/EVT	CV↔ CN, VaR↔ ES,
Symitsi and Chalvatzis (2019)	2011–2017	BTC, CR, GOL, OIL, STK	EW/GMV/CGMV/CGMV-DDC	BTC; GOL → CR, STK → OIL,
Tan et al. (2021)	2010–2018	BTC, VD, BR	GARCH/GJR-GARCH/TGARCH/MSGARCH/TV-MS-GARCH	BTC; VD → BR
Tan et al. (2020)	2013–2018	VO, PP, BTC,	ABL-CARR	BTC; VO > PP
Umar et al. (2021)	2018–2020	VS, BTC, RR	VAR/BEKK-GARCH	VS & RR → BTC
Uzonwanne (2021)	2013–2018	VS, RS, BTC	VARMA-AGARCH	VS ↔ RS; BTC
Walther et al. (2019)	Varry-2019	VO, CR, GRE,	GARCH/GARCH-MIDAS	GRE &VO → CR,
Wang et al. (2019)	2013–2018	VD, VF, BTC	ARJI/GARCH/EGARCH/CGARCH	VD ↔VF → BTC

(ES = Expected Shortfal, BTC=Bitcoin, ETH = Ethereum, XRP = Ripple, LIT = Litecoin, ETC = Ethereum Classic =, RBTC = return of Bitcoin, RBTC = Forecasts for Bitcoin, OED = options exchange Deribit, OBOP = optimum Bitcoin option prices, COV = classical option valuation, CVD = conditional volatility dynamics, CC = conditional correlations, VF = volatility forecasting, PA = prediction accuracy, RV = realized variance, PP = prediction performance, VF = volatility forecasting, VO=Volatility, HR = historical return, RC = Return comparison, URV = unconditional return volatility, CRV = conditional return volatility, PP = predictive performance, CC = cryptocurrencies, TC = traditional currencies, CAV = crypto accepting venues, CV = crypto volatility, BR = bitcoin return, VOL = volume, CV = conditional volatility, CN = conditional non- normality, VD = Volatility dynamics, VS = volatility spillovers, RR = Risk return, RS = return spillovers, GRE = Global Real Economic).

has the same hedging characteristics as Gold and the US Dollar. The literature shows that cryptocurrencies have played multirole in various economic inflation, interest rates, oil, and commodities (Aharon et al., 2021; Marmora, 2022; Ren et al., 2022; Yin et al., 2021) and against financial assets like bonds, gold, stock markets, and traditional currencies (Assaf et al., 2021; Hoon et al., 2019; Maghyereh and Abdoh, 2022). Analysts debated its importance as an investment, just like many analysts and traders made drastic price predictions.

Another sign of Bitcoin price changes is economic uncertainty. Since its inception, the cryptocurrency has established itself as a global safeguard against regional economic instability and centralized fiat currencies. According to the news, if an economy reaches bumps in the road caused by government policy, there is indeed a time of high economic activity on Bitcoin's blockchain. Countries like Venezuela, which have seen their currency hyperinflation, have seen enormous rises in the use of Bitcoin as a medium of exchange and the storage of money. Consequently, it revealed that actions to protect against financial instability, geopolitical risk, and global economic uncertainty are related to cryptocurrency (Aysan et al., 2019; Goodell and Goutte, 2021; Kyriazis, 2021).

Furthermore, the outrageous unpredictability of its market rates, pointed to by its currency exchange against many solid monetary types like USD or EUR, is one of the most debated subjects inside Bitcoin's financial angles. Buchholz et al. (2012) conducted a critical attempt to depict Bitcoin's volatility and demand. They presented the theoretical concept of digital money by uncovering the definite effect on costs during the flourishing period before arriving at its first burst of a bubble in 2013. (Smith, 2015) found a strong correlation between relative prices and other typical exchange rates. The study pointed to the shifting exchange rates as one factor in the price prediction of Bitcoin, consistent with earlier research linking Bitcoin behavior to the effectiveness of the financial market's knowledge base (Bartos, 2015). In addition, the empirical results have added to the existing literature by illustrating the insignificant.

In comparison to some previous studies, the causal link between its price and other macroeconomic factors, as (Aharon et al., 2021; H. Chen and Xu, 2022; Ha and Nham, 2022; Hakim das Neves, 2020). It is widely accepted that Bitcoin price changes are a financial data set within the continuum of financial econometrics and statistical data, models like SARIMA and their combinations should indeed be regarded here as a theory for any scientific studies. The ARIMA technique considered the performance model to predict Bitcoin in the survey (Iqbal et al., 2021). Likewise, (Wirawan et al., 2019) furcated bitcoin based on the ARIMA model (Z. Chen et al., 2020) predicted the Bitcoin prices by numerous machine-learning techniques, including LSTM, and compared the results with statistical models(Livieris et al., 2021; Mudassir et al., 2020; Tandon et al., 2019; Wu et al., 2019). Statistical techniques and machine learning indicated 66 % and 65 % accuracy, respectively. Despite having significant empirical potential, the usage of ANN created by machine learning technologies is still in its infancy compared to time-series econometric techniques. In this pursuit, (Jaquart et al., 2021; Li et al., 2022a) demonstrated the efficiency of machine learning models in predicting the bitcoin market at different short time horizons. (Adcock and Gradojevic, 2019), In comparative forecasting, analysis of DL and ANN bitcoin prices using machine learning outputs is more critical than ARIMAX and other traditional statistic models. (Basher and Sadorsky, 2022b) employ the random forest machine learning model to forecast bitcoin and reports that outcome accuracy ranges between 75 % to 80 % for five days out-of-sample and more than 85 % for 10 to 20 days of prediction. (Hamayel and Owda, 2021), Utilized machine learning approaches LSTM and gated recurrent unit GRU to forecast bitcoins. Based on daily observations of open, high, low, and close prices and RMSE and MAPE features, they conclude that the GRU technique outperformed other methods.

In contrast to the stream studies mentioned above, recent researchers used the Prophet model to forecast different financial assets to avoid the sessions and pitfalls generated by the ARIMA family models and various machine learning types (Chaturvedi et al., 2022; R. Gupta et al., 2022; Saiktishna et al., 2022). Nonetheless, scare studies used the Fb-Prophet to forecast cryptocurrencies. (Rathore et al., 2022) used the Prophet, deep learning, and ARIMA models to predict bitcoin. They explored that Prophet forecasting produces decent findings, Shawn is more performant than deep learning, and ARIMA. (Indulkar, 2021) compare the performance prediction among the cryptocurrencies, namely Bitcoin, Ethereum, Chainlink, and XRP, based on LSTM and Fbprophet. He pointed out that Bitcoin is lower accuracy than Chainlink and Ethereum.

3. Data wrangling and forecasting framework

3.1. Data collection

The data has been collected from Yahoo Finance's dollar-denominated cryptocurrency information. We receive trading details from a popular link https://coinmarketcap.com/. The initial dataset includes open, high, low, close, adjective close and volume of (BTC). The United States Dollar is used to illustrate the Bitcoin exchange rate (USD). We decided on the data of Bitcoin that is traded in dollars by considering the availability of high-frequency data. Our data spans a 24-h (daily) trading day from 01 January 2017 to 30 October 2022 (Fig. 1).

Unlike standard volatility, which uses a close price, Garman-Klass (GK) volatility employ high, low, opening, and closing value (Garman and Klass, 1980). extensive studies used cryptocurrency GK volatility to examine its performance against financial assets (D'Amato et al., 2022; Hemanth Kumar and Patil, 2015; Shen et al., 2021; Tan et al., 2020). It can be described as GK volatility as follows:

$$\mathrm{GK_{it}} = \frac{1}{\mathrm{n}}\left(\sum\nolimits_{n=1}^{n} ln^2\left(\frac{H_t}{l_t}\right) + (2ln(2)-1)ln^2\left(\frac{\mathrm{C_t}}{\mathrm{O_t}}\right)\right) \tag{1}$$

where:

$\mathrm{GK_{it}}$: Garman-Klass volatility.
$\mathrm{T_{it}}$: index at time t.
$\mathrm{T_{t-1}}$: index at time t-1.
$\mathrm{H_t}$: High value at time t.
$\mathrm{l_t}$: low value at time t.
$\mathrm{C_t}$: close value at time t.
$\mathrm{O_t}$: open value at time t.

Bitcoin has got the most volatile trading in history. Beginning in 2010, when the value of one Bitcoin jumped to 0.08$ from nearly 0.0008 $, it was the first cryptocurrency price rise. And since that time, it has seen many different crashes and rallies. The price of Bitcoin has shifted sideways in recent last years. There were indications of improvement in between. In June 2019, for instance, there was an increase in value and trading activity volume, and the price exceeded 10,000$, rekindling expectations of another rally. Through December of that year, however, it dropped to around 7000. Volatility persistence and Market efficiency in cryptocurrencies (also examined by Yaya et al. (2019) during pre-crash and post-crash periods. This work was very useful to cryptocurrency market participants and portfolio managers. One of the most unique and important features of bitcoin is neither constructed nor backed by any big financial institution or governmental body (Fig. 2).

In 2020, the price of Bitcoin exploded again when the economy started shutting down because of the Covid-19 pandemic. The cryptocurrency began at 7200$ for the year. The pandemic recession and the resulting government policy played into investors' concerns about the world economy and fueled the rise of Bitcoin. Bitcoin traded for 18,353$ at the close of November 2020. In December 2020, it was expected to be observed that interest in cryptocurrency further accelerated its price upward, and the cost of Bitcoin hit around 24,000$, a rise of more than 220 % from the beginning of 2020. In January 2021, it required only a couple of weeks for Bitcoin to break its significant price record and hit 40,000$. At its current high, on 08 January 2021, the cryptocurrency

Fig. 1. The trend of Bitcoin close prices.

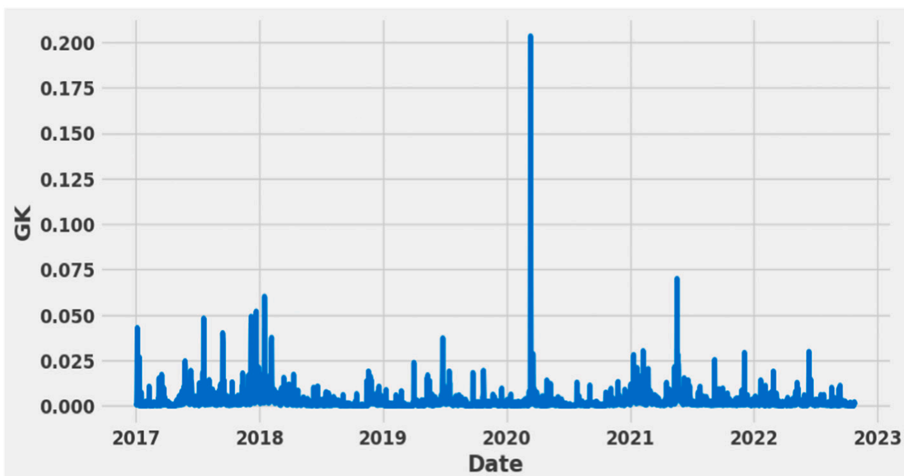

Fig. 2. The trend of Bitcoin Garman-Klass volatility.

increased in value to 41,528$. The price of Bitcoin (BTC) set an all-time peak in 2021, with prices above 65,000 USD in November 2021. However, bitcoin fell below $35,000 due to the Russia -Ukrainian conflict. It still reaches nearly $20,000 through the second half of 2022.

3.2. Time series forecasting models

The machine learning models we will be implementing are called time series models. These models will study the past and search for patterns and trends to predict the future. These models are necessary for all those studies to be performed independently, which would take too much time. We have adopted deep learning, Long Short-Term Memory (LSTM), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Facebook Prophet (Fb-Prophet) models to predict the future prices of Bitcoin based on historical data information. The following section gives an overview of the used models below. Machine learning (ML), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Facebook Prophet are widely employed methodologies in time series forecasting and prediction. Machine learning (ML) models, including linear regression, decision trees, random forests, support vector machines, and deep learning models such as recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks, can be applied in various time series forecasting applications. Machine learning models are a suitable option when a substantial dataset is available and there is a desire to utilize diverse variables and covariates to make predictions.

In contrast to SARIMA or Prophet, utilizing ARIMA models necessitates additional data pre-processing and feature engineering. SARIMA models are capable of adequately addressing both seasonality and autocorrelation. These methods' ability to effectively capture periodic patterns in the data and exhibit resilience in short- to medium-term forecasting is a notable strength. SARIMA models are suitable for analyzing time series datasets showing stationarity and distinct seasonal patterns, enabling accurate forecasting based on these patterns. Datasets that exhibit irregular patterns or varying seasonality are not well-suited for these models. The Prophet model is specifically tailored for predicting time series data characterized by daily observations that exhibit patterns over various time scales, encompassing holidays and other significant occurrences. The Prophet algorithm is a suitable option for datasets that consist of daily or weekly observations. It offers the advantage of efficiently generating accurate forecasts without requiring considerable manual feature engineering. This approach is appropriate for datasets exhibiting irregular seasonal patterns and holidays.

In conclusion, the selection among ML models, SARIMA, and Facebook Prophet is contingent upon the time series data's characteristics and the forecasting task's particular requirements. Machine learning (ML) models provide versatility in handling many data types, while SARIMA models excel in managing pronounced seasonal patterns. On the other hand, Prophet models are particularly well-suited for analyzing daily or weekly data that exhibit irregular seasonality and incorporate vacation effects. When choosing the proper approach, it is essential to consider the features of the data and the modeling aims. Furthermore, the act of ensembling or integrating these models has the potential to yield additional enhancements in the accuracy of predicting.

3.2.1. LSTM model

Integrating real-time series with newly available sophisticated machine learning (ML) techniques is particularly interesting. It can uncover and provide policy-relevant patterns by learning from trial data without being pre-conditioned or -programmed further to solve time series analysis problems. In this pursuit, Artificial Neural Networks (ANN) and recurrent neural network approaches (RNN) have been considerably employed to predict and forecast the economic time series unlike standard Neural Networks, which are based on hidden layers training to process one output layer, Recurrent Neural Networks (RNN). As an extra feature, training input and the activation functions produced by calculating the neurons' output were utilized to learn for forecasting. Long Short-Term Memory (LTSM) is a field of artificial intelligence, deep learning, and the performative Recurrent Neural Network(Waseem et al., 2022). This variant of RNN is used to solve problems involving (Indulkar, 2021). The KNIME open-source Analytics Platform is being considered for data processing in Python. The scenario prediction taking Bitcoin volatility and price input throughout training data expenditure from 01 January 2021 to 31 August 2022 and tensing two last months demonstrates good feature performance and experimental data handling capabilities.

3.2.2. Seasonal Autoregressive Integrated Moving Average (SARIMA) model

A SARIMA model is a multiplicative model that mixes seasonal and nonseasonal elements. The notation can be written as the following definition:

$$ARIMA(p,d,q)x(P,D,Q)_m \tag{2}$$

m: the frequency of observations each year.

For the ARIMA model, the AR (p) A linear process provided by the equation is referred to as a model.:

$$y_t = \alpha + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_{1p} y_{t-p} + \omega_t \tag{3}$$

$y_{t-1}, y_{t-2}, \ldots, y_{t-p}$: lags (Time series data).

$\varphi_1, \varphi_2, \ldots, \varphi_p$: Estimated lag coefficients.

ω_t: white noise.

$\alpha = \left(1 - \sum_{i=1}^{p} \varphi_i\right)\mu$, where μ: is the mean of the process.

The following question defines the MA (q):

$$y_t = \alpha + \omega_t + \theta_1 \omega_{t-1} + \theta_2 \omega_{t-2} + \ldots + \theta_q \omega_{t-q} \tag{4}$$

$\omega_1, \omega_2, \ldots, \omega_t$: Model error terms for the corresponding lags;

If the data is stationary, then ARIMA will be able to fit. The differentiating parameter d is the transformation order to make the dataset stationary. The difference in the second order is seen in the following formula:

$$y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2} \tag{5}$$

At the end, the ARIMA (p, d, q) is defined by this formula:

$$y_t = \alpha + \sum_{i=1}^{p} \varphi_i y_{t-1} + \omega_t + \sum_{j=1}^{q} \theta_j \omega_{t-j} \tag{6}$$

(p, d, q) is a nonseasonal component, as shown here:

- p: Trend autoregressive order;
- d: Trend differencing order;
- q: Trend moving average order;

(P, Q, D) are seasonal components.

- P: Seasonal autoregressive order;
- D: Seasonal differencing order;
- Q: Seasonal moving average order;
- m: Timestamp for single-season order.

3.2.3. Facebook Prophet model

The prophet is a procedure that works best for forecasting time series data and has several seasons of historical data and strong seasonal effects. It is robust to shifts in the trend and missing data, fit with yearly, weekly, and daily seasonality, plus holiday effects, and typically handles outliers well. A Prophet is a Facebook open-source platform used for time series framing and forecasting. It focuses on an additive model where nonlinear patterns match seasonality and additional holiday effects that are daily, weekly, and annual. The prophet handles missing data and changes within the practices and generally manages outliers well. It also helps to accumulate exogenous model variables.

Prophet uses a decomposable time-series model:

$$y(t) = T(t) + S(t) + H(t) + \epsilon_t \tag{7}$$

$T(t)$: Trend (linear/logistic);

$S(t)$ Periodic change/seasonality;

$H(t)$: Effect of the holiday;

ϵ_t: The error term.

This section will describe the dataset we used to predict the bitcoin prices. It also will describe the following model framework. As noticed in bitcoin trends in this section, the close price and Garman-Klass volatility of bitcoin have varied with time, and for this study, we have used the available day data. The first data day of collected, used data started on 01 January 2017, and the end date is 30 October 2022, containing 2128 daily samples.

3.2.4. Forecasting structure

Fig. 3 below describes the prediction and analysis framework of the data by using the Long Short-Term Memory (LSTM), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Fb-Prophet models. The architectural and modeling approaches of the Long Short-Term Memory (LSTM), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Facebook Prophet models might exhibit variations in their predicting structures. LSTM models necessitate the utilization of sequential time series data. The customary procedure involves the preparation of the dataset by partitioning it into separate training and validation sets. Subsequently, the training set is further subdivided into input sequences and corresponding target values. The Long Short-Term Memory (LSTM) is a variant of the recurrent neural network (RNN) architecture that has been specifically developed to process sequential data effectively. The architecture comprises Long Short-Term Memory (LSTM) layers, which incorporate memory cells that can capture and retain long-term relationships within the given dataset. The LSTM model undergoes training by utilizing the training data, wherein the input sequences are inputted into the network. Through this process, the model acquires the ability to make predictions of the target values. The following are the fundamental structures for each model. The configurations and hyperparameters of the model may differ based on the particular forecasting task and dataset. The selection of a model should be contingent upon the specific attributes of the data and the desired aims for forecasting (see Fig. 3).

For the evaluation of predicted models, we utilize these statistical measures:

- Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{\mathrm{N}} \sum_{t=1}^{\mathrm{N}} |y_t - \widehat{y}_t|$$

- Root Mean Square Error (RMSE):

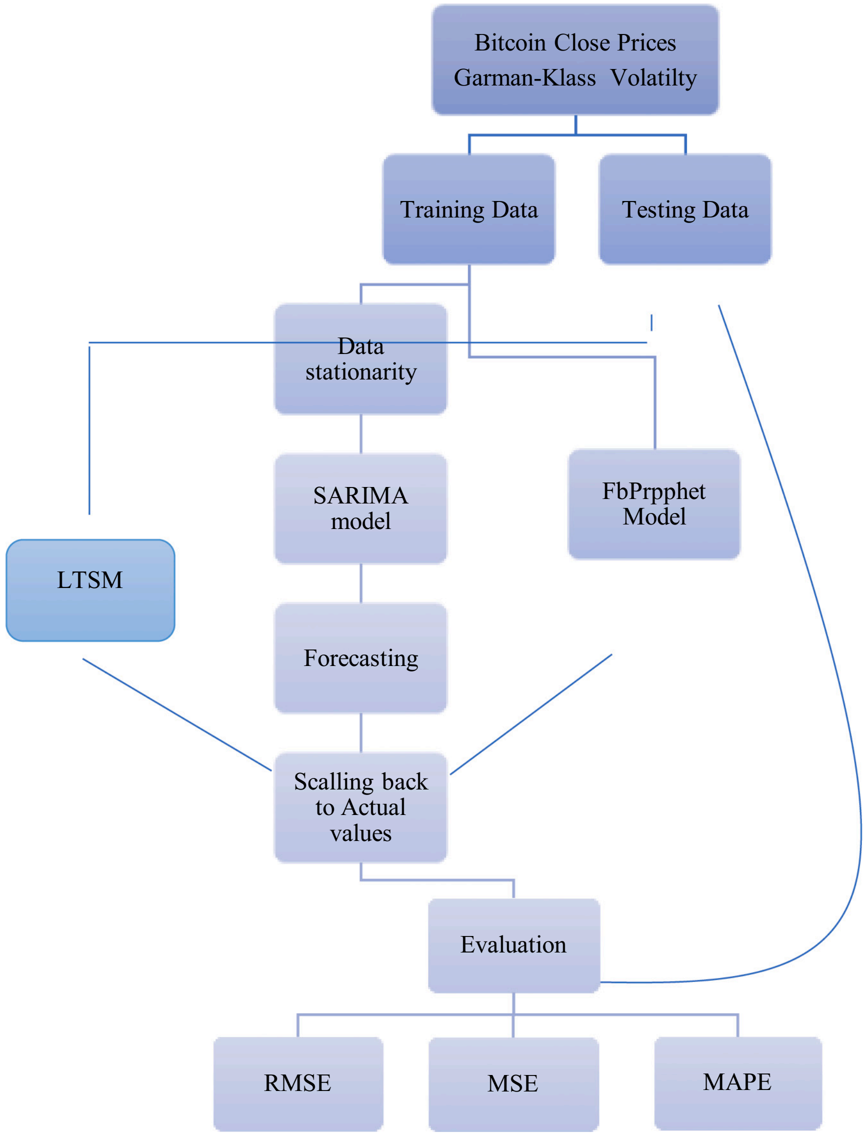

Fig. 3. A framework of the Forecasting models evaluation.

$$\mathrm{RMSE}=\sqrt{\frac{1}{\mathrm{N}}\sum_{t=1}^{\mathrm{N}}(y_t-\widehat{y}_t)^2}$$

- Mean Absolute Percentage Error (MAPE):

$$\mathrm{MAPE}=\frac{100}{\mathrm{N}}\sum_{t=1}^{\mathrm{N}}\left|\frac{y_t-\widehat{y}_t}{y_t}\right|$$

y_t: Actual value;
$\widehat{y}_t$: Predicted value;
N: Total number of testing samples.

4. Model and methodology

The framework we have adopted is implemented in Python 3.10 with the Jupyter Notebook. We used Long Short-Term Memory (LSTM), Seasonal Autoregressive Integrated Moving Average (SARIMA), and FbProphet models from available packages, stats, and FbProphet, respectively. We will discuss in this section predicting the accuracy of adopted models for the Bitcoin Close prices.

4.1. LT SM Forecasting

Figs. 4 and 5 plot the result of the LTSM (Long Short-Term Memory) model for close prices and GK volatility. In addition, the model receives 20 % (more than 426 observations) for fitting the model's performance to empirical data and 80 % (more than 1700 observations) for training. We select the best models based on the accuracy of LTSM experiments, which include the mean square (MSE), and means absolute errors (MAE). This model exhibits good feature performance and the ability to handle experimental results. It discovered that the MAE and MSE performance measures for bitcoin price and volatility are 503,746.37, 624.37, and 1.71e-, 0.00011 respectively.

Moreover, The results show a significant convergence between accurate data and anticipated value for both bitcoin close price and GK volatility. Notably, the outcome explores LTSM GK volatility has outperformed compared close prices in terms of accuracy, which is lower than the evaluation statistics. The utilization of Long Short-Term Memory (LSTM) neural networks has been explored to forecast the

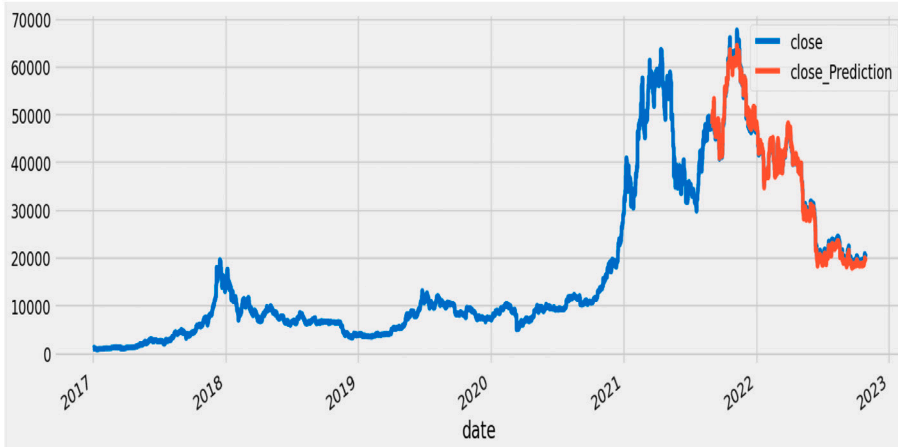

Fig. 4. LTSM prediction result of lose price. Note: MSE = 503,746.37, MAE = 624.37.

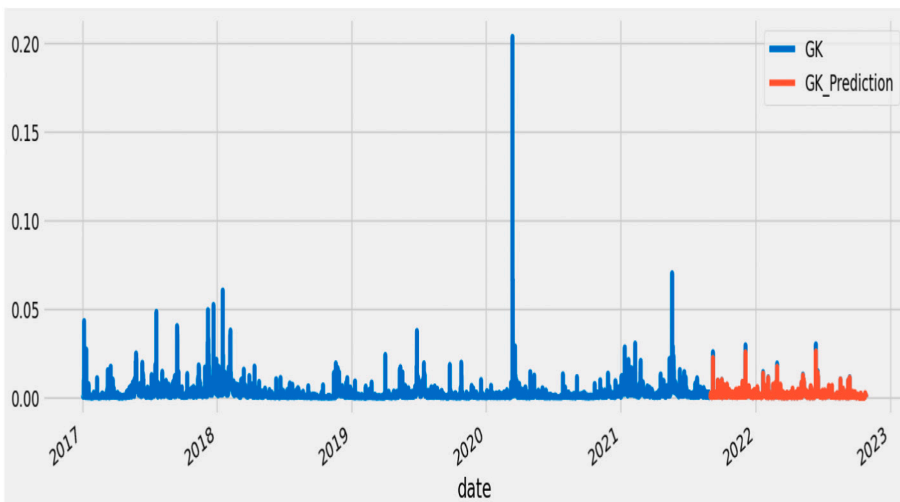

Fig. 5. LTSM prediction result of GK volatility. Note: LSTM: MSE = 1.719215e-07, MAE = 0.00011.

price of Bitcoin. However, it is crucial to acknowledge that predicting the price of Bitcoin, akin to other financial assets, presents significant difficulties due to its substantial volatility and the multitude of factors that exert influence on its valuation. Long Short-Term Memory (LSTM) models represent a single facet among other methodologies that might be employed for this particular objective. Gather historical data on Bitcoin prices, encompassing timestamps and their related values. The acquisition of this data can be facilitated through a multitude of Bitcoin data providers or application programming interfaces (APIs). The data should be pre-processed through the normalization or standardization of price values. Additionally, feature engineering techniques, including technical indicators like moving averages or the Relative Strength Index, can be applied to enhance the dataset. Given the speculative nature of cryptocurrency markets and their susceptibility to external influences, news developments, and fluctuations in opinion, it is imperative to use prudence when engaging in Bitcoin price forecasting.

Moreover, there can be substantial variation in the accuracy of price projections, and it should be noted that past performance does not serve as a reliable indicator of future outcomes. Long Short-Term Memory (LSTM) models represent a singular instrument within a broader array of techniques employed for making predictions. It is imperative to use LSTM models in tandem with other analytical approaches and strategic methodologies (see Figs. 4 & 5).

4.2. *SARIMA forecasting*

In this part, we have used the SARIMA (Seasonal Autoregressive Integrated Moving Average) model to predict future prices. We can use SARIMA for prediction when the data is stationary. The data close is not stationary, unlike the GK volatility. We have applied techniques to make the data stationary for SARIMA estimation and the time series seasonality verification. Thus, we have applied square root scaling and one lag differencing to convert the data into a form of stationarity. The SARIMA model solves this issue by transforming non-stationary time series to stationary data using the differencing transformation(Fang-Mei et al., 2002; Güngör et al., 2021). the ACF and PACF plots in Fig. 6 identified the appropriate values of q and p orders of SARIMA for the close price while Fig. 7 schemes ACF and PACF that Bitcoin GK volatility was indicating stationary data.

To select the final model, we have obtained the least Akaike Information Criterion (AIC) value by an iterative procedure and the AIC minimum value. This has given us the final model. Table 2 and 3 present the best AIC values for bitcoin close price. For the close price, the best order differential transform is used (Table 2), and it is possible to see that the data's trend has been eliminated (Fig. 6). In addition, the stationarity test demonstrates that the *p*-value is smaller than the significance level and is extremely close to zero. The rise in q caused by increasing w is modest.

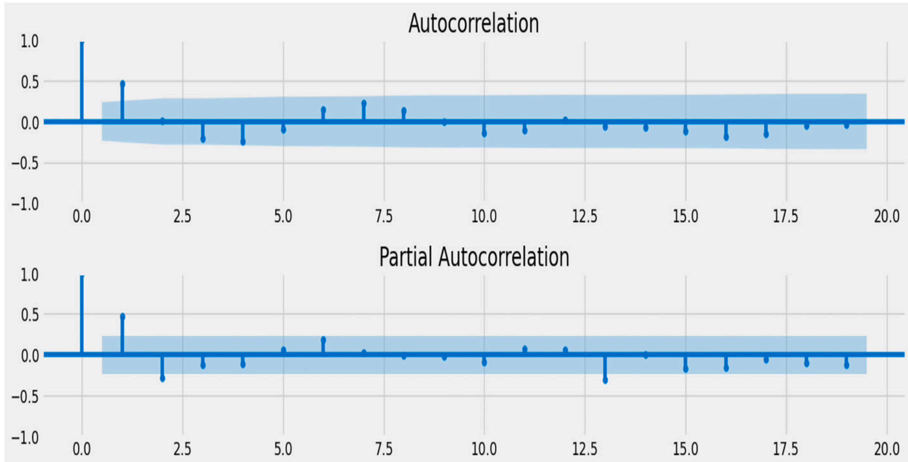

Fig. 6. Time Series close price plots (ACF and PACF).

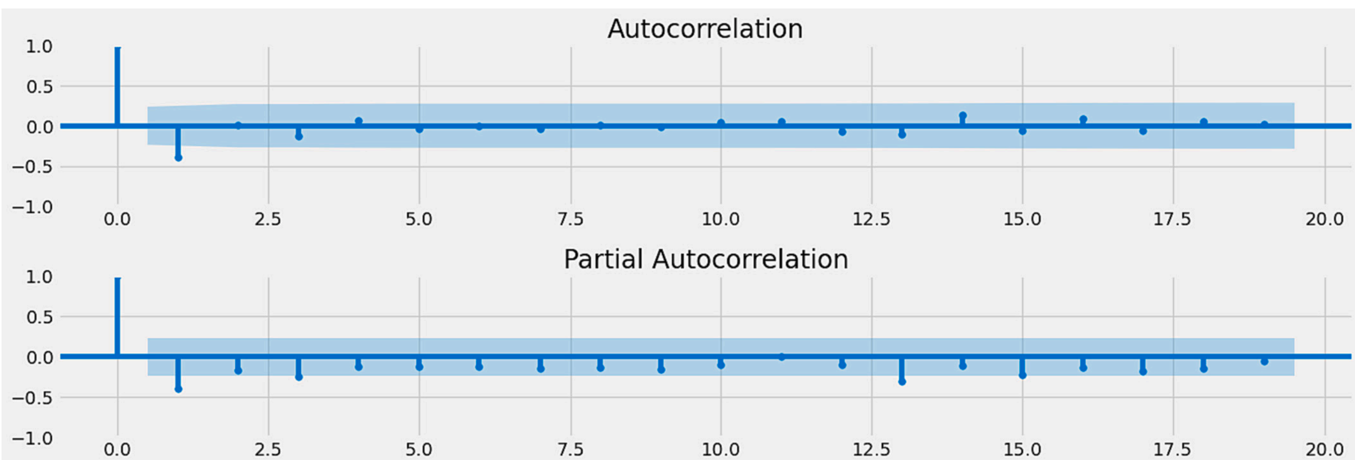

Fig. 7. Time Series GK volatility plots (ACF and PACF).

Table 2
AIC values for close price using SARIMA models.

	coef	std	err	z	P > |z|	[0.025 0.975]
ar.L1	0.2650	0.368	0.720	0.472	−0.456	0.986
ma.L1	0.4087	0.242	1.690	0.091	−0.065	0.883
ma.S.L12	−1.2142	0.183	−6.638	0.000	−1.573	−0.856
sigma2	2.686e+07	6.8e-09	3.95e+15	0.000	2.69e+07	2.69e+07

Source: our elaboration.

Table 3
AIC values for GK volatility using SARIMA models.

	coef	std	err	z	P > |z|	[0.025 0.975]
ar.L1	0.6938	0.066	10.531	0.000	0.565	0.823
sigma2	7.278e-06	5.95e-07	12.224	0.000	6.11e-06	8.45e-06

Source: our elaboration.

Figs. 8 and 9 plot the system's prediction using SARIMA and choosing the best AIC values for close price and GK volatility, respectively. We can observe how the model's button performs using historical Bitcoin price and GK volatility data. We have plotted the actual and predicted values to visualize the model's accuracy. The figure depicts the assessment of the true observation during the period estimation (red color) and the prediction value (blue color). The convergence between predicted and actual data explains the minor error, and the SARIMA also successfully predicts the estimation. It seems that SARIMA parameters have been well-fitted. We have found that predicted values follow the actual and seasonal patterns.

4.3. Prophet forecasting

Using Facebook Prophet has been relatively easier than modeling with SARIMA and LTSM because of Facebook Prophet's simplicity and ease of use. Compared to SARIMA, we have seen how much simpler it is. Firstly, by creating two columns for Close price and GK volatility by adapting and preparing the data, we have jumped directly into modeling because we do not need to check the data stationarity. After modeling, we have moved on to predicting the price and volatility by generating the future dates we would have liked to forecast. These dates have been plotted, showing how the model scales up toward previous data or wherever values might go. The results are shown in Figs. 10 and 13 for the close price and GK volatility, respectively. Blue lines present predicted values, while black dots indicate observed (actual) values, and Blue-shaded regions present lower and upper uncertainty intervals. Figs. 12 and 13 plot the trend, weekly, and daily plot analysis on

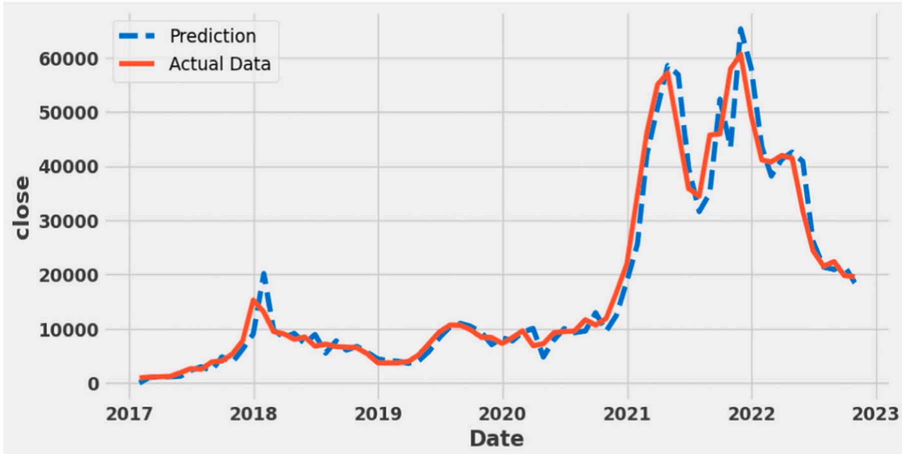

Fig. 8. SARIMA prediction result for close price. Note: MSE = 38,080,003.02 RMSE = 6170.9.

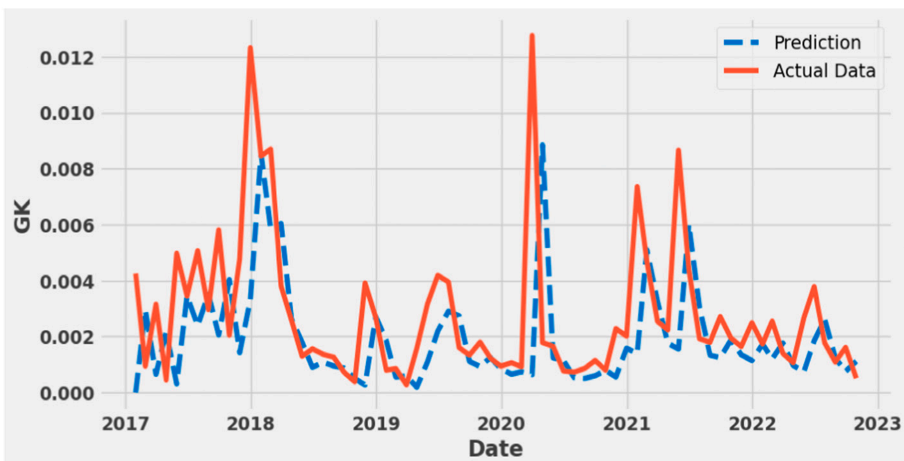

Fig. 9. SARIMA prediction result for GK volatility. Note: MSE = 1.71921e-05, RMSE = 0.0081897.

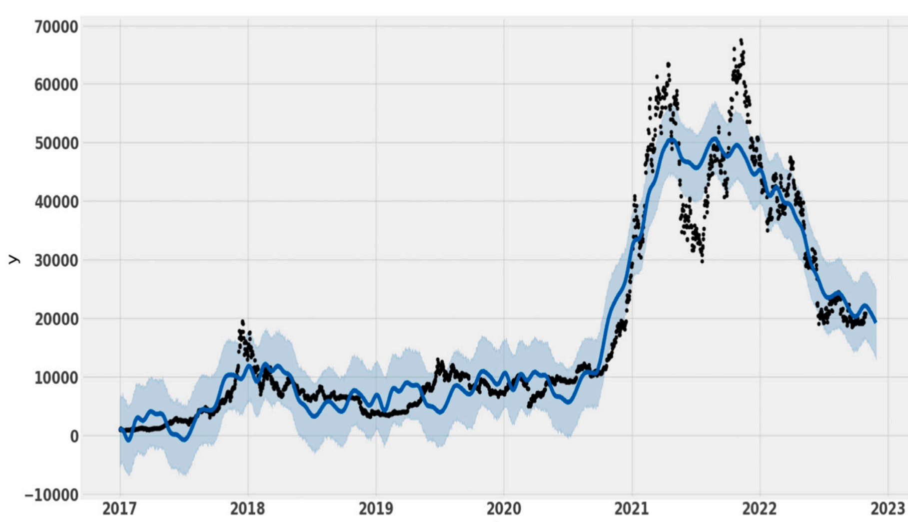

Fig. 10. Facebook Prophet prediction result for close price. Note: MSE = 131,383,832.22, MAE = 7767.94.

FbProphet for close and GK volatility, respectively. The finding explores that prediction outcomes are intriguing during the non-turmoil period (Fig. 11).

On the contrary, The FB-Prophet cannot easily fit within the Russian-Ukrainian conflict period and some periods of COVID-19 periods, so its performance will suffer during the turbulent era. From Figs. 12 and 14,

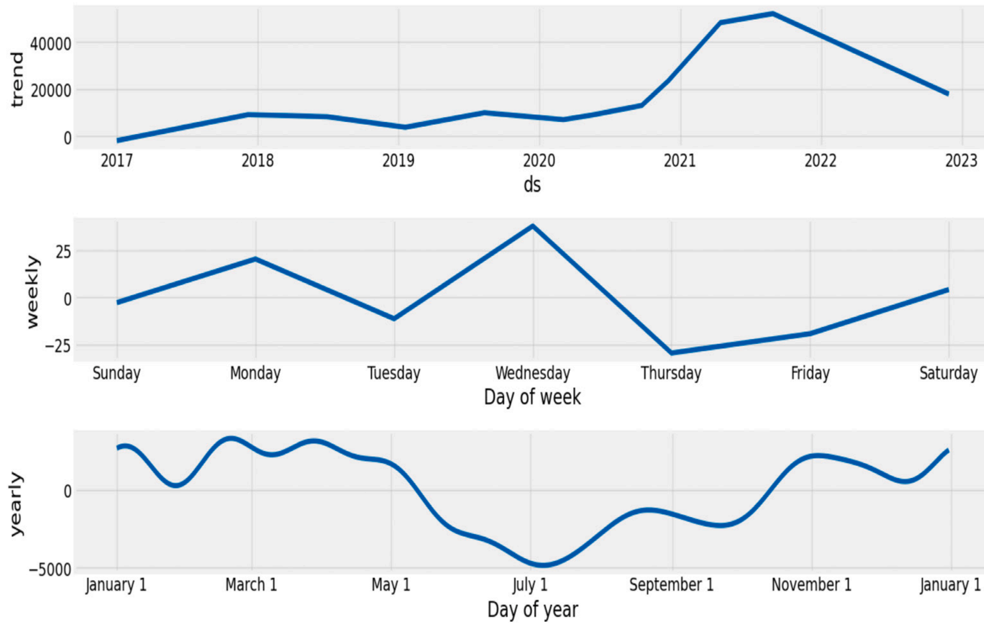

Fig. 11. Trend, weekly, and daily plot analysis on Fb Prophet for close price.

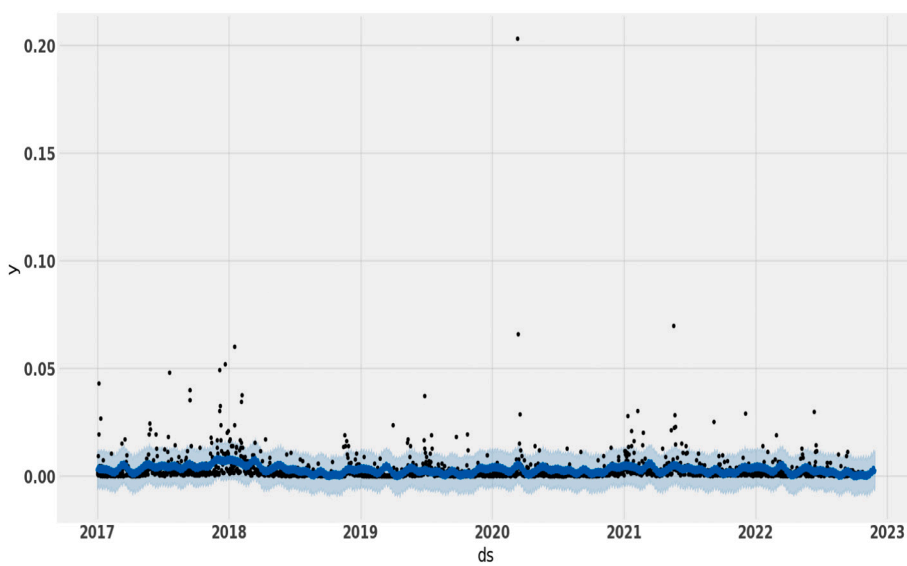

Fig. 12. Facebook Prophet prediction result for GK volatility. Note: MSE = 0.010995, MAE = 0.050787.

we have obtained a robust optimistic trend, and the days when the most people commute are Monday and Saturday, and an annual seasonality. We used seasonality to examine the changes in bitcoin and GK volatility on a weekly and yearly scale. In comparison, the early trend was less stable than weekly. In contrast to volatility, which has a pattern that declines from the first period to the middle and the last period, the trend is likewise stable for comparable prices while increasing in the previous period.

The fitting forecasting has used the statistical metrics, represented by the mean square error (MSE), and mean absolute percentage error (MAPE), to verify the predictability of the price and GK volatility using LTSM, SARIMA, and FbProphet models and their validation. Table 4 shows the performance measures values with fewer values representing the better model prediction.

From Table 4, shown above, we have the best MSE and MAE results for the close price and GK volatility by LTSM followed by SARIMA than Fb Prophet. The system demonstrates that the LSTM, SARIMA, and FB-Prophet are fully adaptable in the prediction of bitcoin values. These results align with the previous research (Basher and Sadorsky, 2022a; R. Gupta et al., 2022; Saiktishna et al., 2022; Waseem et al., 2022; Wirawan et al., 2019).

5. Findings and discussion

The LTSM prediction almost matches the actual values of the SARIMA and Fb- Prophet models. At the same results, the GK volatility appears to have a better outcome than the close price given a small value than close. The LTSM measures deals are better enough than SARIMA and Fb-Prophet, respectively, and have given it the preference for volatility over price prediction within this study. Furthermore, the finding confirmed that Bitcoin values are extremely seasonally volatile and random and are frequently influenced by external variables (or news) such as cryptocurrency laws, investments, or social media rumors. The FB-Prophet cannot easily fit within the Russian-Ukrainian conflict

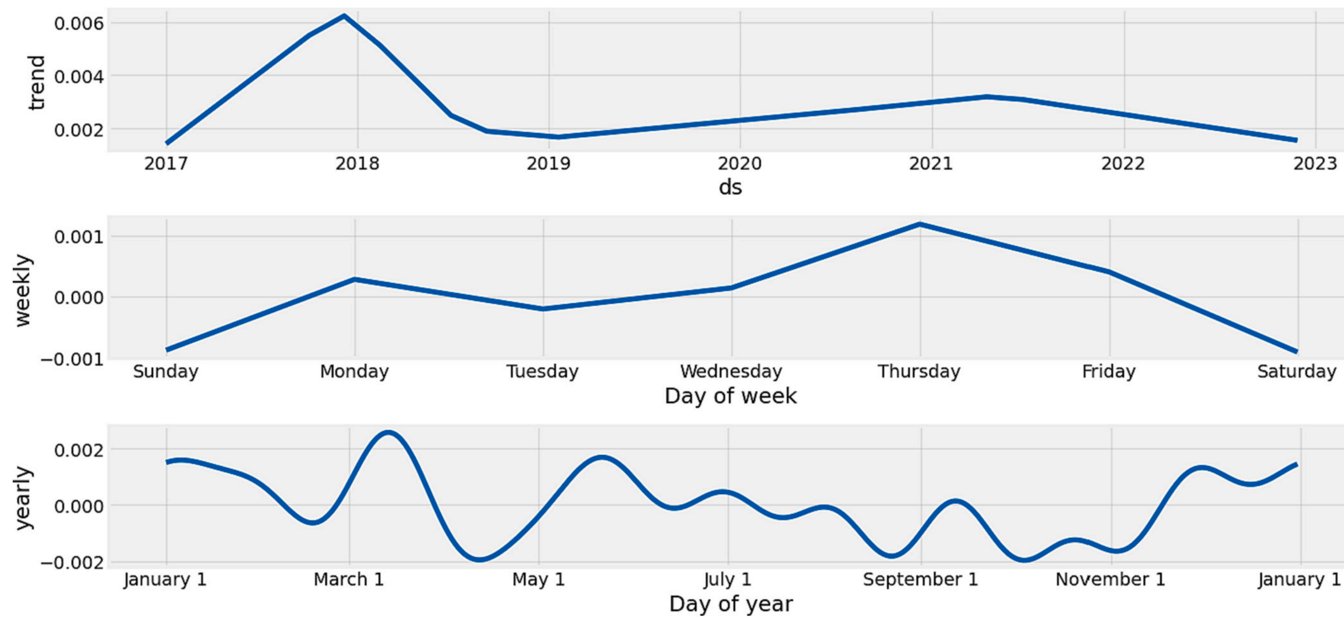

Fig. 13. Trend, weekly, and daily plot analysis on Fb Prophet for GK volatility.

Table 4
The performance measures values.

Model	MSE	MAE
Close price		
LTSM	503,746.37	624.37
SARIMA	38,080,003.02	6170.9
Fb Prophet	131,383,832.22	7767.94
GK volatility		
LTSM	1.719215e-07	0.00011
SARIMA	1.71921e-05	0.0081897
Fb Prophet	0.010995	0.050787

Source: our elaboration.

and some COVID-19 periods, so its performance will suffer during the turbulent era. The trend of the price and volatility of bitcoin using SARIMA and FB-Prophet is more predictable. The forecast error for 2021 and the first half of 2022 is significantly higher than in normal market conditions.

Furthermore, empirical findings show a robust optimistic trend, and the days when most people commute are Monday and Saturday and an annual seasonality. We used seasonality to examine the changes in Bitcoin and GK volatility on a weekly and yearly scale. In comparison, the early trend was less stable than weekly. In contrast to volatility, which has a pattern that declines from the first period to the middle and the last period, the trend is likewise stable for comparable prices while increasing in the previous period.

On the contrary, the LTSM appears more practical to handle long-term predictions and dependencies due to its capacity to store information from the past and recall it when necessary. It has several memory cells. Different gates and states allow each compartment to regulate the data flow through it. Our findings align with the study (Hamayel and Owda, 2021; Waseem et al., 2022), which relied on the best time series forecasting of bitcoin. The trend for volatility appears less stable from 2017 to last year period. This finding aligns with previous studies focusing on the bitcoin crash's volatility (Hakim das Neves, 2020). The results show a significant convergence between accurate data and anticipated value for both bitcoin close price and GK volatility. Notably, the outcome explores that LTSM GK volatility has outperformed relative prices in terms of accuracy, which is lower than the evaluation statistics.

Furthermore, the fitting forecasting of the proposed models has been used with the help of statistical metrics and is further represented by the Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE). For verifying the predictability of the price and GK volatility using LTSM, SARIMA, and Fb-Prophet models and their validation. Findings suggested the best MSE and MAE results for the close price and GK volatility by LTSM followed by SARIMA than Fb-Prophet. The system demonstrates that the LSTM, SARIMA, and FB-Prophet are fully adaptable in the prediction of bitcoin values. All the empirical investigations performed through different models have significantly forecasted the Bitcoin price volatility under uncertain situations like the COVID-19 pandemic and the Russian-Ukrainian conflict. GK volatility and Bitcoin prediction estimated in this study can be used to calculate important metrics like block propagation delay and compare them with altcoins (existing Bitcoin-based cryptocurrencies). These metrics are important indicators to measure the network's security and stability and assess a given cryptocurrency's volatility and viability.

On the other hand, recent recessions, such as the COVID-19 pandemic and the Russo-Ukrainian conflict, have impacted cryptocurrencies significantly at different levels. As investigated by Khalfaoui et al. (2023), in the short term, under normal and bearish market states, all cryptocurrencies are negatively affected by the conflict between Russia and Ukraine. In contrast, it is positively affected when the markets are bullish. Interestingly, the conflict has a more intense impact on bearish-bearish joint distributions at the lowest quantiles. Notably, G7 stock returns were positively affected when the Russia-Ukraine conflict and vice versa negatively impacted cryptocurrencies. For the market agents and mid-term investors, all the cryptocurrencies are safe havens or hedges when the market is bullish under a mid-term perspective due to the negative coherency values.

Furthermore, under bullish market scenarios, mid-term investors may get diversification benefits because of a negative association between the Russia-Ukraine conflict and public attention. Overall, engendering recent price falls and selling to seek liquidity, large cryptocurrency investors consistently respond to the impacts of the Russia-Ukraine conflict. Additionally, when markets are bearish or bullish, and investors focus on short- and long-term hedging strategies, they will get valuable benefits regardless of the liquidity concerns.

6. Conclusion and policy implications

After its first boom period in 2013, bitcoin prices and volatility have fluctuated extraordinarily. With expected bubbles, these investments are at high risk. It is critical to determine the right parameter distributions and the acceptable time model to display certain stylized aspects and some statistical fluctuations in the financial time series behavior. We collected The Bitcoin data over 4 high years from 01 January 2017 to 30 October 2022. Compared to Prophet and SARIMA, LSTM has performed better on the MAP and MSE matrices scale for most of the data. Rapid growth is shown by trend analysis, and the forecast study indicates a significant increase in predicted price movement.

Moreover, many strategies can influence the results of the forecast. Although the installed models have performed well, our analysis is restricted to their effectiveness, which will be improved even more by choosing several prediction models. The learned forecasting outcomes can be improved by accounting for various factors, utilizing deep learning techniques, and using artificial intelligence. Administrative authorities must provide favorable policies under which Bitcoin speculation will not arise since it has been clear that the Bitcoin medium-of-exchange function is not invalidated by the price volatility anymore. Further, constructing an equilibria framework is the need of the hour for conducting the Bitcoin operation smoothly and demonstrating their existence effectively. As seen in the investigation, the price of Bitcoin might depreciate, appreciate, or mix in expectation thereof. Therefore, in both "unconventional" and "conventional" scenario, implications for monetary policy is always helpful for economists, stakeholders, and investors. These findings show the economic value of the forecasting data from external Bitcoin marketplaces for fund managers and investors. When these models are used to forecast financial assets like bitcoin, their superiority becomes even more apparent.

Furthermore, accurate forecasts boost financial market stability, while inaccurate ones hurt portfolio success. However, it is impossible to predict the price volatility and specific other trends of cryptocurrencies like Bitcoin with 100 %. Nevertheless, as estimated in the present study, with the help of Long Short-Term Memory (LSTM), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Facebook prophet models, it is quite possible to predict the future trends and how Bitcoin will perform in the coming years. Present trends, analysts, and expert investigations predict that Bitcoin will go up by 350 % by 2024, and model forecasting of this study is also directed in the same way. These days, the prediction of cryptocurrencies is much needed so investors can make better-informed investment decisions. Therefore, researchers are working on large data sets that can provide valuable insights and accurate predictions about Bitcoin.

Most importantly, cryptocurrencies like BTC, XRP, ETC, and LTC performed differently under the COVID-19 pandemic and the Russo-Ukrainian conflict. Among them, Bitcoin is regarded as a safe hedge. Since it has been built into a crucible for dealing with the recession, moreover, other qualities of Bitcoin, such as an inherently diversified, globally transferable, and secure wealth store, add supply when it is capped and decreased. In the future, more work should be done to establish indexes and systems capable of providing vulnerability diagnostics of model forecasting. More advanced machine learning algorithms built from ML experiments may be helpful and should be systematized to supplement traditional time-series studies. Bitcoin, a form of digital currency and a technology known as blockchain, is a topic of considerable scholarly interest among researchers across multiple disciplines. Investigating scaling solutions such as the Lightning Network and sidechains is significant in academic discourse. A necessity exists to enhance the optimization of these technologies to effectively manage higher transaction volumes while simultaneously upholding principles of security and decentralization. Scholars can explore the economic and behavioral dimensions of the adoption of Bitcoin. This encompasses examining the influence exerted by Bitcoin on conventional financial systems, its use as a means of preserving wealth, and individuals' perceptions and utilization patterns toward it. These research scopes encompass diverse prospects for academics and experts to make valuable contributions to the continuous advancement and comprehension of Bitcoin and its fundamental technology. As the Bitcoin ecosystem undergoes further development, novel research inquiries and obstacles are expected to inevitably arise.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Jiyang Cheng: literature review, editing, supervision, preparing draft.

Sunil Tiwari: Conceptualization, Introduction, Data curation, Supervision.

Djebbouri Khaled: review, editing, introduction, policies.

Mandeep Mahendru: Introduction, software, analysis, concept and reviewing.

Umer Shahzad: discussion, policies, editing, results, implications.

Data availability

Data are available upon request from the corresponding author. Data can also be accessed from data sourced mentioned in the manuscript.

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