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Volatility Forecasting Of Bitcoin Prices: Time Series And Machine Learning Approach

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Abstract

Digital currencies have attracted considerable attention worldwide over the last few years. Bitcoin has the greatest market capitalization among cryptocurrencies; investors, analysts, and financial experts are interested in predicting its price volatility and obtaining optimal returns. Assessing and forecasting the behavior of cryptocurrencies is a difficult endeavor because of the existence of severe events, information asymmetry, and nonlinear characteristics of time series data. Using multiple heterogeneous auto-regressive models and the deep learning approach LSTM, this study aims to explore the risk and return characteristics of Bitcoin. To forecast volatility closing price data of Bitcoin over ten years were utilized. LSTM and GARCH deep learning models were implemented using Phyton libraries. The performance of the Machine Learning and the statistical models were evaluated with performance matrices like root mean squared error (RMSE), and Mean squared error (MSE) using different plots, and loglikelihood methods. The findings of the study reported the superiority of the volatility forecast of the LSTM approach over traditional econometric models. The findings of the study are useful for investors, financial institutions, fund managers and policymakers to establish volatility strategies to adopt new business models.

Key Words: *Cryptocurrency, bitcoin, volatility forecasting, Machine learning algorithms, LSTM.*

Introduction:

Cryptocurrencies play a significant role in the world's financial system. As of December 2021, there are 600 exchanges, with more than $1.38 trillion in market capitalization and Bitcoin continues to dominate this market (Forbes, 2023). The cryptocurrencies are investors' choice because of dynamic hedge properties and their detachment from other financial markets (Bouri E, 2022). The cryptocurrency also possesses attributes of the environment-friendly assets (Richardson, 2023).

However, as the cryptocurrency market is decentralized and lacks governmental backing, it faces the risk of high volatility as well as pricing bubbles (Corbet & Andrew Meegan, 2018). The more precise and accurate forecasting of bitcoin is inevitable and is of great interest to

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investors to make informed investment decisions and to mitigate risk. One of the objectives of the current study is to comprehend the volatility mechanism of cryptocurrency.

The volatility can be defined as the variability of return over time (Woebbeking, 2021). Accurate volatility forecasts can help investors make informed decisions about asset allocation and risk management. Forecasting cryptocurrency volatility can support financial institutions in developing innovative financial products, such as derivatives anchored to cryptocurrency, by leveraging insights about blockchain technology and crypto-asset relations. The theoretical foundation of volatility modelling specifically from the perspective of time series was introduced by (Fama, 1965) (Fama, 1965), the key theories and concepts driving this research include the Efficient Market Hypothesis where price changes are assumed to be random and unpredictable. However, empirical evidence often demonstrates certain patterns like volatility clustering which causes significant price fluctuations to cluster together and result in the persistence of the amplitudes of price changes, is frequently observed in time series of financial asset returns (Cont, 2007), thus testing and potentially challenging the EMH. Financial theory observes that markets respond differently to positive and negative news. This asymmetric response, or leverage effect, is explained by the fact that negative news increases the perceived riskiness of an asset more than positive news reduces it. The theoretical rationale behind employing GARCH models for Bitcoin volatility is based on these financial econometric principles, and the current study applies them to understand and model the complex nature of Bitcoin's price behavior. Financial time series often display characteristics that deviate from the assumptions of normality - specifically, leptokurtosis and skewness. Certain GARCH models, like the tGARCH, can better model to capture asymmetric effects. The GARCH models with alternative error distributions like Student-t, Generalized Error Distribution, or Normal Inverse Gaussian are used to capture these departures from normality. This contributes to the broader theoretical understanding of cryptocurrency markets, which sometimes exhibit more pronounced characteristics compared to traditional financial markets, such as higher volatility and more evident deviations from the normal distribution of returns. So, another objective of current study is to identify the model which have increased efficiency to forecast the volatility crypto currency market generally and bitcoin particularly.

Cryptocurrency markets are susceptible to extreme, unforeseen 'Black Swan' events that can cause structural breaks in the data (Mnif & Jarboui, 2022). These events are inherently unpredictable and challenging to model with GARCH or any time-series models. Moreover, cryptocurrency market is influenced by a rapidly evolving regulatory environment that can induce significant shifts in market behavior and volatility. GARCH models that rely on past data may not fully account for sudden regulatory changes. GARCH models typically do not account for systemic risk that affects the entire cryptocurrency market or financial, so another objective of current research is to select an appropriate model to get more accurate forecast of volatility of bitcoins.

Machine learning techniques have been increasingly applied to predict volatility in financial markets, offering valuable insights for investors and market participants. Studies have shown that machine learning models, such as deep learning-based regression models and hybrid models combining jump models with machine learning, outperform traditional methods in forecasting volatility (Yang, et al., 2020) (He, 2023).. Machine learning algorithms play a crucial role in identifying patterns and trends in financial data sets, aiding in risk assessment and decision-making processes for maximizing investment returns , ML algorithms have better ability to predict volatility of financial markets over traditional heterogeneous autoregressive models (Christensen, Siggaard, & Veliyev, 2023). The use of machine learning in financial market volatility prediction has seen a significant rise and in the realm of deep learning, long short-term memory is an artificial recurrent neural network design. LSTM has feedback connections, in contrast to conventional feedforward neural networks. It is capable of processing large data sequences in addition to individual data points. One kind of recurrent neural network that can recognize order dependence in sequence prediction issues is the Long Short-Term Memory (LSTM) network. In difficult problem domains like speech recognition and machine translation, among others, this behavior is necessary. One intricate subfield of deep learning is LSTMs. Using ML techniques, Long short-term memory (LSTM), the daily volatility of bitcoin forecasted the evaluation matrices of Root Mean Squared Error, Mean Absolute Percentage Error, Normalized Mean Squared Error were used to evaluate the performance of the forecasts. The study results reported that ML methods are better than the traditional volatility model, namely Generalized Autoregressive Conditional Heteroskedasticity (GARCH), to forecast volatility. The study results indicated the Machine Learning Models substantially improve the forecasting performance of volatility forecasting.

The current study contribution to the existing literature is manifold, firstly this study addresses the need for more efficient forecasting techniques by analyzing traditional approaches ARCH, GARCH, gjr GARCH, skewt-GARCH models and with deep learning approaches LSTM for predicting Bitcoin volatility. It raises awareness among business and financial market researchers about the possibilities of deep learning technologies and promotes their regular application in research. To comprehend any distinctions between various deep learning approaches, the research offers a comparative analysis for them by adding in scientific debates of the volatility forecasting topic. Thirdly the visuals of study are created with multiple python libraries and performance matrix results provides superiority of the performance results provides valuable insights to the bitoin volatility forecasting literature. Moreover, this study utilized data of pre, in and post crisis covid time frame , the application of conventional and machine learning applications were implemented through three time zones. The comparison of dispersion of returns of bitcoins through multiple models and evaluation of results accurate forecasting of cryptocurrency volatility is important for investors, financial institutions, policymakers, and academia to optimize decision-making, risk management, and the development of innovative financial products.

Literature Review:

The volatility of cryptocurrencies has been a topic of significant interest in recent research. (Fernández-Villaverde et al., 2020) highlighted the potential of central bank digital currencies to replace demand-deposits in private banks, exposing the central bank to demand-liquidity shocks. Financial markets play a pivotal role in economic growth, and forecasting financial returns is essential for investment decision-making. The dynamism, complexity, and extreme volatility are the characteristics of financial markets. It is difficult to forecast the returns on financial assets because a variety of factors, from macroeconomic conditions to human behavior, influence the financial markets. In literature, three forecasting models are divided into three distinct categories used to predict financial assets returns fair value models (Olga, 2022) (Kevin, 2010) to analyze whether the financial security is underpriced or over priced relative to its intrinsic value , the second is explanatory return models (Xianhua, 2013) (Hendra, 2020) and forecasting models used time series data to predict financial assets returns these models include ARIMA and GARCH (Jeelan, 2023) (Zhixiang, 2022).

The cryptocurrency markets are attributed as a dynamic, volatile and complex market. The most evident feature of bitcoin is its extreme volatility (Ze-Han Shen, 2021) (Renan, 2022) the bubble and the cryptocurrency relationship existed. The ARCH model theory introduced by Engle in 1982, posits that the current period's variance can be modeled as a function of the previous periods' squared innovations. This model addresses time-variant volatility where large changes in returns are likely to follow large changes, and small changes are likely to follow small changes. Bollerslev extended the ARCH model to GARCH by incorporating past variances into the model. It suggests that the best predictor of future volatility is a weighted average of past long-term variance and recent shocks.

In this context, econometric models serve as powerful tools for alpha generation in active asset management. The GARCH model have certain limitations as well as GARCH models can be complex, and selecting the appropriate form (e.g., sGARCH, iGARCH, tGARCH) and distribution assumptions (e.g., Normal, Student-t, GED, NIG) can be challenging. (Gupta & Chaudhary, 2022) analyzed the risk and return of four major cryptocurrencies using the GARCH model, revealing a strong spillover effect and asymmetric impact in volatility among different currencies. The study also examined the causal behavior among cryptocurrencies using Granger causality. (YAM XING QUAN, 2023) has analyzed the Bitcoin's volatility using GARCH models and concluded that Bitcoin exhibits an inverted leverage effect and its volatility tends to increase with good news. An incorrect model choice may not capture all the dynamics of Bitcoin volatility. Financial time series data, and particularly cryptocurrencies, can exhibit non-stationary behavior over long periods, non-stationary aspects in the data can sometimes persist, impacting model performance. There is also overfitting risk as the use of sophisticated GARCH models might overfit the historical data, which could result in poor out-of-sample forecasting accuracy. This occurs when a model captures the noise within the data sample instead of representing the underlying data generating process. (Gbolagade, 2022) applied the GARCH model to predict the volatility in the price of brent crude oil and found that the EGARCH model demonstrated the highest degree of suitability for forecasting future volatility with the lowest coefficient of its asymmetry parameter, indicating that negative news or major events like COVID-19 had a greater impact on the volatility of Brent crude oil. Additionally, study by Doong Toong Lim et al. emphasizes the significance of GARCH models in analyzing stock market volatility and forecasting returns, showcasing the models' ability to capture volatility clustering and provide accurate forecasts for portfolio allocation and option valuation (Doong, 2023). Additionally, the GJR-GARCH model has been highlighted as more powerful than the standard GARCH model due to its ability to capture leverage effects effectively, enhancing the reliability and accuracy of predictions (Farman, 2022). (Siti, 2021) uses GARCH, EGARCH, and GJR models to forecast volatility and found that EGARCH model shows asymmetric impact of positive and negative shocks.

The volatility forecasting is a crucial component of risk management, asset allocation, and investment decision-making. (Wang et al., 2017) proposed a decentralized electricity transaction mode for microgrids based on blockchain and continuous double auction (CDA) mechanism, ensuring consumer interests through digital certification on the blockchain system. On the other hand, (Walther & Klein, 2018) apply the GARCH-MIDAS framework to forecast the volatility of cryptocurrencies, highlighting the importance of exogenous drivers such as Global Real Economic Activity in predicting volatility. Moreover, (Nour et al., 2023) introduce a model for predicting cryptocurrency volatility using the TOPSIS approach and multi-valued neutrosophic set to reduce uncertainty. (Djanga et al., 2023) investigate the benefits of intraday realized volatility commonality in forecasting one-day ahead intraday RV, emphasizing the outperformance of models that leverage cryptocurrency commonality. Furthermore, (Alam et al., 2024) enhance the GARCH-MIDAS model through SB-GARCH-MIDAS to analyze the relationship between cryptocurrencies and monetary policy, revealing the sensitivity of older cryptocurrencies to structural breaks in exogenous variables. (Kaseke, Ramroop, & Mwambi, 2022) compared cryptocurrency volatility with the Johannesburg Stock Exchange, revealing higher volatility and persistence in cryptocurrencies. The study also highlighted an inverse leverage effect in cryptocurrencies compared to the JSE market. (Queiroz & David, 2023) compare the performance of the Realized-GARCH model against other GARCH-based models in predicting cryptocurrency volatility, demonstrating the superior out-of-sample forecasting ability of the Realized-GARCH model.

The application of Machine learning Models and Deep Learning Models has gain significant attention in finance in recent years (Ozbayoglu, Gudelek, & Sezer, 2020) (Charpentier, 2021) (Moscato, Picariello, & Sperlí, 2021) (Hambly, Xu, & Yang, 2023). In time series analysis the application of Long Short Term Memory(LSTM) networks is considered as premier technique for sequential learning (Zhang, Yan, & Aasma, 2020). The LSTM models is not commonly applied for the prediction in financial time series so, there is a need to apply Machine Learning Technique for the prediction of volatility of cryptocurrency. The LSTM is type of RNN, for sequential data the LSTM has an ability to captures the longterm dependencies. On the other hand, (Ammer & Aldhyani, 2022) focused on the decentralized nature of digital currencies like Ethereum and XRP, emphasizing the appeal of cryptocurrencies for investors and researchers. The study presented a LSTM algorithm for forecasting cryptocurrency prices, demonstrating superior performance in predicting values for various cryptocurrencies. Furthermore, (Choi & Shin, 2022) proposed a normal double inverse Gaussian process to model the time series properties of Bitcoin, capturing skewness and fat-tailed properties of returns. The study derived two volatility measures and compared them to historical standard deviation, showing the effectiveness of the NDIG process in capturing observed volatility. (Das & Thulasiram, 2024) addressed the challenge of predicting prices of financial assets using novel encoder-decoder architectures, AE-LSTM and AE-GRU. The study demonstrated the superiority of the AE-GRU architecture in forecasting prices of volatile financial assets across diverse sectors. Overall, these research papers provide valuable insights into the volatility of cryptocurrencies, offering various methodologies and models to analyze and predict cryptocurrency prices but not a consensus drawn on identifying the suitable model to predict cryptocurrency volatility. (Kim, Kim, & Jung, 2021) compares different predictive techniques for forecasting corporate bond yield spreads and finds that neural network forecasts outperform other methods for short and longer forecast horizons.(Hanauer & Kalsbach, 2023) reported that machine learning models outperform traditional linear models in predicting stock returns, especially in capturing non-linear relationships and interactions among characteristics.

The Machine Learning is rapidly evolving tool widely used in predicting financial securities returns like stock returns (Hendra, 2020) for bond returns (Kim, Kim, & Jung, 2021) and currency exchange rates (Abedin, Moon, Hassan, & Hajek, 2021) but still there are lack of studies and consensus on methods suitable in forecasting cryptocurrency volatility. Moreover, LSTM models is not commonly applied for the prediction of financial time series so, there is a need to apply Machine Learning Technique for the prediction of volatility of cryptocurrency. Moreover, despite the different modeling techniques, there is consensus on the importance of accurate volatility estimation for informed investment decisions. To comprehend any distinctions between various traditional volatility capturing model and deep learning approaches, the current research offers a comparative analysis for them by adding in scientific debates of the volatility forecasting topic.

Data and Methodology:

The study retrieves data of daily closing prices of bitcoin in US dollars from 28.04.2013 to 02.01.2024. The volatility of returns was measured with returns r_i by taking first difference of log prices mathematically represented as under:-

$$r_i = \log\left[\frac{p_i}{p_{i-1}}\right]$$

several preliminary statistical tests were run to explore the structure of the bitcoin currency price index Before analysing the volatility. First, to check the normality of distribution descriptive statistics (mean, minimum, maximum, and standard deviation) skewness kurtosis was calculated and Jarque Bera test was performed to assess the suitability of the GARCH model. For univariate time series data that is stationary (AR), has a trend (ARIMA), and has a seasonal component the autoregressive models are suitable. A variation in variance over time is one feature of a univariate time series that these autoregressive models cannot account for. Heteroskedasticity is the property of a time series in which the variance is rising in a systematic manner, e.g., an increasing trend. It's a fancy statistical term for variation that varies or is uneven throughout the series. A technique called ARCH explicitly models how a time series' variance changes over time. To be more precise, an ARCH approach expresses the variance as a function of residual errors from a mean process (zero mean, for example) at a given time step. To assess the stationarity of the time series ADF Test and PP test were performed ((Dickey & Fuller, 1979) (Phillips & P.Perron, 1988) the null hypothesis is Ho = the series has a unit root (non-stationarity) with an alternative hypothesis the series does not have a unit root (stationary) and to assess the residual heteroscedasticity, ARCH effect and to assess the suitability of the GARCH Model the Graphical method and Lagrange Multiplier (LM) test was performed. In 1982 the Auto-Regressive Conditional Heteroskedasticity (ARCH) model was introduced by (R. F. Engle, 1982) to measure the volatility of financial assets via lagged values this model has limitations in capturing the dynamic behavior of volatility. In 1986 (Bollerslev, 1987) introduced the Generalized Autoregressive Conditional Heteroscedasticity GARCH model with an ability to capture volatility clustering with a more flexible lag structure. A moving average component is added to the autoregressive component of the ARCH model to create Generalized Autoregressive Conditional Heteroskedasticity, or GARCH. The model incorporates lag residual errors from a mean process along with lag variance factors (e.g., the observations of modelling the white noise residual errors of another process). The model can now represent changes in the time-dependent variance as well as conditional changes in variance across time thanks to the addition of a moving average component. Conditional variance increases and reductions are a few examples. As a result, the number of lag variance terms is described by a new parameter called "p" in the model: p: The lag variances in GARCH model. q: The lag residual errors contain in the GARCH model. The further development of the GARCH model was made to capture volatility asymmetrical assets returns like EGARACH, tGARCH and gjrGARCH proposed by (Nelson, 1991) (Ding, Engle, & Granger, 1993) (Zakoian, 1994) (Glosten, Jagannathan, & Runkle, 1993).

The mathematical expressions of the models are expressed as under:-

The mean equation is represented as:-

$$r_t = \mu + e_t$$

Where r_t is the return of the bitcoin and e_t is the random error with zero mean and constant variance.

To specify the number of previous residual errors to be included in the model, a lag parameter needs to be given. This parameter can be called "q" using the notation of the GARCH model (explained below). This parameter's original name was "p," and the arch Python package that is used in this paper also has the same.

The GARCH Model (q,p) is as under:-

$$\sigma_t^2 = \omega_o + \sum_{i=1}^{q} \omega_i \, e_{t-i}^2 + + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2$$

e_t is residual and $\omega_o > 0, \omega_i \geq$ for I = 1,2,….q, and $\beta_j \geq 0$ for j = 1, 2, ….,p.

The exponential GARCH Model mathematically expressed as below:-

$$\log(\sigma_t^2) = \omega_o + \sum_{i=1}^{q} \omega_i f(z_{t-i}) + + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2)$$

$$\text{where } f(z_t) = \begin{cases} (\varphi + \gamma)z_t - \gamma E(|z_t|) \text{ if } z_t \geq 0 \\ (\varphi + \gamma)z_t - \gamma E(|z_t|) \text{ if } z_t < 0 \end{cases}$$

gjrGARCH Model is expressed as

$$\sigma_t^2 = \omega_o + \sum_{i=1}^{q} (\omega_i + \gamma_i I_{t-1}) e_{t-i}^2 + + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

For ω_o >0, $\omega_i \geq 0$, $\omega_i + \gamma_i \geq 0$ and $\beta_j \geq 0$ for I = 1, 2, ….q and j = 1,2,….,p where

$$I_t = \begin{cases} 0 \text{ if } e_t \geq 0 \\ 1 \text{ if } e_t < 0 \end{cases}$$

The tGARCH model was developed by (Glosten, Jagannathan, & Runkle, 1993), the generalized model is expressed as :-

$$\sigma_t^2 = \omega_o + \sum_{i=1}^{q} (\omega_i + \gamma_i) e_{t-i}^2 + + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

$\omega_i \geq 0$, $\omega_i + \gamma_i \geq 0$ and $\beta_j \geq 0$ for I = 1, 2, ….q and j = 1,2,….,p

The application of Machine learning Models and Deep Learning Models has gain significant attention in finance in recent years (Ozbayoglu, Gudelek, & Sezer, 2020) (Charpentier, 2021) (Moscato, Picariello, & Sperlí, 2021) (Hambly, Xu, & Yang, 2023). In time series analysis the application of Long Short Term Memory(LSTM) networks is considered as premier technique for sequential learning (Zhang, Yan, & Aasma, 2020). The LSTM models is not commonly applied for the prediction in financial time series so, there is a need to apply Machine Learning Technique for the prediction of volatility of cryptocurrency. The LSTM is type of RNN, for sequential data the LSTM has an ability to captures the longterm dependencies. These models are typically based on a collection of units named neurons that communicate and share information with one another. An input vector (x) representing the input or output data of the other connected neurons is sent to an artificial neuron or unit. By multiplying a vector of weights (w) that the algorithm calculates throughout the learning process, this data is weighted. In this manner, a transformation function g(·), sometimes referred to as the activation function, generates an output value. The output value generated with this function is known as transformation function. The mathematical expression is as under:-f(y) = g(y . w)+a. the value of a represent trend in network analysis RNN has an ability to model sequential data by using its hidden layers to interpret historical trend. If t is the time and C_t is cell at time t, the y_t

Is an input and hidden state h_t in RNN structure the output the output for state time t+1 uses input of time t and for time t the input used as of time t-1. In 1997 this model was proposed by (Hochreiter & Schmidhuber, 1997) to address the long term dependencies issues. By using the gates mechanism LSTM network captures relevant information. The mathematical expression of the model is expressed as under:-

$$i_t = \sigma(w_{ii}.y_t + a_{ii} + w_{hi}.h_{t-1} + a_{hi} \text{ (input gate)}$$

$$f_t = \sigma(w_{if}.y_t + a_{if} + w_{hf}.h_{t-1} + a_{hf} \text{ (forget gate)}$$

$\tilde{c_t} = tanh\,(w_{ic}.y_t + a_{ic} + w_{hc}\,.h_{t-1} + a_{hc}),\ C_t = f_t\,.c_{t-1} + i_t\,.\tilde{c_t}$ (cell state)

$o_t = \sigma\,(w_{io}.y_t + a_{io} + w_{ho}\,.h_{t-1} + a_{ho}$ (output gate)

$h_t = (o_t\,.tanh(\ c_t)$ (hidden state)

Where $w_{ii}, w_{if}, w_{ic}, w_{io}$ are weight metrics , $a_{hi}, a_{hf}, a_{hc}, a_{ho}$, are biased terms, σ is sigmoid and hyperbolic tangent activation function is represented by tanh . the gating method and activation function make LSTM superior over RNN by effectively handling gradient issues.

The model evaluation was made by comparing actual vs predicted results graphically and via performance metrices of , Mean Square Error (MSE), Mean Absolute error MAE and Root mean squared error (RMSE). The Mean squared error (MSE) is the average of the squared deviation of the actual vs predicted values and mathematically expressed as under:-

MSE = $\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2$

Where n is number of observations y_i are observed values and $\hat{y_i}$ are the predicted values. The MSE statistic provide the non negative results and the lower indicates that the deviation of actual from the expected are lowers and better performance.

Another performance metric that was utilized for the the evaluation of results is Mean Absolute error (MAE) expressed as under:-

MAE = = $\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}|$

Unlike to squared deviation this metric take the absolute difference form the actual to predicted observation the lower the value the better fit the model. It indicates on the average what is the deviation of observed values from predicted observations. It is suitable for the data in presence of outliers.

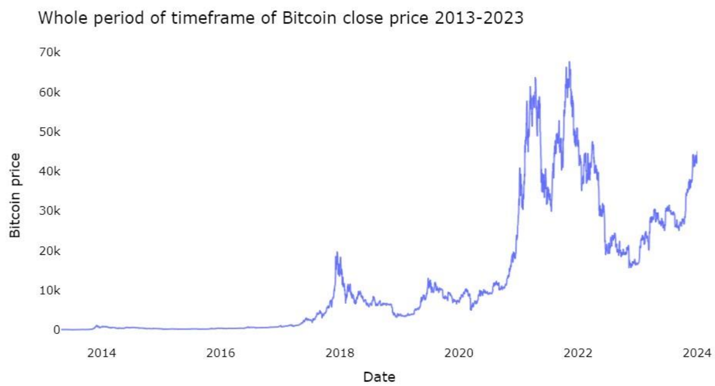
The RMSE metric is more interpretable and calculated by taking square root of MSE, for n number of observations RMSE statistic is :-

RMSE = $\sqrt{= \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2}$

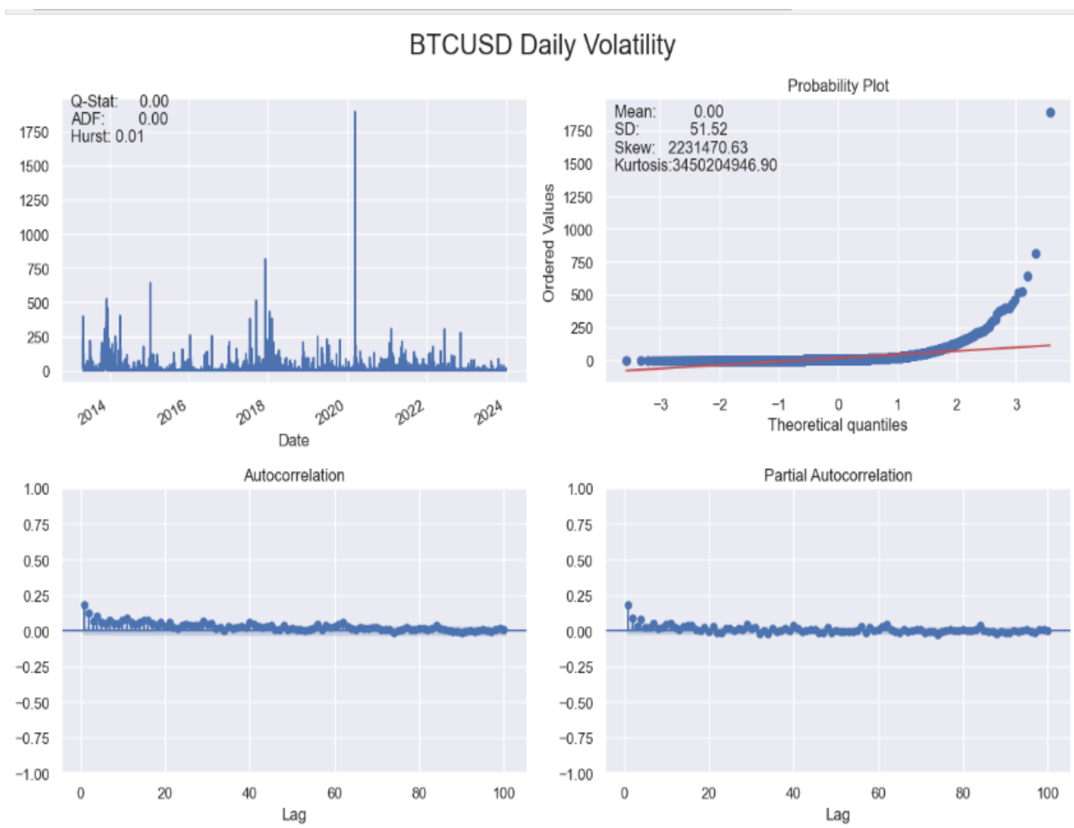
The lower vale indicates the good performance of the model. The performance of the econometric models and LSTM models were also compared through plots and graphs by using matplotlib and seaborn libraries of python.

Findings and Discussions:

To capture the volatility of returns for the period 28.04.2013 to 02.01.2024 and to fit the model the preprocessing of the cryptocurrency data was made first by taking log difference of the price data and addressing the missing observation the exploratory data analysis were made on total of 3901 observations. The figure-1 indicates the presence of volatility clustering in time series data of bitcoin price from 2013-2023.



The log difference data of bitcoin price is presented in figure-II indicates the volatility clustering of time series data of bitcoin prices. The descriptive statistics of presented in Table-1



The logarithmic return of time series data indicates that the mean return of crypto currency is of 0.14863 with the minimum return of -43.3714 and maximum return is of 28.7099. The negative skewness and the high value of kurtosis 8.853868 indicates that the distribution is not symmetrical and evidence of fat tail. The jarque-bera statistic value 12911.843079 with p-value<0.05 indicates that the data significantly deviates from normal distribution.

Table 1 Descriptive statistics	
Mean	0.14863

Maximum	28.7099
Minimum	-43.3714
Skewness	-0.52126
Kurtosis	8.853868
Observations	3899
Jarque-bera	12911.843
Q1	-1.28303
Q2	0.15418
Q3	1.77238
Daily volatility	3.954
Monthly volatility	18.05
Annual volatility	62.54

Source: Author's own calculation

The stationarity test result of the logarithmic returns of bitcoin were presented in Table-2.

Table-2 Stationarity Test of Crypto Currency

Stationary test	Test statistics	1% critical Value	5% critical value	10% critical value
PhillipsPerron	-62.72***	-3.43	-2.86	-2.57
Dickey-Fuller GLS	-4.71***	-2.57	-1.95	-1.63
Augmented Dickey-Fuller	-62.72***	-3.43	-2.86	-2.57
Zivot-Andrews	-17.94***	-5.28	-4.81	-4.57

Source: Author's own calcluation

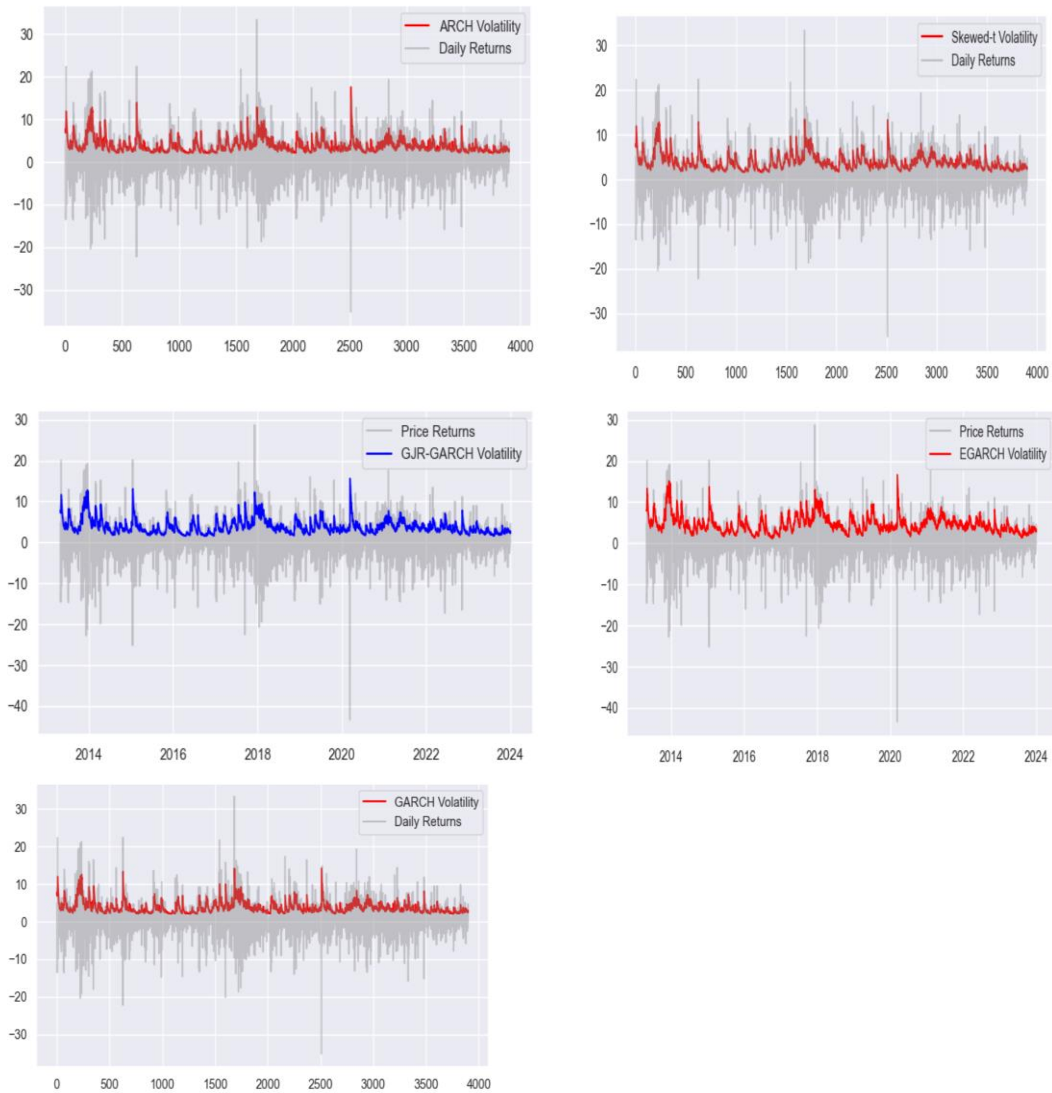
The stationarity test null hypothesis is the series has unit root with alternative the series is staionarity all the test statistics of Phillipsperron, Dickey-Fuller GLS, Augmented Dickey-Fuller and Zivot Andrews are significant at 1%, 5% and 10% level of significance and concluded that the series has no unit root. The Autocorrelation function (ACF) plot and partial autocorrelation function plot exhibts tail off pattern as evident from figure-I indicates persistent effect of shock on cryptocurrency time series data and indicates the need to incorporate past lags to model dynamics of crypto volatility. Now the GARCH (1,1) model EGARCH(1,1) and gjrGARCH(1,1) model implemented and result reported in table-3

Table-3 GARCH, EGARCH and gjrGARCH model results

	ARCH(1)	GARCH(1,1)	EGARCH(1,1)	SkewtGARCH(1,1)	gjrGARCH(1,1)
Omega	0.7246***	0.7293***	0.1209***	0.2751***	0.2805***
alpha[1]	0.1559***	0.1499***	0.3008***	0.1296***	0.1402***
gamma[1]			0.0207		-0.905
beta[1]	0.8116***	0.8133***	0.9826***	0.8704***	0.0000
Maximum Likelihood	-10444.5	-10418	-9930.28	-9960.38	-9955.58

AIC	20894.9	20844	19872.6	19932.8	19923.2
BIC	20913.7	20869	19910.2	19970.4	19960.8

The model fitting results are presented in Figure-III



The LSTM model is applied to make comparison of the results with data driven techniques. LSTM is considered state of the art model to make time series forecast. In current study LSTM used which consist of three layers and to fine tune hyperparameters GA algorithm applied to the model. For the hidden layers rectified linear unit used and for output layer linear activation function used. Adam optimization algorithm was used on a batch size of 32. The R squared of train and test data is 96%. The model performance with the original close price and predicted prices of crypto currency are presented in Figure-IV.

The performance of the models are evaluated with performance matrix result presented in Table -4

	GARCH	EGARCH	gjrGARCH	SkewtGARCH	LSTM
RMSE	50.53	53.32	50.93	50.84	39.13
MSE	2553.664	2843.129	2594.17	2584.241	1531.457
MAE	19.084	24.869	19.789	19.771	17.093

Source: Author's own calculation

The smaller MSE and MAE indicate that the actual results are closer to the forecasted results. The table-4 results indicate that all the models forecasted results are closer to the actual values and the results of the traditional econometric models are similar to the findings reported in the study of (Wang, Andreeva, & Barragan, 2023) , the suitability of GARCH Models to predict values in financial markets is also supported in studies of (Yıldırım & Bekun, 2023). The evaluation and comparison of the models indicate that the Machine Learning models have superiority of return forecasting in comparison to traditional econometric models as providing the lowest errors in terms of predicting volatility the results conform to the findings reported in studies of (Hanauer & Kalsbach, 2023) where the machine learning models have provided better forecast results in predicting stock returns.

Conclusion:

Cryptocurrency markets have garnered significant attention in recent years due to their unprecedented growth, volatility, and potential for substantial returns. However, the highly volatile nature of these markets poses unique challenges for investors and traders, underscoring the importance of effective volatility forecasting models. The findings of the current study add to the literature by providing a comprehensive comparison of the statistical and machine learning techniques in forecasting the volatility of cryptocurrency markets. The findings of the study report that the LSTM model outperforms the traditional econometric models of volatility forecasting. The findings of the study will provide insight to the policymakers to make strategies to hedge risk to earn optimal returns and also helpful for the investors and the fund managers to make informed decisions in a rapidly evolving environment. The current study only utilized the data of cryptocurrency for the evaluation of forecasting models further studies through incorporating multiple currencies of bitcoin will provide an interesting area for future research.

References:

Abedin, M. Z., Moon, M. H., Hassan, M. K., & Hajek, P. (2021). Deep learning-based exchange rate prediction during the COVID-19 pandemic. Springer Nature. doi:doi: 10.1007/s10479-021-04420-6

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. Review of Economics and Statistics, 69(3), 542-547.

Bouri E, K. L. (2022). Bitcoin and the S&P 500: co-movements at high-order moments in the timefrequency domain. PLOS ONE, 17(11).

Charpentier, A. (2021). Reinforcement Learning in Economics and Finance. Computational Economics, 62, 425-462.

Christensen, K., Siggaard, M., & Veliyev, B. (2023). A Machine Learning Approach to Volatility Forecasting. Journal of Financial Econometrics, 21(5), 1680-1727. doi:https://doi.org/10.1093/jjfinec/nbac020

Cont, R. (2007). Volatility Clustering in Financial Markets: Empirical Facts and Agent-Based Models. (G. K. Teyssière, Ed.) Berlin, Heidelberg: Springer. doi:https://doi.org/10.1007/978-3-540-34625-8_10

Corbet, S., & Andrew Meegan, C. L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. Economics Letters, 165(C), 28-34. doi:10.1016/j.econlet.2018.01.004

Dickey, D., & Fuller, W. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427-431.

Ding, Z., Engle, R., & Granger, C. (1993). Long memory properties of stock market returns and a new Model. Journal of Empirical Finance, 1(1), 83-106.

Doong, T. L. (2023). Estimation of stock market index volatility using the GARCH model: Causality between stock indices. Asian Financial Review. doi:doi: 10.55493/5002.v13i3.4738

Fama, E. F. (1965). Random walks in stock market price. Financial Analysts Journal, 21(5), 55-59.

Fama, E. F. (1965). The behavior of stock-market prices. The Journal of Business, 38(1), 34-105.

Farman, A. P. (2022). Modelling time-varying volatility using GARCH models: evidence from the Indian stock market. F1000Research. doi:doi: 10.12688/f1000research.124998.1

Gbolagade, S. O. (2022). Performance of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Models in Modeling Volatility of Brent Crude Oil Price. Ilorin Journal of Science, 9. doi:https://doi.org/10.54908/iljs.2022.09.01.002

Glosten, L., Jagannathan, R., & Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48(5), 1779-1801.

Hambly, B., Xu, R., & Yang, H. (2023). Recent advances in reinforcement learning in finance. Mathematical Finance, 33(3), 437-503. doi:https://doi.org/10.1111/mafi.12382

Hanauer, M. X., & Kalsbach, T. (2023). Machine learning and the cross-section of emerging market stock returns. Emerging Markets Review, 55. doi:https://doi.org/10.1016/j.ememar.2023.101022

He, D. M. (2023). Realised volatility prediction of high-frequency data with jumps based on machine learning. Connection Science. doi:10.1080/09540091.2023.2210265

Hendra, H. D. (2020). Financial performance analysis for return on assets with a multiple linier regression approach. jurnal ilmiah mathematika, sains dan teknologi, 8(2). doi:https://doi.org/10.34312/euler.v8i2.10405

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780.

Jeelan, B. V. (2023). Forecasting the Sensex and Nifty Indices using ARIMA and GARCH Models. journal of finance and accounting. doi:10.17492/jpi.mudra.v10i1.1012304

Kevin, J. D. (2010). Finding Fair Value in Global Equities: Part II—Forecasting Returns. The Journal of Portfolio Management. doi:10.3905/JPM.2010.36.3.056

Kim, J.-M., Kim, D. H., & Jung, H. (2021). Applications of machine learning for corporate bond yield spread forecasting. The North American Journal of Economics and Finance. doi:https://doi.org/10.1016/j.najef.2021.101540

Mnif, E., & Jarboui, A. (2022). Resilience of Islamic cryptocurrency markets to Covid-19 shocks and the Federal Reserve policy. Asian Journal of Accounting Research, 7(1), 59-70. doi:https://doi.org/10.1108/AJAR-01-2021-0004

Moscato, V., Picariello, A., & Sperlí, G. (2021). A benchmark of machine learning approaches for credit score prediction. Expert Systems with Applications, 165. doi:https://doi.org/10.1016/j.eswa.2020.113986

Nelson, D. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica: Journal of the Econometric Society, 59(2), 347-370.

Olga, L. K. (2022). A Fair Value Approach to Forecasting Value versus Growth Returns. The Journal of Portfolio Management. doi:10.3905/jpm.2022.49.2.162

Ozbayoglu, A. M., Gudelek, M. U., & Sezer, O. B. (2020). Deep learning for financial applications : A survey. Applied Soft Computing, 93. doi:https://doi.org/10.1016/j.asoc.2020.106384

Phillips, P., & P.Perron. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

R. F. Engle. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of UK inflation. Econometrica, 50(4), 987-1007.

Renan, D. D. (2022). Bubble detection in Bitcoin and Ethereum and its relationship with volatility regimes. Journal of Economic Studies. doi:10.1108/jes-09-2021-0452

Richardson, J. (2023). How Can Cryptocurrency Be More Environmentally Friendly. Retrieved from The Renewable Energy Hub UK: https://www.renewableenergyhub.co.uk/blog/how-can-cryptocurrency-be-more-environmentally-friendly

Siti, M. M. (2021). Stock market volatility on shipping stock prices: GARCH models approach. The journal of economic asymmetries. doi: doi: 10.1016/J.JECA.2021.E00232

Wang, Y., Andreeva, G., & Barragan, B. M. (2023). Machine learning approaches to forecasting cryptocurrency Considering internal and external determinants. International Review of Financial Analysis, 90, 1-21.

Woebbeking, F. (2021). Cryptocurrency volatility markets. Digital Finance, 3, 273-298. doi:https://doi.org/10.1007/s42521-021-00037-3

Xianhua, D. H. (2013). A Predictive Functional Regression Model for Asset Return. Journal of Mathematical Finance. doi:10.4236/JMF.2013.32030

YAM XING QUAN, T. X. (2023). ASYMMETRIC VOLATILITY AND RISK ANALYSIS OF BITCOIN CRYPTOCURRENCY MARKET. Journal of Quality Measurement and Analysis, 19(2). Retrieved from Yam, Xing Quan, Thai, Xue Yang, Choo, Yun Fei, & Chin, Wen Cheong. (2023). Asymmetric volatility and risk https://core.ac.uk/download/586568893.pdf

Yang, R., Yu, L., Zhao, Y., Yu, H., Xu, G., Wu, Y., & Liu, Z. (2020). Big data analytics for financial Market volatility forecast based on support vector machine. International Journal of Information Management, 50, 452-462. doi:https://doi.org/10.1016/j.ijinfomgt.2019.05.027

Yıldırım, H., & Bekun, F. V. (2023). Predicting volatility of bitcoin returns with ARCH, GARCH and EGARCH models. Future Business Journal, 9. doi:https://doi.org/10.1186/s43093-023-00255-8

Zakoian, J. M. (1994). Threshold heteroskedastic models. Journal of Economic Dynamics and Control, 8(5).

Ze-Han Shen, Q. W. (2021). Bitcoin Return Volatility Forecasting: A Comparative Study between GARCH and RNN. Journal of Risk and Financial Management, 14(7). doi:10.3390/JRFM14070337

Zhang, Y., Yan, B., & Aasma, M. (2020). A novel deep learning framework: Prediction and analysis of financial time series using CEEMD and LSTM. Expert Systems with Applications, 159(30). doi:https://doi.org/10.1016/j.eswa.2020.113609

Zhixiang, D. Y. (2022). The Application of ARIMA and Mean-variance Models on Financial Market. BCP Business and Management. doi:10.54691/bcpbm.v26i.2069