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Bitcoin volatility forecasting: a comparative analysis of conventional econometric models with deep learning models

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ABSTRACT

The behavior of the Bitcoin market is dynamic and erratic, impacted by a range of elements including news developments and investor mood. One well-known aspect of bitcoin is its extreme volatility. This study uses both conventional econometric techniques and deep learning algorithms to anticipate the volatility of Bitcoin returns. The research is based on historical Bitcoin price data spanning October 2014 to February 2022, which was obtained using the Yahoo Finance API. In this work, we contrast the efficacy of generalized autoregressive conditional heteroskedasticity (GARCH) and threshold ARCH (TARCH) models with long short-term memory (LSTM), bidirectional LSTM (Bi-LSTM), and multivariate Bi-LSTM models. Model effectiveness is evaluated by means of root mean squared error (RMSE) and root mean squared percentage error (RMSPE) scores. The multivariate Bi-LSTM model emerges as mostly effective, achieving an RMSE score of 0.0425 and an RMSPE score of 0.1106. This comparative scrutiny contributes to understanding the dynamics of Bitcoin volatility prediction, offering insights that can inform investment strategies and risk management practices in this quickly changing environment of finance.

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1. INTRODUCTION

Since 2009, when Bitcoin was first proposed by Satoshi Nakamoto, the digital currency market has attracted a lot of attention. Since April 2019 [1], Bitcoin has grown to be the most profitable and well-known cryptocurrency worldwide. Because businesses that are listed on stock markets already possess Bitcoin, several financial institutions have started to invest in the digital asset's worth. But as a financial tool, Bitcoin is also renowned for its extreme volatility [2]. Numerous factors, such as transaction volume and frequency, affect this volatility. These notable variations need to be taken into account by investors when choosing their investments. Studies have indicated that the volatility of Bitcoin demonstrates a pro-cyclical tendency, increasing in tandem with heightened global economic activity. The volatility of Bitcoin reacts differently to increased volatility in the US stock market than does the gold market [3], [4]. Previous studies have modeled the volatility subtleties of digital currencies and found that out-of-sample value at risk (VaR) forecasting techniques for cryptocurrencies deviate from optimal in-sample generalized autoregressive conditional heteroskedasticity (GARCH)-type parameters [5].

This paper addresses the problem of accurately forecasting Bitcoin's volatility, a crucial task for investors and financial analysts given Bitcoin's significant price fluctuations. The proposed solution involves a comparative analysis of conventional econometric models and advanced deep learning algorithms. Specifically, for volatility forecasting we use highly complex multivariate bidirectional long short-term memory (Bi-LSTM) networks. Bi-LSTM networks demonstrated very high versatility in different prediction tasks, which is evidence for their suitability in the constantly evolving Bitcoin market [6], [7].

From the results achieved in this study it can be concluded that modelling with the multivariate Bi-LSTM models is more effective than the classical econometric procedures in Bitcoin volatility forecasting. The deep learning models achieve more accurate and robust of volatility forecasts since the models the interdependence of the input variables involved. The contribution of this work is to extend the existing knowledge about the nature of Bitcoin’s volatility and to offer responses to practitioners and investors dealing with uncertainty attached to the process of operating on cryptocurrency markets.

The rest of the manuscript is organized as follows: Section 2 describes the materials and methodologies. Section 3 covers the model descriptions. Section 4 presents the result analysis, followed by the conclusion and future scope of this work in section 5.

2. MATERIALS AND METHODS

Bitcoin daily return refers to the variation in Bitcoin's price from the end of one day to the next, expressed as its natural logarithm. Calculating Bitcoin's realized volatility involves analyzing its daily opening, high, low, and closing prices. The BTC-USD exchange rate dataset used in this study is sourced from the widely used Python library Yahoo Finance API, spanning from October 2014 to February 2022. The dataset includes timestamps, opening, high, low, and closing prices, as well as volume_(BTC), returns, and log_returns. The distribution plots of the dataset's returns and log returns are shown in Figure 1.

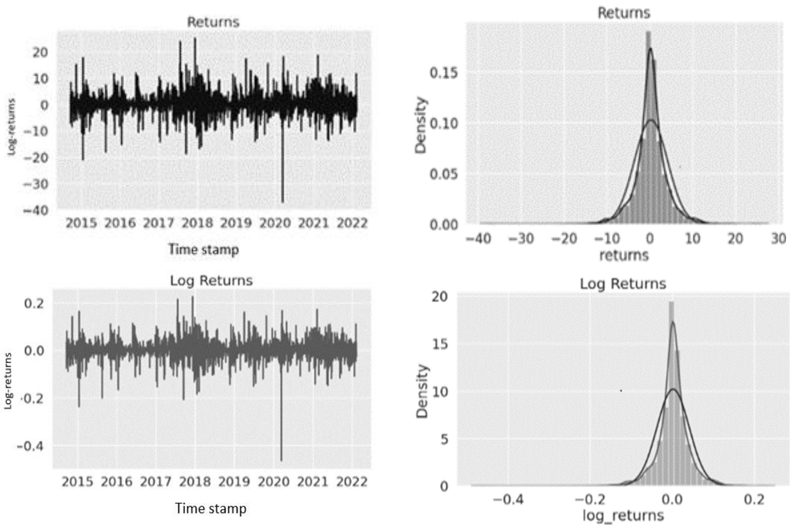

Figure 1. Distribution plots of returns and log returns

The pricing of Bitcoin is highly sensitive to speculative trading mostly in the short-term as traders use price swings to gain quick income. Choice of models and understanding the data structure requires examination of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of Bitcoin price data [8]. Particularly, the ACF determines the level of relation between the time series and the lagged or the previous values of the variable at distinct intervals to determine whether the data obeys the rule of seriation dependence. In this case, it becomes possible to determine the degree of autocorrelation in the prices of Bitcoin and this will enable one to predict future price movements. Just like the PACF, it helps in identifying how closely a time series and lag values are related and hence it helps in identifying the appropriate lag order of time series models [9]. This analysis is mainly important in the process of satisfactory modeling of BTC-USD data. Arithmetic returns and logarithmic returns standardize the price changes, this makes use of returns to analyze assets flexible and uniform at different time horizons. Since these are nominal values that exclude the actual price scale, they express as percentage variations in price; hence, they can be useful in determining the variation extents in the price over time [10], [11]. Normalization or scaling is important as it ensures that all the extracted features contribute equally to the learning process of the model, rather than one characteristic overpowering those for equal significance. Methods like imputation or deletion of the missing values help in managing these gaps while in the preprocessing step. Data preprocessing is crucial in Bitcoin prediction as it makes data fit to be used in modeling and analysis. This in turn improves the already produced forecasts and increases their level of reliability [12].

3. MODEL BUILDING

The analysis of the specified economic indicators and data analysis methods is more widespread used in the usage of the cryptocurrency prediction models that provides the understanding of the specified market trends. The models of prediction that have been well developed try to correct information asymmetric and, in this way, they help in the price discovery of Bitcoin thus improving market efficiency and transparency in this market. All in all, statistical models tend to take less time for the implementation in most of the cases which makes them useful when time is the constraint. Nonetheless, deep learning models are able to help to decrease the load of human feature engineering since they are able to learn all the necessary features from scratch from raw data.

3.1. Generalized autoregressive conditional heteroskedasticity (GARCH)

One of the most admired econometric models suitable for time series analysis and forecasting is the GARCH model for those sectors where there is a volatility clustering observed. Recursively adjusting the volatility estimates with BTC-USD data as it becomes accessible is one way to accomplish this. Figure 2 shows the GARCH model projected BTC-USD price [13]. For distribution of log returns $r_t = \log(\frac{S_t}{S_{t-1}})$, $b_t = r_t - C_{t-1}[r_t]$ is the modernization at time t. By including $r_t = \mu + \epsilon_t$ at time t, where μ is the mean constant. The mathematical formulation of GARCH (1,1) model is given in (1) to (3).

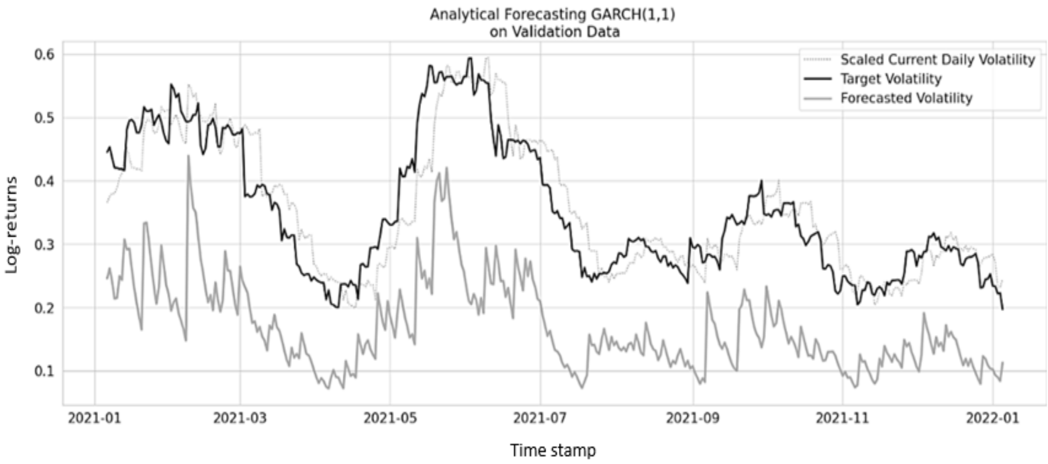

Figure 2. GARCH model predicted BTC-USD price

For log returns series $b_t = r_t - C_{t-1}[r_t]$ be the innovation. Then b_t follows a GARCH (p, q) in mean model if,

$$b_t = \sqrt{h_t}\, e_t \tag{1}$$

$$h_t = \alpha_0 + \sum_{t=1}^{q} \alpha_1 b_{t-1}^2 + \sum_{t=1}^{p} \beta_1 h_{t-1} \tag{2}$$

$$\sqrt{h_t} = \alpha_0 + \sum_{t=1}^{q} \alpha_1 (|b_{t-1}| - \eta_1 a_{t-1}) + \sum_{t=1}^{p} \beta_1 \sqrt{h_{t-1}} \tag{3}$$

The GARCH (p, q) model is static if, $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i \leq 1$. Further, $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i = 1$, then the GARCH (p, q) process is integrated GARCH (IGARCH).

3.2. Threshold ARCH (TARCH)

The influence of previous volatility shocks on present volatility is incorporated into the TARCH model, which expands upon the conventional GARCH model. Equation (4) presents the fundamental equation of the TARCH (p, q) model.

$$\sigma_t^2 = \omega + \alpha p_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma p_{t-1}^2 \,.\, 1_{\{p_{t-1} < 0\}} \tag{4}$$

Here σ_t^2 is the conventional variance of the time series at time t, ω is the constant term, $\alpha, \beta,$ and γ is the coefficient of the lagged error term [14]. The TARCH model allows capturing the asymmetric retort of fluctuation to shocks, both positive and negative by the term $\gamma p_{t-1}^2.\ 1_{\{p_{t-1<0}\}}$. This term adjusts the conditional variance based on the sign of the lagged squared error term p_{t-1}^2. The TARCH model's ability to account for asymmetric volatility impacts is one of its main features. Given that market sentiment changes quickly and price movements frequently show asymmetry in the context of Bitcoin, the TARCH model's capacity to independently represent positive and negative volatility shocks can lead to more precise forecasts. Figure 3 shows the TARCH model forecast BTC-USD price [15], [16].

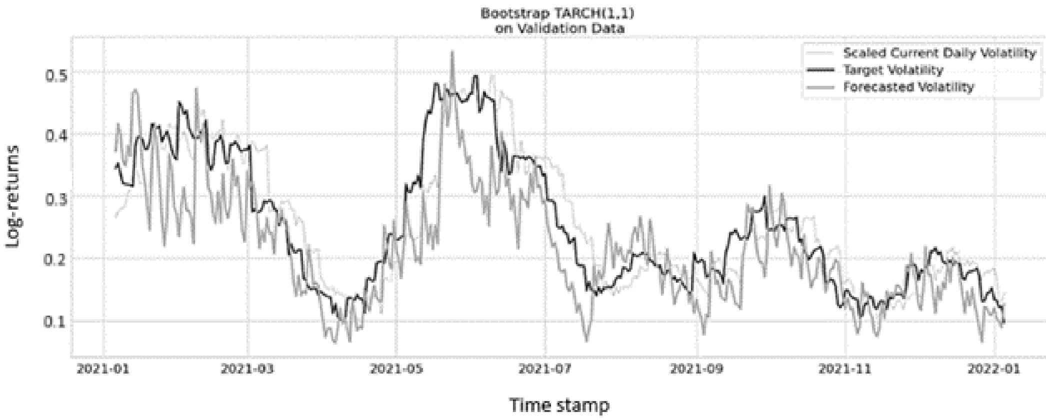

Figure 3. TARCH model predicted BTC-USD price

3.3. Long short-term memory (LSTM)

Bitcoin price data often exhibits long-term relationships and intricate patterns, which can lead to more accurate forecasts of future price variations. These complex correlations with Bitcoin values are effectively modeled using LSTM models. LSTMs are powerful nonlinear function approximators that enhance the reliability of predictions. In this study, an LSTM layer with 20 units is employed, utilizing input sequences spanning 14 days (or 14-time steps) and corresponding target values. This layer captures and processes temporal dependencies from the input sequences. Figure 4 illustrates the LSTM model's forecast of BTC-USD prices [17], [18]. The mathematical formulations of the basic LSTM model are presented in (5) to (7).

$$f_t = \sigma(W_{f\,.}\ [h_{t-1}, x_t] + b_f) \tag{5}$$

$$i_t = \sigma(W_{f\,.}\ [h_{t-1}, x_t] + b_t) \tag{6}$$

$$C_t = f_t * C_{t-1} + i_t * \tanh\,(W_{c\,.}\ [h_{t-1}, x_t] + b_c) \tag{7}$$

where f_t, i_t, and C_t indicate that the input, output, and forget gates are activated. C_t and h_t denote the activation vector.

3.4. Bidirectional LSTM (Bi-LSTM)

To improve the model's ability to detect temporal trends, we employ a Bi-LSTM architecture that captures data from both preceding and subsequent time steps. The initial bidirectional LSTM layer, comprising 32 units and returning sequences, facilitates information propagation to subsequent layers while preserving temporal context. A second bidirectional LSTM layer with 16 units integrates data from both directions. The final dense layer, equipped with a single neuron, predicts the Bitcoin price. The simplified Bi-LSTM model is mathematically represented in (8) and (9).

$$f_t^{forward} = \sigma(W_f^{forward}[h_{t-1}^{forward}, x_t] + b_f^{forward}) \quad (8)$$

$$i_t^{forward} = \sigma(W_i^{forward}[h_{t-1}^{forward}, x_t] + b_i^{forward}) \quad (9)$$

According to (8) and (9), where, x_t is the input vector, $h_t^{forward}$ is the hidden state vector. Figure 5 shows the Bi-LSTM model predicted BTC-USD price. The marketplaces for cryptocurrencies are extremely volatile and prone to sudden shifts over time. Because bidirectional LSTMs can capture long-range relationships and modify their internal states in response to past and future data, they are excellent at representing temporal dynamics. As a result, the model can adjust to shifting market conditions and produce precise forecasts over a range of time periods [19], [20].

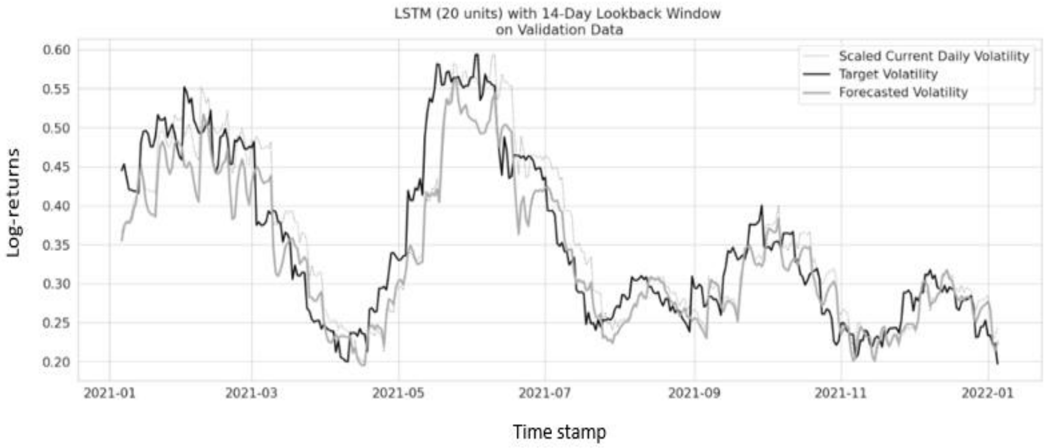

Figure 4. LSTM model predicted BTC-USD price

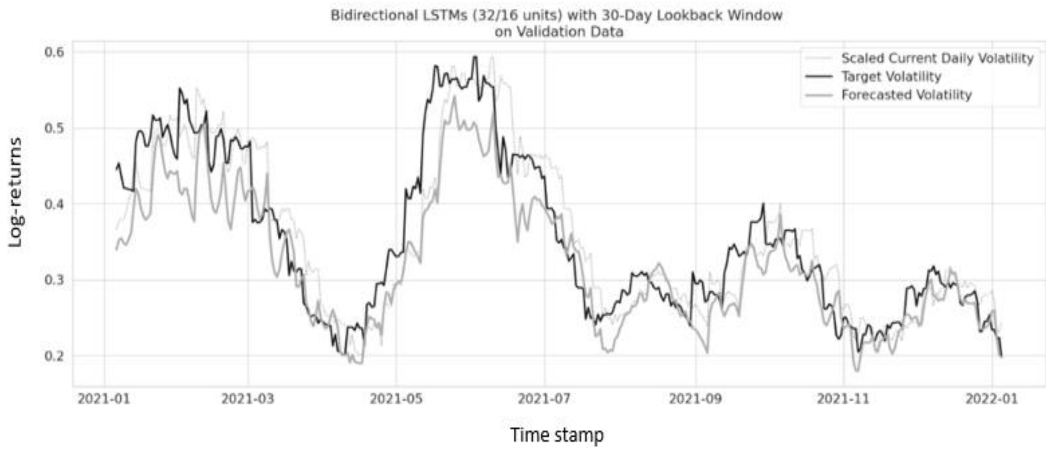

Figure 5. Bidirectional LSTM model predicted BTC-USD price

3.5. Multivariate Bi-LSTM

Multivariate Bi-LSTMs excel at capturing these relationships by processing inputs both forward and backward [21]. The predicted price of BTC-USD as per the multivariate Bi-LSTM model is as shown below in Figure 6. Multivariate Bi-LSTMs are also more beneficial in learning the temporal characteristics of data since it uses past and future information during learning. This approach is very useful for BTC forecasting as historical is known for boosting the predictive potential [22]. Fundamental multivariate Bi-LSTM model is mathematically characterized in (10) to (15):

$$f_t = \sigma(W_f\ [h_{t-1}, x_t] + b_f) \quad (10)$$

$$i_t = \sigma(W_i\ [h_{t-1}, x_t] + b_i) \quad (11)$$

$$\widetilde{c_t} = tanh(W_c\ [h_{t-1}, x_t] + b_c) \quad (12)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \widetilde{c_t} \quad (13)$$

$$o_t = \sigma(W_o\ [h_{t-1}, x_t] + b_o) \quad (14)$$

$$h_t = o_t \odot \tanh\ (c_t) \quad (15)$$

where x_t is the input vector at time step t, h_t is the hidden state at time t, c_t is the cell state, W and U as weight matrices and b as the bias vector. LSTMs can learn representations of the input data at different levels of abstraction and hence reveal information about what are the underlying reasons driving fluctuations in Bitcoin's price in standard regularity. The interpretability can be useful for both making intelligent trading decisions as well as having an understanding of market dynamics [23]–[25].

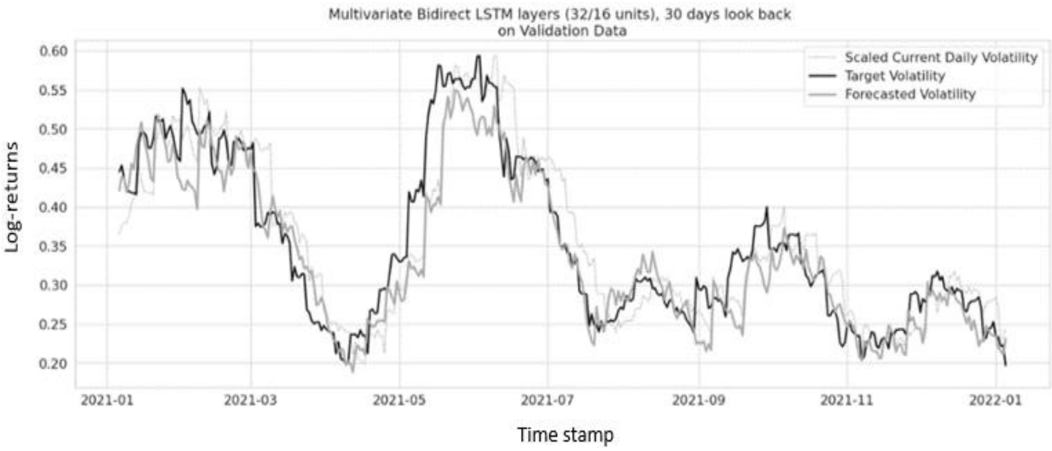

Figure 6. Multivariate Bi-LSTM model forecast BTC-USD price

4. RESULT ANALYSIS

Traders and investors rely on volatility forecasts as important tools in dealing with risks more efficiently [26]. The error scores from Table 1 compare different models used to predict Bitcoin volatility. GARCH model's error metrics are higher with root mean squared error (RMSE) of 0.1930 and root mean square percentage error (RMSPE) of 0.5334, indicating that it is not good at capturing the intricate patterns of Bitcoin's volatility correctly. On the other hand, TARCH has improved significantly evidenced by an RMSE of 0.0702 and RMSPE of 0.1752 which indicates a better fit to bitcoin's asymmetric volatility characteristics when compared to GARCH. When coming to deep learning models, LSTM shows a much-enhanced performance having an RMSE value of 0.0448 and RMSPE value of 0.1155 which surpasses those for both GARCH and TARCH models alike. The Bi-LSTM model, on the other hand, produces competitive results with an RMSE of 0.0519 and an RMSPE of 0.1288, indicating bidirectional data processing, which strengthens its capacity for making predictions. But the incorporation of several predictors, the Multivariate Bi-LSTM model records a lower error score: RMSE=0.0425; RMSPE=0.1106. This means that it is more accurate in forecasting the future values of Bitcoin volatility. This work sheds light on the potential use of deep learning systems for digital currency forecasting, since they can provide valuable insights into risk management and investment approaches in chaotic financial markets.

Table 1. Error score of each model

Model name	RMSE	RMSPE
GARCH	0.1930	0.5334
TARCH	0.0702	0.1752
LSTM	0.0448	0.1155
Bi-LSTM	0.0519	0.1288
Multivariate Bi-LSTM	0.0425	0.1106

A bar diagram comparing the RMSE and RMSPE scores of estimated values against actual values from different models was shown in Figure 7, which presents a visual representation of how accurate and reliable each model is when compared to one another. As shown in this figure, the multivariate Bi-LSTM model has a low RMSE and RMSPE score. The multivariate Bi-LSTM model's RMSE score is 0.0425 while the RMSPE score is 0.1106. We take a variable $best\_lr$ while assigning it a 6.9e-5 value. The learning rate represented by this number, 6.9e-5, is commonly employed in deep learning methods. Specifically, it is utilized in gradient descent and other optimization techniques to define the step size chosen during each iteration of updating the model parameters. In this instance, 6.9e-5 is written in scientific notation, where e-5 stands for 6.9 times 10 raised to the power of -5. 6.9e-5 is therefore equal to 0.000069. Forecasting volatility has an impact on how widely cryptocurrencies are used for regular transactions and applications. If the value of cryptocurrencies fluctuates a lot, people could be reluctant to accept them as payment or use them as a means of exchange. More precise forecasts of volatility reduce this worry and encourage broader use. Figure 8 shows the training MSE vs training RMSPE plot.

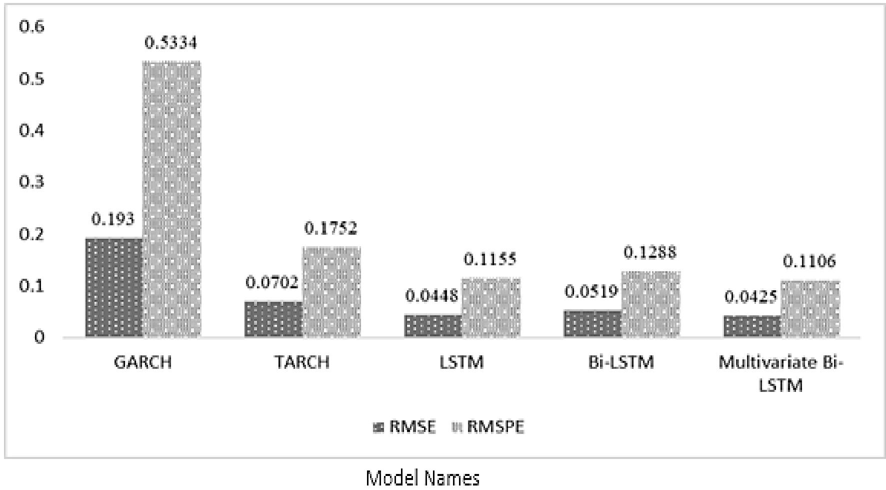

Figure 7. Histogram plot of RMSE and RMSPE of each model

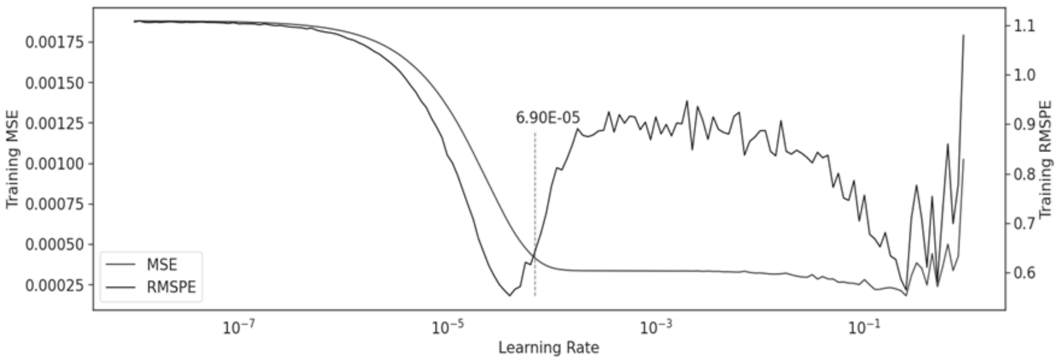

Figure 8. Training MSE vs training RMSPE plot

5. CONCLUSION

We have examined and projected financial time series related to cryptocurrencies, primarily concentrating on Bitcoin, the most recognized specimen of this kind of digital asset. Our approach uses multivariate Bi-LSTM models, which are adept at merging historical and real-time data, to familiarize the shifting market conditions. We show how these models can detect anomalies and foresee potential issues, improving reliability and transparency in cryptocurrency trading. Precisely forecasting the fluctuations in Bitcoin can impact not just particular trading strategies but also broader elements such as enhanced risk mitigation and informed market governance. Modern analytical methods and deep learning models like

Bi-LSTMs offer stakeholders crucial instruments for handling complex market conditions as the cryptocurrency ecosystem evolves. Future studies could focus on enhancing the model's functionality, adding more data sources for increased predictive accuracy, developing real-time monitoring systems, exploring effective risk management strategies, and examining the regulatory implications of volatility forecasts. Through these efforts, we seek to increase our understanding of Bitcoin markets and establish a more stable and robust environment for digital assets.

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