

Bitcoin Price Volatility Prediction on Technical Indicators with GARCH and LSTM

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Abstract. Bitcoin is one of the most volatile cryptocurrency assets, influenced by technical factors, market sentiment, and macroeconomic conditions. This high volatility poses both challenges in risk management and opportunities for market participants. This study aims to predict Bitcoin price volatility by developing a hybrid GARCH-LSTM model that combines the strengths of statistical approaches and deep learning. Historical Bitcoin data from June 2009 to June 2025 was collected through scraping from TradingView and enriched with seven technical indicators (SMA, EMA, RSI, Stochastic Oscillator, OBV, and MFI). Dimensionality reduction using PCA produced two principal components explaining 82.9% of the variance. Stationarity was confirmed using the ADF test, while GARCH (1,2) was selected based on AIC and BIC criteria to capture short-term volatility patterns. GARCH outputs then integrated into LSTM to learn long-term non-linear patterns. Model performance was evaluated using MAE, RMSE, and MAPE. Results indicate that the hybrid GARCH (1,1)-LSTM model achieved the best performance, with MAE = 0.24981, RMSE = 0.39597, and MAPE = 7.8%, demonstrating high accuracy for highly volatile cryptocurrency data. Although long-term forecast accuracy declined, this model shows strong potential for applications in Value-at-Risk strategies, short-term trading decisions, and asset portfolio allocation. Future research is recommended to incorporate external variables such as market sentiment and macroeconomic factors to enhance adaptability to dynamic market conditions.

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1 Introduction

Bitcoin is a form of digital currency (cryptocurrency) that is decentralized and operates without centralized authority. Through the utilization of cryptographic systems and blockchain structure, Bitcoin transactions are permanently recorded in a digital block chain that is transparent and immutable unless the proof-of-work process is repeated (1).

Nevertheless, Bitcoin is known for its high level of volatility. This volatility arises from the influence of various combined factors, including macroeconomic elements such as interest rates and inflation, market sentiment, and fundamental conditions of the crypto market. According to (2).

Market sentiment factors have a significant influence on Bitcoin price movements. Emotions such as fear and greed triggered by news and public opinion contribute to irrational price fluctuations. This phenomenon creates opportunities for market manipulation by actors who exploit psychological responses to losses and gains (3). On the other hand, conventional fundamental factors such as financial statements are not relevant for Bitcoin, as the asset does not generate income like stocks or bonds, and therefore cannot be analyzed fundamentally (4).

The use of technical indicators for predictive models can significantly increase the accuracy of predictive models for several cryptocurrencies, one of which is Bitcoin (5). Using technical indicators in LSTM (Long-Term Model) training can improve the model's predictive performance. Model performance can be enhanced by incorporating technical indicator features. With more training time and computing resources, the model can be trained with more combinations of technical indicators. This can provide a better indication of the overall predictive power of technical indicators (6)

This research using technical indicators as input features improves the accuracy of LSTM models. Their findings show that models incorporating these indicators are more capable of identifying market patterns compared to baseline models (8) Long Short-Term Memory (LSTM) is a deep learning model developed from Recurrent Neural Networks (RNN), with advantages in processing complex time-series data. Unlike RNN, LSTM can retain historical information through its memory gate mechanism consisting of forget gate, input gate, and output gate (7).

However, in the context of volatility, LSTM still has limitations in handling volatility clustering patterns and heteroskedasticity in financial data. For this reason, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) statistical approach is employed, which is designed to capture fluctuations in residual variance in time-series data. GARCH models conditional variance as a function of past residuals and previous variances, making it suitable for high-volatility financial markets such as cryptocurrency (8). Therefore, the GARCH model is more adaptive and capable of modeling the volatility clustering effect commonly found in financial markets, including crypto markets (8)

Therefore, this study aims to develop a Bitcoin price volatility prediction model using the hybrid GARCH-LSTM approach by integrating several technical indicators as input variables. The main focus lies in improving volatility prediction accuracy through the combination of statistical and deep learning model strengths. Considering that volatility is a crucial element in investment decision-making, risk management strategies, and portfolio protection, the proposed model is expected to contribute significantly to more precise and adaptive digital asset management (9).

2 Data and Methodology

The methodology of this study is systematically designed by following the Cross Industry Process for Data Mining (CRISP-DM) framework, which is a standardized data mining process where data passes through each clearly defined and structured phase (10) to predict Bitcoin price volatility using a hybrid model through six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment, as illustrated in **Fig. 1**

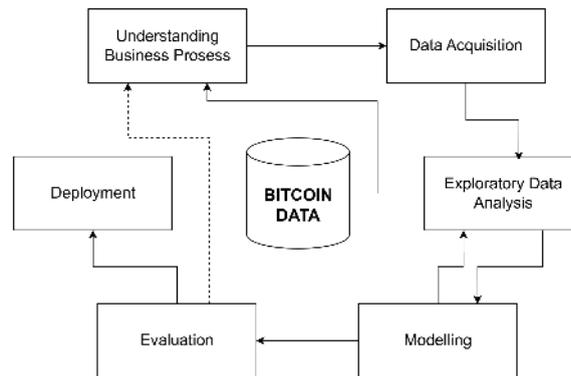


Fig. 1 CRISP-DM Methodology

The data mining process starts with Understanding Process, defining business goals and creating an initial plan. Then, Data Acquisition involves collecting and exploring data to identify issues and hypotheses. Exploratory Data Analysis cleans, selects, and transforms data for modeling. In Modeling, techniques are applied and parameters tuned, sometimes requiring data adjustments. Evaluation checks if the model meets objectives and reviews prior steps. Finally, Deployment integrates the model into decision-making through reports or automated systems (11).

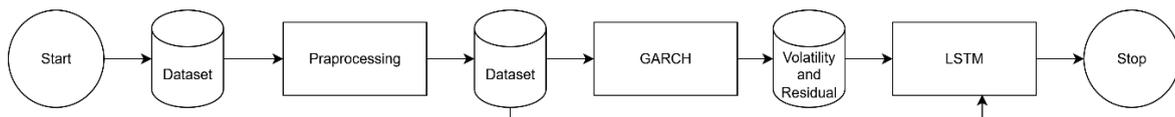


Fig. 2 Hybrid Model

In **Fig. 2** The data preprocessing phase begins with cleaning the historical Bitcoin dataset to remove rows with zero volume and anomalies. Then, a log-return transformation is performed on the closing price to stabilize the data distribution for volatility modeling (8). Next, technical indicators such as the SMA, EMA, RSI, Stochastic Oscillator, OBV, and MFI are extracted from the OHLCV data. Given the large number of indicators, dimensionality reduction is performed using Principal Component Analysis (PCA) to retain only the principal components with the largest contributions (12). After the data is confirmed stationary using the Augmented Dickey-Fuller test, the hybrid modeling phase is performed.

First, a GARCH (1,1) model is trained to capture linear volatility patterns and volatility clustering (13). The residuals from the GARCH are then used as additional input to the LSTM, which functions to learn non-linear patterns and long-term dependencies in time series data. With this combination, GARCH stabilizes variance fluctuations so that LSTM can learn more consistent residual patterns, resulting in more accurate volatility predictions. Previous research has also shown that the hybrid GARCH–LSTM approach can outperform a single model in predicting the volatility of high-risk assets, as it can simultaneously integrate linear and nonlinear characteristics (14).

2.1 Pre-processing Data

Historical Bitcoin data was collected from Tradingview, including opening, closing, lowest prices, volume, and corresponding date-time records. This step included the removal of data containing anomalies, such as the excessive occurrence of uniform values. Such conditions typically occurred during specific time intervals when certain attributes consistently held zero values, likely due to limitations in data recording or documentation during those periods. This anomaly poses a risk of disrupting model performance during the training process (15)

After data cleaning, seven technical indicators extracted to improve the dataset’s relevance and predictive power. Most indicators use a 14-period, optimal for capturing the Volatility Index because it balances responsiveness and minimizes false signals. Shorter periods are overly sensitive, while longer ones react too slowly to volatility

changes. (16). The use of a 12-period EMA, in particular, is based on empirical practice and market convention, proven effective in detecting momentum shifts (17)

The issue of an excessive number of input features which can lead to overfitting and hinder the LSTM model from retaining relevant information Principal Component Analysis (PCA) was applied. This technique transforms a set of variables into new features with lower dimensions and summarizes the seven technical indicators into a few components that represent at least 70–90% of the explainable variance from the original indicators (12). Furthermore, selecting relevant features helps focus the model on the most informative data, enhances interpretability, and improves overall performance. This step contributes to building a stronger, more versatile, and accurate prediction model (18).

This analysis is essential because many time series models assume stationarity (19). In this phase, the data was tested using the Augmented Dickey-Fuller (ADF) Test for stationarity. Once stationarity was confirmed, the data was transformed into logarithmic returns of the closing price (Target), as the closing price represents the final value of an asset during a trading period and is considered the most representative measure for daily value changes (8). Log returns chosen as the primary prediction target in various predictive models and are used to capture the heteroskedastic nature of financial assets such as cryptocurrencies (20).

2.2 GARCH Model

After the EDA stage is completed and the data is prepared accordingly, it can proceed to the training of the first model, namely GARCH. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is employed as the initial model to capture linear elements and model the volatility of the Bitcoin price time-series data. This process serves as the first phase within the hybrid model framework before the data is further processed by the Long Short-Term Memory model (14)

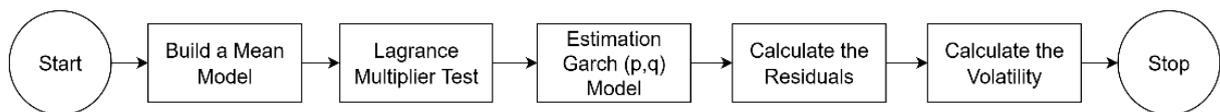


Fig. 3 Flow Process GARCH Model

As shown in **Fig. 3**, the first step before constructing the GARCH model is to perform a test to detect the presence of ARCH effects using the Lagrange Multiplier (LM) test (21). This test aims to ensure that the data residuals exhibit heteroskedasticity (non-constant variance), which is a prerequisite for proceeding with GARCH modeling (22).

2.3 LSTM Model

The Long Short-Term Memory (LSTM) model in this study is designed to improve the prediction accuracy of the GARCH model, this process begins with data preparation, hyperparameter tuning, model evaluation, and retraining for future predictions.

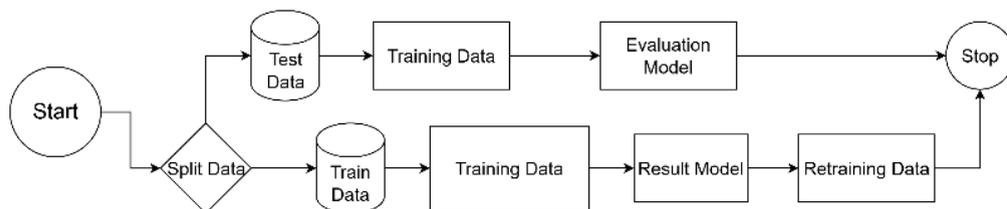


Fig. 4 Flow Process LSTM Model

In **Fig. 4** the target to be predicted is garch_volatility. The data is then structured into sequential format suitable for the LSTM model, where the model learns from a defined number of historical time steps (window_size) to predict future values (23). To identify the best hyperparameter combination, a grid search process was conducted. This tuning step is essential prior to training to determine the optimal parameters (6). The parameters tested include the number of units, dropout rate, batch size, epochs, and learning rate. Each model's

performance is assessed, and the combination with the best validation performance is selected. The training also utilizes the Adam optimizer for optimization (24) and the early stopping technique to prevent overfitting. To objectively assess the model's performance, evaluation was conducted using the 20% test set that had been separated from the beginning. The best-performing model obtained from the process was then evaluated using three primary metrics MAE, RMSE, and MAPE.

3 Result and Discussion

The dataset consists of daily Bitcoin prices Open, High, Low, Close, and Volume (OHLCV) along with trading volume from 2009 to 2025, obtained through scraping from TradingView. The raw data was cleaned by removing anomalies, such as 201 entries with zero volume in the early period, to ensure consistency for analysis. Subsequently, seven key technical indicators was extracted: Simple Moving Average (SMA, 14-day), Exponential Moving Average (EMA, 12-day), Relative Strength Index (RSI, 14-day), Stochastic Oscillator (%K and %D, 14-day), On-Balance Volume (OBV), and Money Flow Index (MFI, 14-day).

To avoid the curse of dimensionality and potential overfitting in the LSTM model, the seven technical indicator features reduced using Principal Component Analysis (PCA). As a result, two principal components (PC1 and PC2) obtained, which together explain approximately 82.9% of the total variance from the original seven indicators. The target variable for volatility modeling is the logarithmic return of daily closing prices. An Augmented Dickey-Fuller (ADF) test on the log-return series produced a p-value 0.00009 (Below 0.05), confirming stationarity. Testing for ARCH effects on residuals showed significant heteroskedasticity, supporting the use of GARCH modeling.

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (1)$$

The GARCH(p, q) model (Generalized Autoregressive Conditional Heteroskedasticity) is used to model time-varying volatility in time series data. This model defines the conditional variance (σ_t^2) as a function of a constant (ω), past squared residuals (ϵ_{t-i}^2) with coefficients (α_i) the ARCH component, and past variances (σ_{t-j}^2) with coefficients (β_j) by the GARCH components.

Table 1 GARCH Model Result Evaluation

No	Model	AIC	BIC	P-value Residual
1	GARCH (1,1)	28866,42	28906,04	0.31800712388733876
2	GARCH (1,2)	28862,29	28908,51	0.318007123887338871
3	GARCH (2,1)	28868,42	28914,64	0.318007123887338871
4	GARCH (2,2)	28864,29	28917,11	0.318007123887338871

Several GARCH (p,q) models in **Table 1**; GARCH (1,2) had the lowest AIC (28862.29), outperforming GARCH (1,1), (2,1), and (2,2), indicating the best fit for historical volatility data. The model captures volatility clustering, where high volatility periods are followed by similar volatility. Residual diagnostics show incomplete absorption of medium- to long-term autocorrelation. The Ljung-Box test indicates no significant autocorrelation at lag 1 ($p = 0.318 > 0.05$), but at lag 10, $p < 0.05$, revealing remaining long-lag patterns likely due to non-linear dynamics or long-memory effects not captured by GARCH. From the selected GARCH (1,2) in **Fig. 5** visualization result of extraction volatility value after training a model.

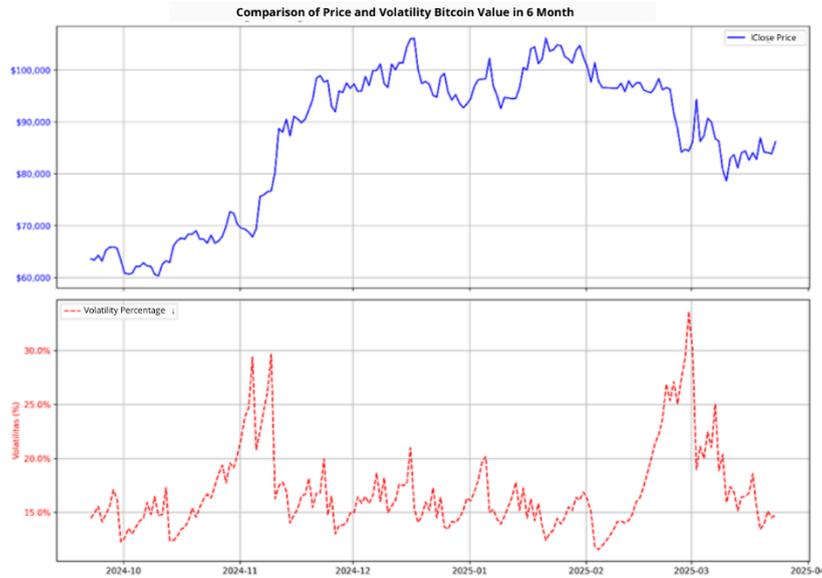


Fig. 5. Price and Volatility Bitcoin Value

The LSTM model was developed to learn volatility patterns from the Bitcoin time-series data by incorporating long-term non-linear information. Prior to training, a comprehensive grid search was conducted to determine the optimal combination of hyperparameters. The parameters tuned included the number of LSTM neuron units, dropout rate, batch size, number of epochs, and learning rate on **Table 2**. This tuning process ensures that the model is neither too simple (underfitting) nor too complex (overfitting). After obtaining the best set of hyperparameters, the LSTM model was trained on the training data (80%) and evaluated separately on the test data (20%).

Table 2 Hyperparameter Values

No	Parameter	Values
1	Units	32, 50, 64, 128
2	Dropout	0.2, 0.3, 0.5
3	Batch Size	32, 64
4	Epoch	20, 50, 100
5	Learning Rate	0.001, 0.0005

LSTM was retrained using the entire historical dataset (combining training and test data) to leverage all patterns before projecting future volatility. By incorporating the GARCH output as an input feature, the model becomes a hybrid GARCH-LSTM. Model performance was quantitatively evaluated using MAE, RMSE, and MAPE on the test data.

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \quad (2)$$

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * C_t \quad (4)$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \quad (5)$$

The LSTM model regulates information flow using three gates: the forget gate (f) decides what past information to retain, the input gate (i_t) determines which new information to store, and the output gate (C_t)

controls what part of the updated cell state is output as the hidden state. The cell state (o_t) acts as long-term memory, updated by combining retained past content and new candidate input.

Table 3 LSTM Results Value

No	Evaluation	GARCH (1,1)	GARCH (1,2)	GARCH (2,1)	GARCH (2,2)
1	MAE	0,24981	0,28966	0,25946	0,29770
2	RMSE	0,39597	0,46488	0,40728	0,47082
3	MAPE	7,78%	9,07%	8,22%	9,39%

This study reports the evaluation results on **Table 3** for several hybrid GARCH-LSTM configurations with different GARCH orders. The GARCH(1,1)-LSTM model delivered the most accurate predictions, achieving MAE = 0.24981, RMSE = 0.39597, and MAPE = 7.8%. This means the average absolute error in volatility is 0.24 (log-return scale), and the percentage error is about 7.8% of actual daily volatility—remarkably accurate for highly volatile cryptocurrency data.

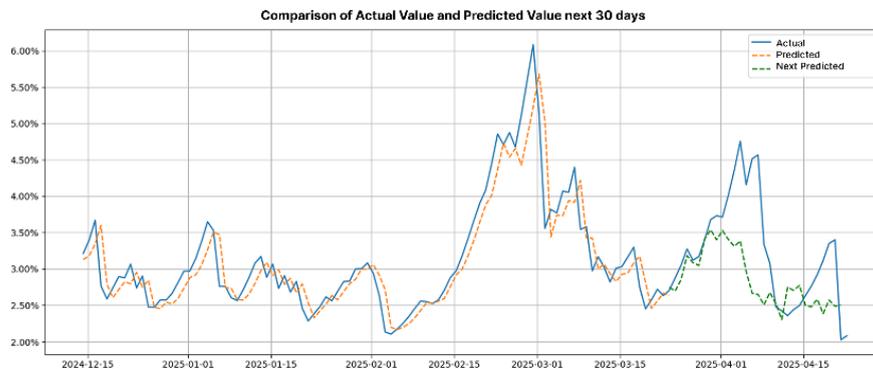


Fig. 6 Comparison Actual Volatility and the next 30 days Predict Volatility

In the forward-looking prediction **Fig. 6**, it is observed that the model's forecasts begin to diverge and no longer follow the actual volatility movement. The projected pattern becomes increasingly flat and fails to reflect the true dynamics of the market, where the actual values exhibit more complex fluctuations. This indicates that the model's accuracy declines as the prediction horizon extends.

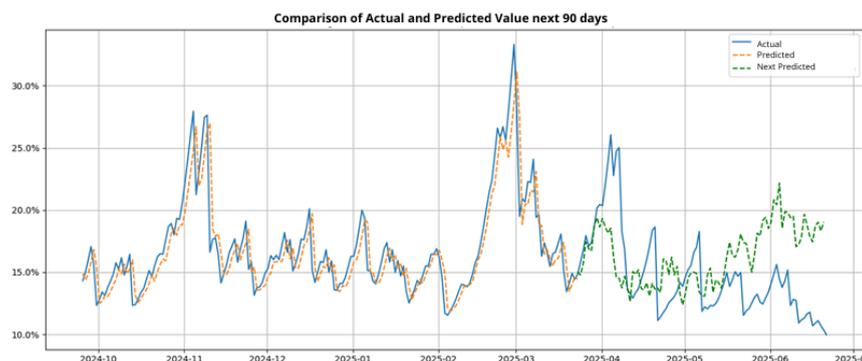


Fig. 7 Comparison Actual Volatility and the next 30 days Predict Volatility

In **Fig. 7** When the three-month timeframe is extended, the model's predictions become increasingly divergent and no longer follow the actual volatility direction. The projected patterns become flatter and less reflective of actual market dynamics, with actual values actually showing more complex fluctuations. This indicates that the model's accuracy decreases as the prediction horizon expands.

4 Conclusion

This study develops a hybrid GARCH-LSTM model to predict Bitcoin volatility using historical data from June 2009 to June 2025. After cleaning the dataset and removing zero-volume rows, the data was enriched with seven technical indicators and reduced in dimensionality using PCA, resulting in two principal components explaining 82.9% of the variance. Stationarity and heteroskedasticity tests confirmed data suitability, with the GARCH (1,2) model selected based on AIC and BIC, despite residual mid-term autocorrelation. The LSTM model was then trained using log returns, volume, PCA components, GARCH residuals, and GARCH volatility, optimized via Grid Search.

Results indicate that the hybrid GARCH (1, 1)-LSTM model achieved the best performance (MAE = 0.24981, RMSE = 0.39597, and MAPE = 7.8%), delivering accurate short- to medium-term volatility forecasts, though accuracy declined in the long term due to mean reversion and market complexity. Predictive accuracy decreases over longtime horizons because the model relies solely on historical price data and technical indicators, thus missing extreme volatility patterns often triggered by external factors. Bitcoin volatility is influenced not only by past price trends but also by market sentiment, regulation, institutional adoption news, and global macroeconomic conditions. Because these factors are not included as inputs, the model tends to produce flatter and mean-reverting projections, thus losing its ability to reflect true market dynamics over the long term.

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