Bitcoin Price Volatility Prediction Using the GARCH-LSTM Model

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ABSTRACT

Predicting cryptocurrency price trends is crucial for helping investors make better decisions, avoid losses, manage risks, and increase profits. Unlike traditional financial markets, cryptocurrency markets are known for their high and unpredictable volatility. This intense price fluctuation can greatly impact the accuracy of prediction models, making it necessary to consider volatility first. To address this challenge, it is essential to model price volatility before attempting to predict prices. In this study, a hybrid GARCH-LSTM method was used to improve prediction accuracy. GARCH is effective in analyzing price volatility, while LSTM excels at processing time-series data and capturing complex patterns. The analysis was conducted over a two-year period, from August 2, 2021, to August 2, 2023, showing how this combined approach can tackle the unique challenges of forecasting in the volatile cryptocurrency market. According to the results, the mean squared prediction error for Bitcoin was 0.0006, with the maximum prediction error being 0.002. In other words, the predictive power of this hybrid model is 99.0%, indicating a high reliability of the estimated results with this method.

Keywords: price Prediction, Bitcoin, GARCH-LSTM, volatility

1. Introduction

The cryptocurrency market has grown rapidly since its introduction in 2009, attracting significant attention from investors. Starting at zero value in 2009, this market reached around $2 trillion in 2024, with nearly 400 million investors participating. This highlights its impressive growth. Unlike the stock market, which primarily finances businesses and reflects their value through stock prices, the cryptocurrency market revolves around trading smart contracts on blockchain technology. Cryptocurrencies are considered alternatives to traditional currencies, with their value mainly derived from the underlying technology, which supports other smart contracts (Amous, 2008). While the cryptocurrency market offers opportunities to profit from technological advancements, it comes with substantial risks, including the potential for total investment loss. According to CoinMarketCap website, around 4,000 cryptocurrencies disappeared between 2008 and 2024, resulting in significant losses for investors.

Another key feature of cryptocurrencies is their decentralized nature, which makes governmental regulation challenging. Unlike regulated financial markets, the cryptocurrency market lacks effective tools for oversight. This decentralization, inherent to blockchain technology, raises concerns for governments. Cryptocurrencies also pose a threat to national currencies, potentially undermining governments' monetary policies (Topscott & Topscott, 2018). As a result, many governments have implemented restrictive policies or declared cryptocurrencies illegal, making this market riskier than others.

Investors must also be cautious of the extreme volatility in cryptocurrency prices. For example, Bitcoin has experienced seven drops of over 50% and 13 drops exceeding 20% since 2009. In contrast, the U.S. stock market, even after the Great Depression of 1929, recorded only five drops greater than 20%. This demonstrates that the cryptocurrency market is not only more volatile but also prone to more frequent fluctuations. Thus, accurate prediction becomes essential for managing the risks and opportunities in this market.

Volatility is a critical factor in predicting cryptocurrency prices. However, the unique nature of this market makes prediction more challenging. Conventional methods borrowed from other financial markets often fail to account for the high volatility of cryptocurrencies, reducing their effectiveness (Shou et al., 2020). Therefore, developing precise and tailored forecasting tools is crucial for effective risk management in this market.

Various methods have been developed to predict financial markets using historical data. These can be categorized as linear or nonlinear, machine learning or statistical approaches. A more practical grouping divides them into classical and intelligent methods. Classical methods, like regression and ARIMA, assume that future prices follow a linear trend of past values. In contrast, intelligent methods, such as neural networks, fuzzy logic, support vector machines, and Markov models, address the nonlinear nature of financial data (Cavalcante & et al., 2016).

Comparative studies have shown that intelligent methods, by overcoming the limitations of linear models, demonstrate better predictive capabilities and higher accuracy compared to classical methods (Padmaja, 2020; Yan et al., 2017; Adebiyi & et al, 2014). Moreover, leveraging the strengths of new methods and combining the favorable features of different models can enhance accuracy. Recent studies aim to combine various models to take advantage of their unique strengths, thereby providing improved predictions of price trends (Li et al., 2023; Wang, 2020; Tabar et al., 2020; Shou et al., 2020; Maroutti et al, 2019; Hasan, 2009). Thus, using modern intelligent methods with suitable characteristics, combined with other approaches, is expected to yield more accurate and reliable results.

One of the most widely used techniques in this domain is artificial neural networks (ANNs) (Atsalakis & Valavanis, 2009; Tkáč & Verner, 2016; Goodfellow, 2016; Yu et al, 2018). Neural networks offer numerous advantages over other methods, making them attractive to researchers. These include the ability to handle nonlinear functions, perform parallel computations, learn from data, and utilize qualitative information. The superiority of neural networks lies in their capacity to process nonlinear relationships, which enables a more accurate evaluation of input data. Additionally, their parallel computational capabilities reduce the time required for predictions (Limsombunchai et al., 2004).

Alongside its many advantages, neural networks also have limitations. The primary issue with neural networks is their tendency to overfit the data, including noise, and the need for reconfiguration when the data range changes (Hasan & Nath, 2005; Naderi et al., 2024; Hasan & Nath, 2005). Another challenge is the network's bias toward placing more importance on recent events while giving less weight to past occurrences. This limitation means that in cases where the dataset is large, neural networks often exhibit a forgetting property for older data. Consequently, even though the network might have learned an event from the distant past, it may fail to accurately predict similar occurrences in the future due to the reduced significance assigned to past data (Schmidhuber & Schröter, 1997).

To address these challenges, Schmidhuber and Schröter (1997) introduced the Long Short-Term Memory (LSTM) model, which has resolved many of the issues associated with neural networks. LSTM has since been widely adopted across various domains, from image processing to language processing and general time-series forecasting. Given its robust features and capabilities, LSTM has been extensively used in financial markets, particularly for price prediction (Limsombunchai et al., 2004; Goodfellow, 2016; Yu et al., 2018; Patel et al., 2020; Graham, 2022).

Considering the characteristics of the cryptocurrency market on one hand and the advanced features of the LSTM model on the other, this study aims to model cryptocurrency market volatility using the GARCH model and subsequently predict Bitcoin price fluctuations with the LSTM approach.

The structure of this paper is organized as follows:

- Section 2 presents a review of the theoretical literature and previous research.
- Section 3 outlines the methodology, including the introduction of the models and the implementation process.
- Section 4 discusses the results of the model implementation.
- Finally, Section 5 provides conclusions and a summary of the findings.

2- Theoretical literature and previous research

The cryptocurrency market is the youngest financial market globally, with asset values based on blockchain technology and the aspiration to replace traditional currencies. Like traditional money, cryptocurrencies fulfill the four primary functions of currency. However, their value is not influenced by printing or manipulation by governments or other authorities.

In the cryptocurrency ecosystem, all processes, from mining to total supply, are predetermined. Any changes to a cryptocurrency's rules result in a network split, or "fork," creating a new, distinct cryptocurrency. This system, alongside solving technical challenges like double spending, addresses trust issues often associated with central banks. Cryptocurrencies act as a medium of exchange with all the essential features of traditional money. However, unlike fiat currencies, whose supply is arbitrarily controlled by central banks, cryptocurrency supply is governed by fixed and unchangeable rules.

This fixed supply is a stark contrast to the increasing and volatile supply of traditional money, which leads to currency depreciation and worsens inflation—a persistent global issue (Amous, 2018; Topscott & Topscott, 2018). Factors such as technological advancements, trust in market mechanisms, and the spontaneous social order in Western societies, along with rapid growth in the service sector, have fueled the adoption of cryptocurrencies.

In modern economies, where about 80% of GDP comes from services (compared to pre-1990 developed economies, where 80% came from goods production), wages are less shielded against inflation. This makes inflation more impactful on service-sector wages, which are more vulnerable than those in goods production. As a result, economic agents increasingly turn to currencies that are less prone to inflation caused by government interventions.

In this context, and alongside technological progress, Satoshi Nakamoto introduced Bitcoin in 2009 as the first cryptocurrency based on blockchain technology. Bitcoin has a limited supply, with mining, transaction verification, and oversight governed by the principle of "one computer, one vote." This decentralized mining process, involving numerous miners, ensures no single entity can dominate the network. The system operates autonomously, enabling secure and decentralized mining, transactions, and payments (Narayanan et al., 2016).

Cryptocurrencies maintain their monetary supply strictly based on initial agreements, free from government or centralized control. Over time, the cryptocurrency ecosystem has resolved challenges like transaction speed and transfer efficiency within a decentralized framework. Notably, transactions in this system are faster and more cost-effective than those in both domestic and international banking systems.

The optimism surrounding cryptocurrencies and their technological utility has driven investors worldwide to participate in this market, creating a vast network of individuals with shared interests. Between 2008 and 2024, the market value of cryptocurrencies reached approximately $2 trillion. However, despite their potential, significant risks introduce considerable uncertainty for market participants. One major concern is the possibility of cryptocurrencies losing their entire value. Since 2008, nearly 4,000 cryptocurrencies have vanished, resulting in billions of dollars in losses for investors.

Another issue is the use of cryptocurrencies for illegal transactions, as their decentralized nature makes them difficult for governments to monitor. This has created opportunities for illicit activities. Additionally, many governments and societies view cryptocurrencies negatively, leading to restrictive regulations or outright bans, as seen in countries like China.

The cryptocurrency market, still in its early stages, has faced legal challenges, uncertainty, and concerns about the loss of value for individual cryptocurrencies.

This has caused significant fluctuations in the investor base and extreme price volatility. For example, Bitcoin's value has, at times, dropped between 10% and 90% within a few months, only to recover later. While the cryptocurrency market shares some traits with traditional financial markets, its frequent and severe price swings set it apart. Without proper risk management, investors in this market are highly vulnerable to serious losses.

To address these risks, robust forecasting methods are essential. Accurate predictions play a critical role in managing risks and optimizing portfolios. Cryptocurrencies like Bitcoin are highly volatile, creating challenges for investors. Predictive models help assess risks, enabling investors to make informed decisions about portfolio allocation. By forecasting returns, investors can balance risk and reward to optimize their portfolios. Precise predictions also improve market efficiency and give investors an informational advantage. Furthermore, they support market oversight and regulation, which are essential for maintaining order in financial markets (Simaran & Sharma, 2023; Patel et al., 2024).

On this basis for decades, financial market experts have studied markets and identified patterns to make predictions, using a combination of pattern recognition and empirical observation of cause-and-effect relationships and also numerous software applications have been developed to assist in this decision-making process, serving as prediction engines. Theoretical literature categorizes researchers' views on financial market predictability into two main groups:

1. **Predictability Proponents:**
   These researchers argue that markets follow identifiable patterns. While these patterns may range from simple to complex and easy to challenging to detect, they believe patterns do exist. By analyzing past trends and market behaviors, they suggest that historical data can reveal recurring patterns that are likely to repeat in the future. This approach assumes that market movements are cyclical and predictable based on historical performance.
2. **Predictability Skeptics:**
   This group believes that financial markets cannot be predicted. They argue that price movements are not influenced by past trends but are instead shaped by future events and their impact on economic indicators. For instance, if an economy experiences growth, investors, anticipating its positive impact on markets, may increase demand for shares, driving up financial indices. Thus, they emphasize that economic growth and investor expectations about future conditions determine market trends, rather than historical price movements (Fotros et al., 2021; Simaran & Sharma, 2023; Patel et al., 2024).

In conclusion, while there is debate over the predictability of financial markets, understanding patterns and leveraging predictive models remain crucial for investors to navigate the risks and opportunities inherent in the cryptocurrency market.
The existing literature on price prediction in financial markets takes a cautious stance, acknowledging the challenges posed by the dynamic nature and high volatility of these markets. However, despite this issue, a significant portion of the research literature remains dedicated to exploring and proposing prediction methods due to the critical importance of forecasting in financial markets.

Lee et al. (2023), applied a fuzzy model combined with a Hidden Markov Model (HMM) to predict time series data. The model was tested using data from the New York Stock Exchange, Istanbul Stock Exchange, and Bitcoin. However, results showed that the fuzzy model without the Markov component performed better across all tested markets, suggesting the Markov component reduced accuracy. Penmetsa and Vemula (2023), this study predicted the prices of Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC) Using Long Short-Term Memory (LSTM) models. The researchers found that incorporating features like volatility and momentum significantly improved the accuracy of LSTM models compared to simpler versions. Seabe et al. (2023), compared three models—Bi-LSTM, GRU, and LSTM—for predicting Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). Results revealed that Bi-LSTM achieved superior predictive accuracy compared to the other two models. Sudhakaran et al (2024), were predicted Bitcoin prices using Recurrent Neural Networks (RNN) and LSTM models, with factors such as trading volume, market volatility, hash rate, and Google search trends included as inputs. The findings demonstrated that LSTM models outperformed RNNs in terms of predictive accuracy. Purnama (2024), used LSTM to predict Bitcoin prices over a period from 2014 to 2023. It was observed that larger training datasets improved prediction accuracy, highlighting the critical role of data volume in enhancing model performance. So recent studies emphasize the effectiveness of LSTM in delivering better predictive results. But these studies often overlooked the frequent and severe volatility of the cryptocurrency market compared to conventional financial markets, which introduces significantly higher risks for traders.

Given these challenges, shifting the focus from direct price prediction to volatility modeling could yield more reliable and practical results. To address this, the present research combines the strengths of LSTM, known for its superior performance in price prediction, with the GARCH model, which specializes in modeling volatility. This hybrid approach aims to provide a deeper understanding of price dynamics in the cryptocurrency market and enhance prediction accuracy.

3- Methodology

A Recurrent Neural Network (RNN) is theoretically capable of learning sequences with any level of complexity. However, in practice, RNNs struggle to retain information from past inputs over extended periods. This limitation weakens their ability to model long-term dependencies, and this "forgetfulness" can lead to instability during sequence generation (Hansson & Rostami, 2019). Therefore, having a more robust long-term memory provides a stabilizing effect. Even if the network fails to derive a correct understanding from recent history, it can still complete its prediction by referencing information from the distant past.

Long Short-Term Memory (LSTM) is an advanced architecture of RNNs designed to improve information storage and retrieval compared to traditional RNNs (Xiao, 2011). LSTMs are a type of RNN that can learn long-term dependencies (Patel et al., 2020). While they share a similar structure with RNNs, the recurring unit in an LSTM has a relatively different design. Unlike standard RNNs, an LSTM network can decide whether to retain or discard the current memory using introduced gates.

Intuitively, if an LSTM unit detects a significant feature in the early steps of an input sequence, it can easily carry this information through a long sequence, thereby capturing and maintaining potential long-term dependencies (Chen, Wei, & Zhou, 2017).

In the LSTM algorithm, each network undergoes four activations at each step, enabling it to capture and process distant information more effectively. This unique mechanism allows LSTMs to overcome the memory limitations of traditional RNNs and makes them a powerful tool for tasks involving sequential data.

$$f_t = \sigma\left(W_f \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_f\right) \quad \textit{Forget gate}$$

$$\tilde{C} = tanh\left(W_e \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_c\right) \quad \textit{New Informations}$$

$$i_t = \sigma\left(W_i \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_i\right) \quad \textit{Input gate}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}$$

$$O_t = \sigma\left(W_i \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_O\right) \quad \textit{Output Gate}$$

$$h_t = O_t \cdot \tanh(C_t)$$

(1)

Steps of LSTM Operation

Step 1: Forget Gate

LSTM determines which unnecessary information from the previous neural network state should be discarded. This decision is made using the Forget Gate and a sigmoid activation function, which outputs values between 0 and 1. In other words, it identifies which data should be removed from the cell state. A value of 1 indicates that the information will be retained, while 0 means the information will be discarded (Patel et al., 2020).

Step 2: Update Gate

The second step involves updating the information through the Update Gate, which utilizes a hyperbolic tangent (tanh) activation function. This step decides what new information should be stored in the cell state. It consists of two parts:

1. The Input Gate determines which values will be updated.
2. A candidate value is generated by applying the Tanh layer.

These two values are then combined to create an updated cell state (Patel et al., 2020).

Step 3: Input Integration

This step involves combining new data with the output from the previous gate. This is handled by the Input Gate using a sigmoid activation function, which determines the final output. The filtered representation of the cell state serves as the foundation for the output.

Step 4: Output Determination

The final step involves specifying the output value, which is calculated using the Output Gate with a sigmoid activation function. The sigmoid function identifies which parts of the cell state should be revealed. Then, the tanh function is applied to the cell state, and its result is multiplied by the output of the sigmoid gate, determining the filtered output (Patel et al., 2020).

Each of the gates mentioned above is itself a fully connected neural network. In practice, each LSTM block operates through the interaction of four fully connected neural networks to execute the algorithm. The output of these four networks is finally passed to a fully connected layer, and the prediction result is computed using the softmax function (Patel et al., 2020).

4- Implementation and Results

4-1- Implementation

This model was evaluated under two scenarios based on daily prices and historical stock returns, using publicly available data from Yahoo Finance. The data used for predicting the price of Bitcoin spans the period from 02/08/2021 to 02/08/2023. Of the total dataset, 90% was allocated for training and 10% for testing.

Each observation in the dataset contains three distinct values representing the fractional changes in:

1. Daily closing price,
2. High price, and
3. Low price.

These features were used to capture the dynamics of Bitcoin's price fluctuations and to build a predictive model.

(1)

$$O_{k1} = (\frac{close-open}{open}, \frac{high-open}{open}, \frac{open-low}{open}$$

$$O_{k2} = (\frac{garchclose-garchopen}{garchopen}, \frac{garchhigh-garchopen}{garchopen}, \frac{garchopen-garchlow}{garchopen}) \quad (2)$$

$$O_k := (fracClose, fracHigh, fracLow) \quad (3)$$

The array O_k is a three-dimensional array composed of actual values.

Following the training phase, we tested our model by predicting the daily closing prices of stocks for various time intervals. For each day in the target period, the prediction process involved the following steps:

1. Selecting the Last Observations**:** We considered the latest latency−1=9 available observations, representing the past 9 days.
2. Creating a 10-Day Sequence: Each potential output for the current day D was added to form a 10-day sequence. This sequence now included 9 historical observations and one hypothetical observation for the next day. Probabilities $n_{fc}.n_{fH}.n_{fL}$ for the current day were calculated for possible outcomes.
3. Probability Calculation and Prediction: The likelihood of each sequence being generated by the trained model was computed. Finally, the observation with the highest likelihood was selected as the prediction for the next day.

Special Cases and Adjustments

In specific cases, it may occur that the likelihood of emitting historical observations combined with any hypothetical observation is zero or extremely close to zero. This may result from numerical errors or inherent model limitations. However, it is observed that incorporating a dynamic window can enhance model performance.

To address this issue, the prediction algorithm was modified as follows:

- If the highest likelihood obtained is zero, the prediction algorithm is repeated while gradually reducing the delay by one day.
- By reducing the delay, the aim is to find an appropriate solution where the emitted probabilities are non-zero.

This delay reduction process is repeated iteratively until a solution is found, ensuring that the historical sequence remains sufficiently long. In this scenario, a minimum requirement of four days for the historical sequence has been set.

4-2- Results

Before presenting the results related to GARCH, it is essential to confirm the presence of GARCH effects in the data. For this purpose, the ARCH effects test is employed. The results of this test confirm the existence of these effects. Therefore, the GARCH method can be used for modeling price volatility.

Table 1: ARCH Effects Test

Prob > chi2	chi2	Test
0.005	7.154	ARCH TEST

Source: Research Findings

The null hypothesis of this test assumes the absence of ARCH effects. However, based on the results, the test statistic does not fall within the confidence interval. Consequently, the null hypothesis is rejected, indicating that the data exhibits ARCH effects. As a result, the GARCH method can be applied for modeling. Figure 1 illustrates the output of the GARCH model.

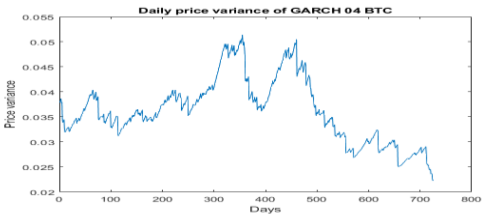

Figure 1: GARCH Model

Source: Research Findings

As shown in the figure above, volatility is low at the beginning of the period, increases during the middle of the period, and decreases toward the end.

Next, the Long Short-Term Memory (LSTM) neural network is used to predict Bitcoin price volatility. LSTM is a specialized type of Recurrent Neural Network (RNN) that resolves the issue of long-term memory in traditional RNNs. LSTM networks have internal mechanisms known as gates, which control the flow of information. These gates determine which data in the sequence are important and should be retained and which should be discarded. In this way, the network passes important information through the sequence chain to produce the desired output.

In other words, an LSTM is essentially a standard neural network with a loop in its structure. At each step, the output from the previous step, along with new input, is fed back into the network. This looping mechanism helps the network retain prior information alongside new data, enabling it to produce the required output based on the combined information. This unique feature of RNNs allows them to work effectively with sequential data, such as text, audio, and more.

The following section presents the output of the hybrid method used for predicting Bitcoin price volatility.

As shown in Figure 2, the model achieved appropriate convergence at iteration 300.

Figure 3 shows the data forecast. As mentioned in the previous section, the performance evaluation metric in this study is the average prediction error. In Figure 4, the prediction error is illustrated more precisely for a 70-day forecast. Based on the results of the GARCH-LSTM model, the maximum prediction error is estimated at 0.002, with a mean error of 0.0006. In other words, the predictive power of this combined model is 99.0%, which indicates a high reliability of the estimated results using this method. Therefore, this approach can be confidently used for predicting future Bitcoin price trends.

Additionally, in Figure 5, the predicted and actual values of Bitcoin price fluctuations are plotted, which clearly demonstrates the effectiveness of the GARCH-LSTM combined method.

As can be seen, the red line (predicted values) aligns closely with the blue line (actual values). A very important point that highlights the significance of this fitting is that Bitcoin experiences significant price fluctuations during this period, and the model has been able to simulate this behavior quite well in the past.

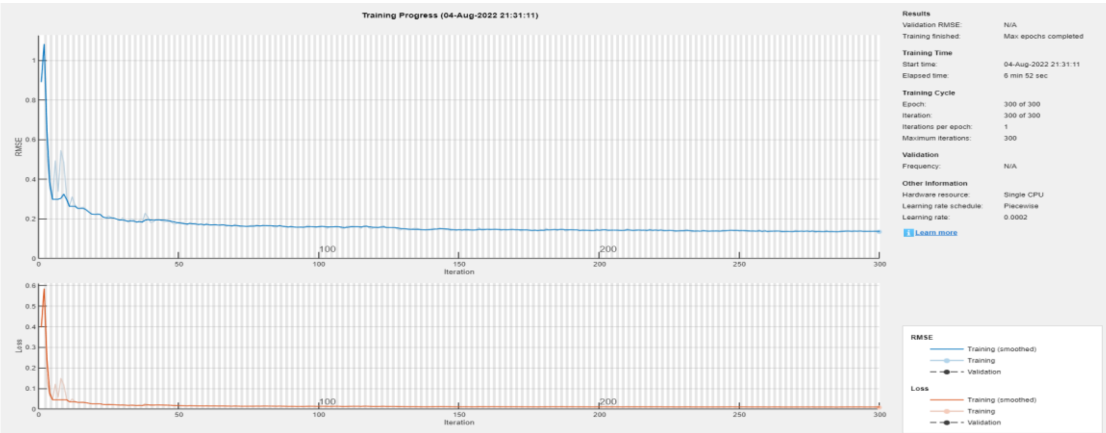

Figure 2: Convergence Chart for Number of Iterations

Source: Research Findings

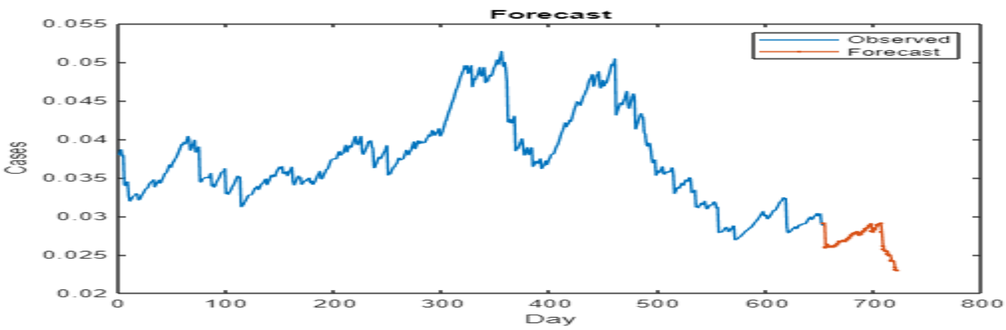

Figure 3: Bitcoin Price Volatility Prediction

Source: Research Findings

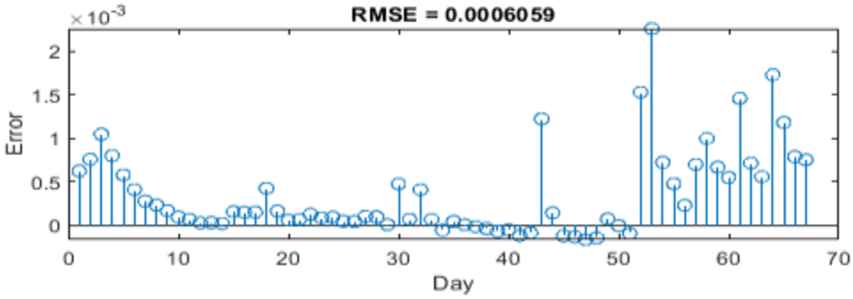

Figure 4: GARCH-LSTM Model Prediction Error
Source: Research Findings

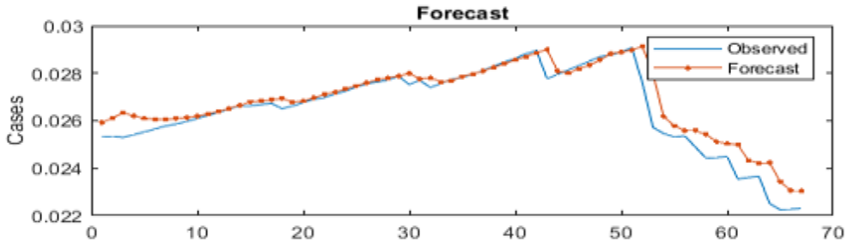

Figure 5: Predicted and Actual Values
Source: Research Findings

5- Discussion

As discussed, the main difference between cryptocurrency markets and other financial markets is the extensive and severe volatility in these markets. Therefore, considering the significance of these fluctuations, various studies have utilized novel heuristic methods for price forecasting in this market. However, an important point that this research emphasizes is that unusual volatility in the cryptocurrency market can reduce the performance of price forecasting models. Based on this, it is better, especially in cryptocurrency markets, to model price volatility before making predictions. This study examined a hybrid forecasting model for analyzing and predicting Bitcoin prices over a two-year period (from August 2, 2021, to August 2, 2023). The results demonstrated that the model achieved a 99.0% prediction accuracy, with a Mean Squared Error (MSE) of 0.0006 and a maximum prediction error of 0.002. The average prediction error in the study by Pournama (2023) for Bitcoin was 0.001. It is worth noting that the research period of this study is about 10 years, and given the importance of the input size for training the LSTM and consequently its predictive performance, it seems that combining the LSTM method with GARCH enhances the capabilities of this model. Also, compared to the study by Seabe et al (2023), which reported the performance of the LSTM method at 0.002 and LSTM Bi- at 0.0008, the prediction result using the GARCH-LSTM method was much better. It is worth mentioning that many recent studies, due to the good performance of the LSTM Bi- method, use it for prediction. However, in this research, it is clear that the use of the GARCH model has improved the performance of the LSTM model even more than the Bi- LSTM. Therefore, it seems that in the cryptocurrency market, considering its volatility characteristics, the use of the GARCH model can enhance prediction performance. It is thus recommended that in future studies, the GARCH method be combined with newer models such as Bi - LSTM to further investigate the model's performance in this context.

The high accuracy of this model indicates its stability and reliability in forecasting highly volatile financial markets. This approach not only provides a significant improvement over traditional econometric models such as ARIMA and GARCH, but also enables better risk management and more informed decision-making for investors and financial analysts. Furthermore, the findings suggest that incorporating additional market-influencing factors, such as sentiment analysis and reinforcement learning, could further enhance the model's predictive power. Future research should focus on developing multivariate models that integrate fundamental, technical, and sentiment-based data, which can lead to greater forecasting accuracy and reduced uncertainty in cryptocurrency markets. In conclusion, this study demonstrates that the proposed hybrid forecasting model is an effective and precise tool for analyzing and predicting cryptocurrency prices. It can serve as a valuable resource for investors, financial analysts, and researchers in this field.

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