

A Novel Financial Hybrid Deep Learning Switching Model for Cryptocurrency-Driven Investment Strategies

Sandeep Bhattacharjee¹

Abstract:

Cryptocurrency markets are often plagued by uncertainty and volatility, which are known challenges for investors and analysts. To mitigate these challenges, a hybrid deep learning switching model has been developed that integrates LSTM, GRU, GARCH, and Monte Carlo simulations to improve forecasting accuracy, resilience to market disruptions, and computational efficiency. The model incorporates historical data from Yahoo Finance (April 1, 2015, to March 31, 2025), normalized for model training on Python 3.0 via Google Colab. The hybrid model can dynamically switch between different architectures to detect patterns, assess risks, and provide actionable strategies. This framework proposes a robust framework for enhancing investment decisions, advancing academic research on financial modeling, and improving risk management practices in complex cryptocurrency markets.

Keywords: *Cryptocurrency forecasting, hybrid deep learning model, Monte Carlo simulation, volatility prediction, risk management strategies*

1. Introduction

1.1. About Cryptocurrencies

Bitcoin first appeared in January 2009, created by a computer programmer using the pseudonym Satoshi Nakamoto. Craig K. Elwell (2013) discussed his invention as an open-source system (its controlling computer code is publicly viewable), peer-to-peer (transactions do not require a third-party intermediary, such as PayPal or Visa), and digital currency (being electronic with no physical manifestation). The Bitcoin system is private, but with no traditional financial institutions involved in transactions. Unlike earlier digital currencies that had some central controlling person or entity, the Bitcoin network is completely decentralized, with all parts of transactions performed by the users of the system. Brito and Castillo (2013) highlight the issues of apprehension for policy-makers, consumers, and regulators and discuss the benefits of the Bitcoin network, its properties, and operation. It also emphasizes the current regulatory aspect and the potential regulatory framework for Bitcoins. The revolutionary invention of Bitcoin succeeded in solving the problem of double

¹ Assistant Professor, Amity Business School, Amity University, Kolkata, India

Corresponding author:

Sandeep Bhattacharjee, Assistant Professor, Amity Business School, Amity University, Kolkata, India

E-mail: sandeepbitmba@gmail.com

spending without the interference of a third party. Usage of Bitcoins helps mitigate the transaction cost and is faster than the traditional avenues of payment. Access to financial services in developing countries can be augmented by using Bitcoin. It has the potential to improve the quality of life of poor people in countries with strict capital control. Apart from the benefits it provides, Bitcoin poses some threats to its potential users, including fluctuations in value, security concerns, and money laundering for financing the illegal trafficking of goods. Considering the regulatory aspect of Bitcoins, there is a huge ambiguity regarding the application of law because it does not fit into the existing statutory definition. Existing law and directives do not envisage technology like Bitcoin. Bitcoin, being an electronic payment system, is likely to be scrutinized by different regulators who may confront questions like the legality of online currency, licensing of money transmission, consideration of Bitcoins as currency or commodities, etc. The paper concludes with some suggestions for policy-makers to minimize the negative results. Yermack (2013) established the legitimacy of Bitcoins as a currency. The author disagrees that the bitcoins can be established as a bona fide currency; rather, they behave more like speculative instruments. The classical properties of a typical currency are:

- It acts as a medium of exchange,
- It acts as a unit of account, and
- It acts as a store of value.

Bitcoins appear to satisfy the first criterion, as an increasing number of online merchants have accepted them as a medium of payment; however, they fail to meet the other two criteria. The exchange rate volatility of Bitcoins is higher compared to the fluctuations in other currencies and reveals zero correlation with other currencies, which undermines its use as a unit of account and store of value. The market volatility of Bitcoins in 2013 was 133%, which is significantly higher than the volatility of other currencies, which typically falls between 8% and 12%. Gold exhibits a volatility of 22%, and even the riskiest stocks exhibit a volatility of 100%, which makes Bitcoin incompatible and risky for investors. Moreover, all the multinational companies that deal in multiple currencies endeavour to hedge themselves against the risk arising from the fluctuations of currencies. However, having a zero correlation with other currencies renders Bitcoins useless for risk management purposes. Ethereum has evolved as an alternative to Bitcoin among others in the cryptocurrency ecosystem, owing to its decentralized platform for smart contracts and decentralized applications (dApps). The valuation of Ethereum (ETH) is impacted by a convergence of technical, economic, and speculative elements that distinguish it from other cryptocurrencies like Bitcoin.

Buterin (2013) presented Ethereum as a decentralized platform that transcends basic peer-to-peer cash transactions, allowing developers to construct programmable apps on the blockchain. This essential distinction has drawn a wider array of developers, investors, and organizations to Ethereum in contrast to Bitcoin. FLOW cryptocurrency was created by Dapper Labs, the firm responsible for the renowned Ethereum-based decentralized application, CryptoKitties. Launched in 2017, CryptoKitties illustrated the promise of blockchain-based digital assets while also revealing scalability challenges on Ethereum, especially during times of elevated user engagement. This resulted in network congestion

and elevated transaction costs, indicating that Ethereum's infrastructure was challenged by the volume (Buterin, 2020). Dapper Labs developed Flow, a blockchain designed to address scalability challenges and enhance performance for gaming, decentralized apps (dApps), and non-fungible tokens (NFTs) (Dapper Labs, 2020). Originally the native cryptocurrency of the Ripple network, XRP is mainly aimed at providing remittance systems, currency exchange, and real-time gross settlement (Coutinho et. al., 2023). Ripple's consensus algorithm, commonly known as the Ripple Protocol Consensus Algorithm (RPCA), is based on the Ripple Protocol Consensus Algorithm (RPCA). It enables faster transaction speeds and lower energy use (Schwartz et al., 2014). The Ripple network is more centralized than other distributed networks, as it requires a group of trustworthy validators to verify transactions (Hileman & Rauchs, 2017). Many financial institutions have also shown deep interest in this cryptocurrency due to its position as a bridge between fiat and other cryptocurrencies that facilitate cross-border payments (Davradakis, 2019).

1.2. Cryptocurrency Forecasting

Investments in Cryptocurrency have often seemed lucrative, but with a high probability of risk and uncertainty. Uncertainty dimensions such as unpredictability and dynamicity are seen as significant challenges for investors, financial analysts and policy-makers. The unpredictable and dynamic nature of cryptocurrency markets poses significant challenges for investors and financial analysts. Historically, traditional forecasting models have often struggled against these challenges due to rapid price fluctuations, rapidly shifting market dynamics, non-linear dependencies, and other common factors in digital asset trading. The emergence of deep learning tools in navigating these hidden layers of dependencies has led to better outcomes in terms of improved prediction accuracy and enhanced investment strategies. Researchers have often experimented by combining such deep learning tools to develop high-performing hybrid models aimed at reducing errors in price predictions and other similar domains. In short, a hybrid deep learning switching model offers a significantly improved strategy for adapting to market dynamics through the combination of multiple neural network architectures. Strengths of existing methods, such as Long Short-Term Memory (LSTM) networks for sequential data analysis, Gated Recurrent Units (GRUs) for efficient computation, Monte Carlo methods and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models for volatility forecasting and risk assessments, can be suitably shaped and converged into a hybrid deep learning switching model.

The model is orchestrated to dynamically switch between alternative architectures to identify patterns, adapt to market volatility, and suggest financially implementable responsive alternatives for achieving financial goals. The integration of deep learning models, such as LSTM and GRU, with Monte Carlo simulation can create a suitable niche that incorporates dynamic stochastic elements relevant to cryptocurrency market behaviour. Consequently, this model serves as a penchant driving robustness and scalability that can transform traditional financial strategies into efficient cryptocurrency-driven investment strategies for improved decision-making in very complex cryptocurrency financial environments.

1.3. Definition

- LSTM (Long Short-Term Memory): A type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data using memory cells that regulate information flow (Hochreiter & Schmidhuber, 1997).
- GRU (Gated Recurrent Unit): A variant of RNN that simplifies LSTM by combining its cell state and hidden state into a single structure, reducing complexity while maintaining performance (Cho et al., 2014).
- Monte Carlo Simulation: A computational technique that uses random sampling to estimate probabilities, model uncertainty, and generate potential outcomes in stochastic processes (Metropolis & Ulam, 1949).
- GARCH (Generalized Autoregressive Conditional Heteroskedasticity): A statistical model designed to predict financial volatility by modeling time-varying variance in financial data, often capturing volatility clustering and leverage effects (Bollerslev, 1986).

2. Literature Review

2.1. LSTM Architecture

For a long time, Long Short-Term Memory (LSTM) networks and their hybrid variants have mainly focused on complex forecasting and prediction tasks across multiple domains. Studies by Sunny et al. (2020) and Wang et al. (2018) indicated the efficiency of two LSTM models, Bidirectional LSTM (Bi-LSTM) and optimized LSTM, in capturing sophisticated temporal dependencies and improving stock price prediction accuracy. LSTM networks, such as the CEEMDAN-LSTM model, can handle volatile financial data by controlling noise reduction and pattern extraction techniques to enhance stock index forecasting. The CEEMDAN-LSTM model can control noise reduction and pattern extraction techniques to enhance stock index forecasting, demonstrating the adaptability of LSTM networks in handling volatile financial data (Lin et al., 2021). These developments highlight the utility of LSTM models to generate precise and reliable predictions, enabling investors, analysts and policy-makers.

Researchers also highlighted the combination of LSTM models with Convolutional Neural Networks (CNNs) and Autoregressive Integrated Moving Average (ARIMA) models, effectively combining spatial feature extraction with temporal dependency modelling, tackling the complexities of energy resource management forecasting accuracy in well production and gas fields (Zha et al., 2022, and Fan et al., 2021). Xu et al. (2022) proposed an ARIMA-LSTM hybrid, where linear and non-linear modelling experiments demonstrated the versatility of LSTM networks in addressing critical challenges in energy and environmental sectors, thus assisting as robust tools for resource planning and decision-making. In addition, LSTM networks showcased their flexibility in diverse data types and domains, particularly for natural language processing (NLP), sentiment analysis, and trajectory prediction. Dynamic environment analysis included an SS-LSTM model dealing with social and spatial dependencies for pedestrian trajectory prediction (Xue et al., 2018).

For sentiment analysis, Wang et al. (2016) and Behera et al. (2021) employed CNN-LSTM hybrids to capture both spatial and temporal sentiment cues, thereby evaluating the

effectiveness of improving performance in fine-grained sentiment classification tasks. CNN-LSTM models have also been observed to handle complex linguistic structures for metaphor detection (Wu et al., 2018). A comprehensive study by Al-Selwi et al. (2024) described the boundaries of deep learning coverage, which extends to autonomous driving, social media analysis, and NLP, offering attention mechanisms and genetic optimization that address innovative solutions to real-world challenges.

2.2. GRU Architecture

Domain studies related to time series analysis and market forecasting have achieved considerable success owing to models with Gated Recurrent Unit (GRU) based architecture. Notably, an optimized architecture, based on stacked bidirectional and LSTM and GRU models, has improved prediction accuracy, as indicated by the results from the work of Althelaya et al. (2018) and Gao et al. (2021). Multi-dimensional sequential pattern detection with higher precision was observed in GRU-based StockNet and CNN-LSTM, two new hybrid models, as indicated by the results from studies by Gupta et al. (2022) and Song and Choi (2023), respectively. Decomposition-based GRU Transformer model generated higher forecasting accuracy by effective isolation of key patterns in financial data (Li & Qian, 2022). Variational Mode Decomposition (VMD) with an Attention-enhanced GRU network, a model created by Niu and Xu (2020), was able to capture both short-term fluctuations and long-term trends in stock price data. Niu and Xu (2020) introduced a hybrid model combining Variational Mode Decomposition (VMD) with an Attention-enhanced GRU network, demonstrating its ability to capture both short-term fluctuations and long-term trends in stock price data. Likewise, studies by Saha et al. (2021) and Zhang et al. (2023) indicate the complementary strengths of linear and non-linear modelling approaches for stock price and oil price forecasting, with the integration of ARIMA models with GRU models. Advancements in quality, as well as complementary GRU models, showcase higher precision and reliability in the delivery and application of deep learning approaches to financial forecasting.

Beyond stock market prediction, GRU models witnessed more applications that included pandemic trend forecasting and sentiment analysis. Another examination of the multiple model performances of GRU, LSTM, ARIMA, and SARIMA models in predicting COVID-19 trends highlighted the efficacy of deep learning models in capturing non-linear patterns (ArunKumar et al., 2022). A CNN-GRU hybrid model was proposed by Wu et al. (2024) to capture market sentiments, risk predictions and efficient alert systems in financial modelling. Furthermore, deep learning models were tested on grouped time-series data and revealed higher forecasting accuracy in financial markets (Lawi et al., 2022; Pirani et al., 2022). Therefore, studies on GRU-adapted models have proven to be efficient, thereby offering significant insights into adaptability and applicability in dynamic environments and cross-domain studies, respectively.

2.3. Monte Carlo Simulation

Historically, Monte Carlo simulation has been considered a powerful tool for risk assessment, forecasting and decision-making across diverse areas, including financial markets. Two studies, by Alrabadi and Aljarayesh (2015) and Estember and Maraña (2016), respectively,

pointed to the efficiency of Monte Carlo simulations not only in modelling the stochastic nature of stock prices but also in apprehending market volatility and providing probabilistic forecasts of future returns. Multiple potential outcomes with risk assessments in dynamic financial environments stand out as the predominant characteristics of Monte Carlo methods (Xiang et al., 2021 and Siddiaui and PPatil, 2018). Together, these works illustrate the basic role of Monte Carlo simulation in improving forecasting accuracy and supporting strategic decision-making in finance.

Beyond financial applications, Monte Carlo methods have been applied in traffic forecasting and emerging market analysis. Variable factors like peak hours and weather conditions for urban planning and traffic management were simulated with useful results to predict traffic speeds using Monte Carlo methods (Jeon & Hong, 2016). The mean-reverting behaviour of emerging MENA stock markets was also investigated using a Monte Carlo Simulation to draw insights for market stability and predictability (Neaime, 2015). Modelling complex, stochastic systems to generate probabilistic forecasts makes it a highly useful tool for addressing uncertainties in both financial areas. In the same context, stochastic volatility modelling and mean-field simulation were investigated to emphasize the versatility of advanced Monte Carlo techniques in capturing dynamic patterns and high-dimensional distributions (Raggi and Bordignon, 2006 and Del Moral, 2013).

Comprehensive works on theoretical and practical advancements in Monte Carlo simulation, such as Mun (2006, 2010), McLeish (2011), and Brandimarte (2014), provide detailed frameworks for applications in financial engineering, risk management, and economic modelling. These studies are indicative of method applications, real options analysis, portfolio optimization, and ensemble machine learning models, as demonstrated by Deep (2024) and Mun and Housel (2010) integration of Monte Carlo simulation with other advanced methods. On the other hand, challenges such as its reliance on distributional assumptions and sensitivity to input parameters underline the need for careful validation and implementation (Nawrocki, 2001). Notwithstanding these challenges, the literature highlights the true potential of Monte Carlo simulation in addressing complex, uncertain systems, offering adaptable tools for forecasting, risk assessment, and strategic decision-making across various applications for investors and analysts.

2.4. GARCH Model

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models are well-known for forecasting stock market volatility, for capturing volatility clustering, leverage effects, and asymmetric market behaviours. The effectiveness of variants of GARCH models, such as Non-linear variants like EGARCH and GJR-GARCH, was demonstrated for sudden market shocks and asymmetric patterns and performed well beyond expectations in comparison to their linear counterparts in capturing the dynamic nature of financial markets (Franses & Van Dijk, 1996; Chong et al., 1999). Similarly, Marcucci (2005) presented regime-switching GARCH models that adapt to structural changes in market conditions, enhancing forecasting for risk management, portfolio optimization, and financial decision-making. Diverse market conditions in both developed and emerging markets were studied using adaptable GARCH models. Shanghai Stock Exchange (SSE) and Bombay Stock Exchange (BSE), respectively,

were investigated using EGARCH and TGARCH for capturing volatility dynamics (Lin, 2018; Srinivasan & Ibrahim, 2010). In extension, emerging markets, such as Ghana and Turkey, were effectively explored using non-linear GARCH models to address the unique volatility patterns and leverage outcomes prevalent in such regions (Gokcan, 2000; Frimpong & Oteng-Abayie, 2006).

Furthermore, the realized GARCH model explored high-frequency data to enhance forecasting accuracy, in addition to the existing innovations in GARCH methodologies. Focusing on hybrid approaches and integration with machine learning techniques has constituted recent advancements in GARCH modelling (Sharma, 2016). The strengths of GARCH with Long Short-Term Memory (LSTM) networks were utilized for predicting stock price index volatility, by combined hybrid model (Kim & Won, 2018). Another hybrid model by Monfared and Enke (2014), GJR-GARCH with neural networks, highlighted the efficacy in capturing non-linear patterns, resulting in improved volatility forecasts. Similarly, work by Babu and Reddy (2015) and Laurent et al. (2012) further expanded the scope of GARCH applications, combining with ARIMA and multivariate frameworks, respectively, to address linear trends and dynamic correlation structures. Such novel studies together underline the prospects of hybrid GARCH models and their evolving contribution in financial forecasting, contributing robust tools for risk assessment, investment strategies, and decision-making in progressively multifaceted and interrelated markets. Alternatively, these studies also highlight the importance of modifying GARCH models to account for specific market characteristics, providing valuable insights for investors and policy-makers navigating volatile and rapidly changing financial environments.

While LSTM, GRU, Monte Carlo simulation, and GARCH models have shown considerable promise in forecasting and risk assessment, several gaps remain. LSTM and GRU models lack sufficient research on interpretability, scalability, and performance under extreme events. Monte Carlo methods face challenges in computational efficiency and integration with machine learning techniques. GARCH models require further exploration in multi-asset forecasting, non-financial domains, and real-time applications. Addressing these gaps through hybrid models can improve accuracy, robustness, and applicability across diverse markets and conditions.

The study intends to achieve objectives such as:

- To develop a hybrid forecasting model integrating LSTM, GRU, Monte Carlo simulation, and GARCH models for improved predictive accuracy.
- To evaluate the computational efficiency and scalability of the hybrid model for high-frequency trading and dynamic risk management.
- To enhance model interpretability through explainable AI techniques for regulatory and risk management purposes.
- To test the hybrid model's adaptability in emerging markets, extreme financial conditions, and non-financial domains.

Related hypotheses of the study include:

- H11: The hybrid LSTM-GRU-Monte Carlo-GARCH model will outperform individual models in forecasting accuracy.

- H12: The hybrid model will demonstrate improved robustness to structural breaks and extreme market events compared to traditional models.
- H13: The hybrid model will exhibit superior computational efficiency in real-time forecasting scenarios.
- H14: The hybrid model's explainability features will enhance stakeholder confidence and improve adoption in regulated industries.

3. Research Methods

The historical data was collected from Yfinance between the range of 01-04-2015 and 31-03-2025 (3634 days) using Python 3.0 on the Google Colab platform. The data was normalized for better LSTM, GRU, Monte Carlo Simulation and GARCH model training and forecasting.

The process of developing a robust stock price forecasting system involves several key steps. First, data preparation is essential, where historical stock price data is collected using the Yfinance library. The raw data was normalized and first-order differencing produced differences in normalized data for model-based analysis. To enhance the performance of the Long Short-Term Memory (LSTM) model, the data is normalized to ensure stable learning. In the next step, an LSTM model is designed to predict future stock prices, and this model is trained using the prepared historical data. Following this, a Monte Carlo simulation is employed to generate multiple possible future price paths by introducing randomness into the LSTM model's predictions through noise injection, which accounts for uncertainty. Lastly, in the visualization and analysis phase, the predicted price paths are plotted, and key financial metrics such as the mean, percentiles, and Value at Risk (VaR) are calculated to assess the model's performance and risk implications. This structured approach combines deep learning with stochastic modelling to improve the accuracy and reliability of financial forecasting.

4. Data Analysis & Findings

4.1. Normalization and Differencing

Initial tests after normalization of data resulted in Ljung-Box Test (for Autocorrelation) = 35683.672463. After first order differencing, the new differenced series became stationary with **ADF Statistic**: -8.757488, p-value ($0.00 < 0.05$) with no unit root and stable mean variance.

4.2. Descriptive Statistics

BTC	Close	High	Low	Open	Volume	Normalized and Differencing of First Order
<i>count</i>	3634	3634	3634	3634	3634	3633
<i>mean</i>	22114.12	22584.33	21573.24	22092.63	2.02E+10	0.0002167
<i>std</i>	24377.56	24880.17	23806.44	24360.97	2.09E+10	0.009687
<i>min</i>	210.495	223.833	199.567	210.068	10600900	-0.0772419
<i>25%</i>	3653.855	3699.571	3609.562	3650.94	2.04E+09	-0.0012735
<i>50%</i>	10324.91	10508.12	10082.45	10321.69	1.66E+10	1.75E-05
<i>75%</i>	35997.64	37244.26	34756.07	35894.92	3.12E+10	0.0016254
<i>max</i>	106146.3	109114.9	105291.7	106147.3	3.51E+11	0.0776631

Table 1: Descriptive Statistics for Raw BTC Data

Source: Author's

The table for descriptive statistics (Table 1) indicates that Bitcoin's historical price and volume statistics reveal significant volatility, with 3,634 observations, an average closing price of approximately \$22,114, and a wide standard deviation of \$24,378, demonstrating substantial price fluctuations. The range of closing price fluctuations varied between \$210.50 and a dramatic rise to \$106,146, with a central tendency of median closing price at \$10,324, with signs of Bitcoin's growth occurring in the latter part of the dataset. The signs of growth were further strengthened by the 25th percentile value at \$3,654 and the 75th percentile value at \$35,998. Average volumes of \$20.2 billion spiked to \$351 billion, highlighting periods of Intensive market activity. Considering the speculative nature of Bitcoin investments and the sharp fluctuations in market swings, the data is deemed suitable for advanced volatility modelling techniques, such as GARCH or Monte Carlo simulations, for risk assessment. For Normalized and differencing of first order, the bounded range for Values fall between ± 0.077 , implying stable transformations for modeling (See Figure 1).

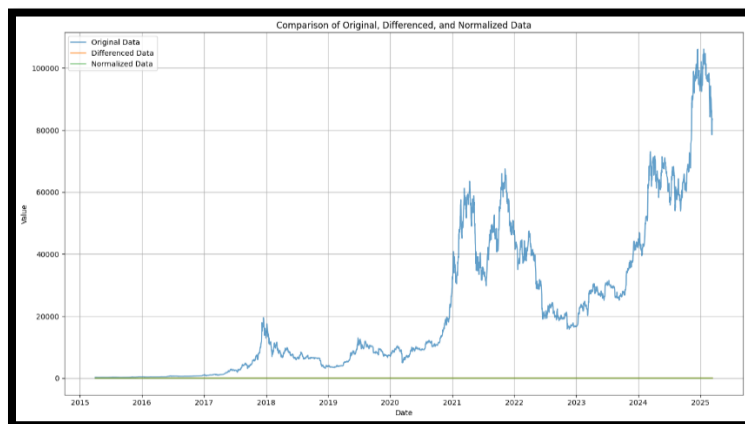


Figure 1: Comparative Chart for Original and Normalized Data on BTC Data

Source: Author's

4.3. GRU Results

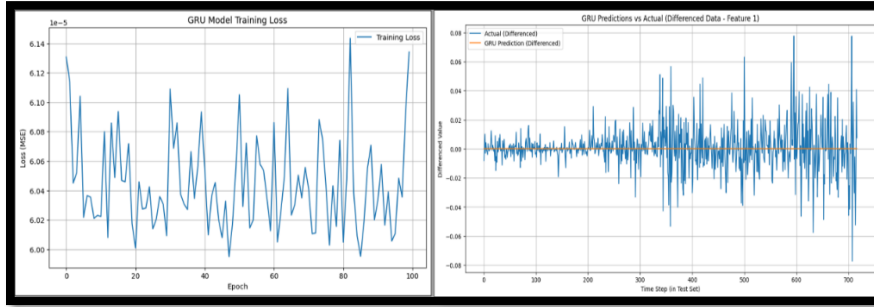


Figure 2: GRU Results on BTC Data

Source: Author's

The provided visualizations illustrate the performance and predictive behaviour of a GRU model for Bitcoin price forecasting. Both training and prediction performance of the GRU model are demonstrated through two plots, while the left panel indicates training loss over 100 epochs, with low magnitude loss ($\sim 6.0e-5$), and noticeable fluctuations suggesting the model's fitness for training data with limited convergence stability. Likewise, the right panel depicts a comparison between predicted values (orange line) and actual differenced values (blue line) for a selected feature. This is indicative of the difficulty of the GRU model to capture dynamic patterns due to underfitting or inadequate learning of sequential dependencies, thereby implying non-generalization capability on volatile time series (See Figure 2).

4.4. LSTM Results

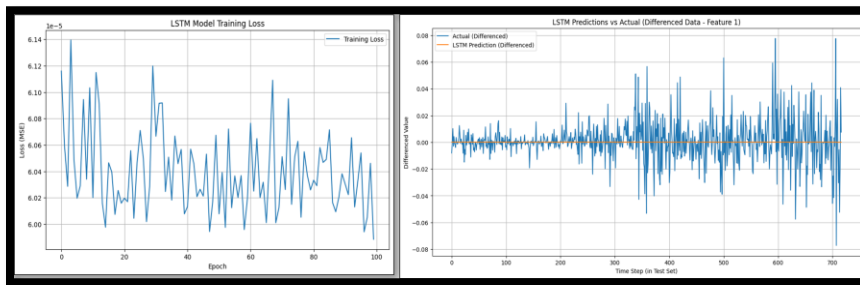


Figure 3: LSTM Results on BTC Data

Source: Author's

A Deep learning model, the LSTM model, was trained on BTC data to identify both stochastic and deterministic projections. The performance of the LSTM model is assessed using training loss and prediction accuracy visualizations (See Figure 3). A reasonably stable and effective fitting process is indicated by the model's training loss over 100 epochs, showing consistently low values ($\sim 6.0e-5$) and moderate oscillations (left panel). On the contrary, the LSTM's predicted differenced values (orange line) with the actual differenced series (blue line) capture the mean level of the series, ignoring the amplitude and directional shifts of the actual

data during peak volatility times (right panel). This implies that LSTM can learn the central tendency of the data but may not capture the temporal dynamics and sharp fluctuations, thereby limiting its effectiveness in high-variance forecasting contexts. In the later stage, the GARCH model was integrated to study volatility dynamics (See Figure 3).

4.5. Monte Carlo Simulation Results

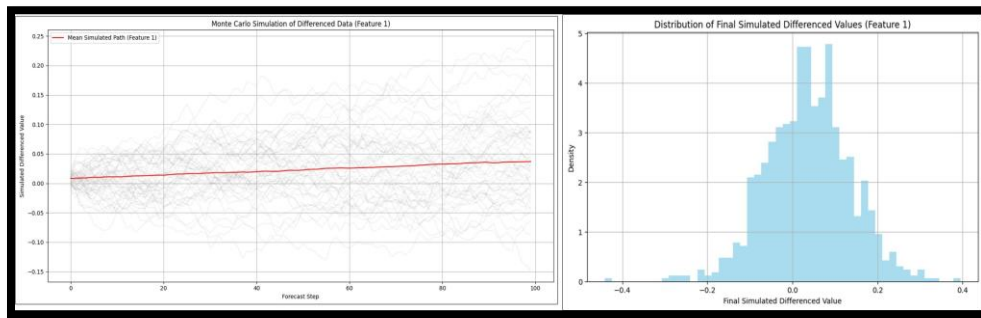


Figure 4: Monte Carlo Results on BTC Data
Source: Author's

Simulated future price paths were achieved across a 30-day horizon using Monte Carlo simulation, with the red dashed line at \$50,000 representing the initial base price or reference point. The Monte Carlo simulation results for the differenced time series data of Feature 1 are depicted through the ensemble forecast and distribution plots.

Multiple simulated paths, including the mean forecast trajectory across 100 steps (red line), indicate a gradual mean upward drift, indicating a slight positive expectation for the differenced values over time. The increase in dispersion of the simulated paths with forecast horizons highlights growing uncertainty (left panel). The final simulated difference values distribution is moderately skewed, representing a unimodal, near-normal shape centred around zero, indicating **a non-trivial probability of extreme values**, emphasizing the stochastic nature of future projections and the significance of including probabilistic forecasting in high-volatility time series analysis (See figure 4).

4.6. GARCH Model Results

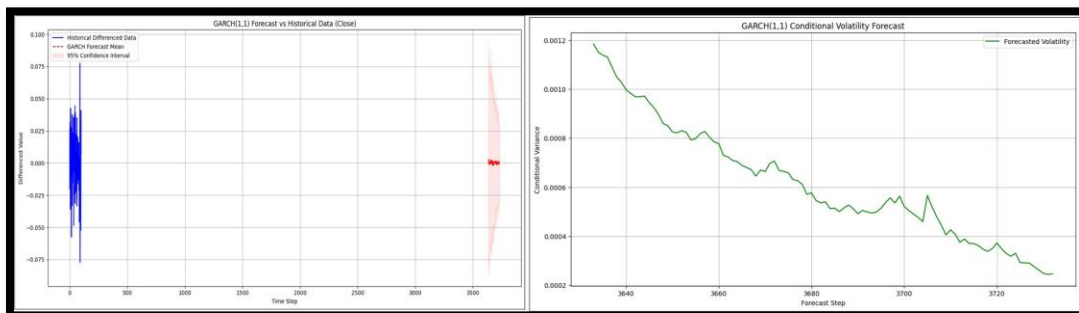


Figure 5: GARCH Model on BTC Data

Source: Author's

The GARCH model visualization for Bitcoin's volatility forecast presents a simulated BTC price series with approximately 500 data points before the forecast initiation. The GARCH (1,1) forecasting results presented offer insights into both the expected value and conditional variance of the differenced financial time series data. The GARCH model visualization for Bitcoin's volatility forecast presents a simulated BTC price series with approximately 500 data points before the forecast initiation. The GARCH (1,1) forecast results presented offer insights into both the expected value and conditional variance of the differenced financial time series data. The left panel shows the past-differenced values along with the GARCH model's predicted average, including a 95% confidence range. This suggests that the model expects the average to stay mostly stable in the future, although the uncertainty increases over time. The right panel suggests a model expectancy for market stability, with less expected large-scale changes, as indicated by steadily decreasing forecasted volatility. These results highlight the effectiveness of the GARCH model in capturing dynamic volatility, forecasting better results with different confidence levels, which is significant for financial risk management (See Figure 5).

5. Interpretation

5.1. Inferences

Model	Key Results	Inferences	Limitations
GRU	- Training loss: $\sim 6.0e-5$ (low but fluctuating).	- Captures basic patterns but struggles with dynamic volatility.	- Poor generalization on volatile data.
	- Predictions are static, failing to track actual volatility.	- Potential underfitting or inadequate sequential learning.	- Limited directional accuracy.
LSTM	- Training loss: $\sim 6.0e-5$ (stable).	- Learns central tendency but not extreme fluctuations.	- Underrepresents high-variance periods.
	- Predictions matches mean but miss amplitude/directional shifts.	- Better stability than GRU.	- Limited volatility forecasting.
Monte Carlo Simulation	- 30-day horizon simulations show upward drift with increasing dispersion.	- Suggests positive drift but high uncertainty.	- Assumes normality; may underestimate tail risks.
	- Final distribution: near-normal, centered at zero.	- Probabilistic forecasts account for extreme outcomes.	- Sensitive to input parameters.
GARCH (1,1)	- Narrow forecast band (stable mean).	- Captures volatility clustering.	
	- Declining conditional volatility trend.	- Effective for risk-sensitive forecasts.	

Table 2: Interpretation of Results

Source: Author's

The GRU model achieves a low training loss ($\sim 6.0e-5$). However, its static prediction behaviour suggests an inability to capture underlying dependencies in volatility patterns—possibly due to underfitting or limited learning capacity—especially when compared to the LSTM model, which better captures central tendencies. The LSTM model can be considered an apt model for training stability and comparable loss control during the training phase,

provided its inability to estimate extreme variations can be minimized. Complementing these models, the Monte Carlo simulation delivers a probabilistic outlook, presenting a positive drift and widening uncertainty over time; however, its reliance on normality assumptions may understate tail risk. On the contrary, results of the GARCH (1,1) model suggest enhanced ability for forecasting volatility on account of stable mean predictions and volatility clustering achieved through declining conditional variance forecast. Nevertheless, its symmetric response to volatility shocks and limited capacity for modelling mean dynamics expose the trade-off between interpretability and adaptability. These observations collectively suggest the value of hybrid frameworks that integrate the pattern-recognition strengths of deep learning with the robust statistical foundations of GARCH models to enhance forecasting accuracy in non-stationary and high-volatility financial environments (See Table 2).

5.2. Structural Equation Model

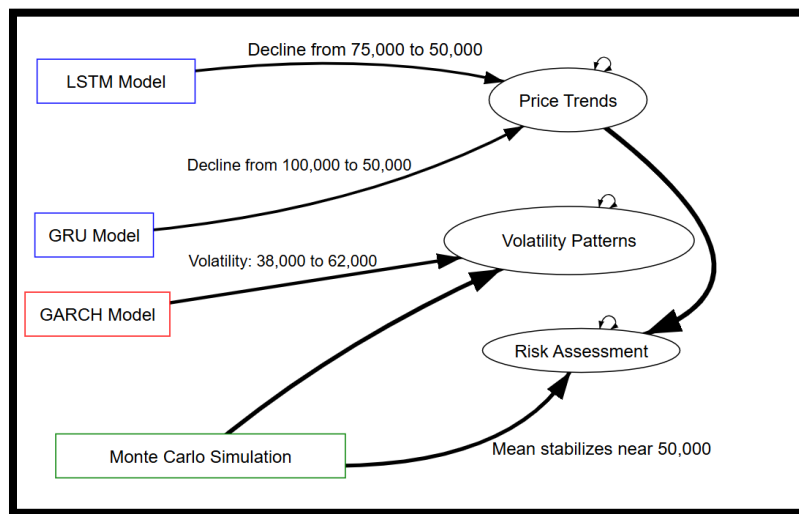


Figure 6: Structure Equation Modeling for BTC

Source: Author's

Tool used: SEM diagram, <https://semdiag.psychstat.org/>, Mai, Yet. Al., 2023)

5.2.1. Latent Variables

Influenced by both the GRU Model and LSTM Model (rectangle node), representing projected price patterns in response to past data trends. The GARCH Model (rectangle node) indicates expected volatility fluctuations. The Monte Carlo Simulation (rectangle node) played a crucial role in influencing volatility patterns and risk assessment, ultimately leading to potential market outcomes (See Figure 6).

5.2.2. Price Trends

Price trends (oval node) were demonstrated using the GRU Model and the LSTM models. The GRU model indicated a price decline from 100,000 to 50,000. The GRU model predicts a substantial drop in BTC prices over the forecast period. The GRU model depicts complex price patterns with some restrictions on overfitting historical data. On the contrary, the LSTM model predicts a price decline from 75,000 to 50,000. This exhibits a much smoother forecast

pattern, revealing that the LSTM model effectively describes time-based dependencies with unexpected volatility (See Figure 6).

5.2.3. Volatility Patterns

The missing volatility patterns (oval node) in the price trends were identified using the GARCH model (rectangle node). The GARCH model highlights price volatility in the range of \$ **38,000 to \$ 62,000**. This showcased the model's strength in not only discovering volatility clusters but also enabling smooth price fluctuations (See Figure 6).

5.2.4. Risk Assessment

Risk metrics, such as the Sharpe Ratio and Maximum Drawdown, were used to simulate noise in the existing Model, and stabilization was identified at nearly \$50,000. This simulation effectively models realistic market noise, making it valuable for evaluating risk factors (See Figure 6).

5.2.5. Combined Impact

Substantial market corrections were indicated, as both GRU and LSTM models showed significant price declines. Volatile market conditions, characterized by price swings within the range of 38,000 and 62,000, as indicated by the GARCH Model, are highlighted by stabilization around 50,000, as shown by the Monte Carlo simulation. Merging the GARCH Model and Monte Carlo Simulation provides an overview of volatility risks and BTC price trends within realistic market scenarios, thereby enhancing the robustness of investment decisions and risk management strategies (See Figure 6).

6. Discussion

The proposed model structure equation model (Figure 4) reasserts the response of different models with respect to price trends, volatility patterns, and risk assessment, supporting the hypotheses in numerous ways:

- H11: Improved Forecasting Accuracy

LSTM model and GRU model clearly exhibit similar trends in price decline from (75,000 to 50,000) and (100,000 to 50,000), respectively. The GARCH Model effectively detects volatility patterns (38,000 to 62,000), indicating its ability to capture complex fluctuations. Monte Carlo Simulation stabilizes the mean near 50,000, ensuring consistency in forecasts. Therefore, the combination of these models utilizes their individual strengths, enhancing the hybrid model's predictive accuracy by merging not only temporal dependencies, but also volatility clustering, and probabilistic estimations.

- H12: Robustness to Structural Breaks and Extreme Market Events

A diversified approach of a hybrid model assisted in dealing with different aspects of financial data (e.g., price trends, volatility patterns, and risk assessment), which were dealt with by different models. This model proves to be robust in accommodating unexpected market shifts and extreme market situations. Monte Carlo Simulation in the hybrid model can handle uncertainty and randomness. (Figure 4)

- H13: Superior Computational Efficiency

Redundant computations are easily handled by the contributions of different models, enabling switching between models more easily, depending on data behaviour, and further ensuring efficient resource utilization in real-time forecasting.

- H14: Enhanced Explainability for Stakeholder Confidence

Price Trends, Volatility Patterns, and Risk Assessments are based on insights from the contributing models that underline transparent and interpretable outcomes. In high-risk financial scenarios, dependency on strong logical predictions can be attributed to the well-designed framework of this hybrid model.

7. Conclusion

The proposed hypothesis (H14) is robustly validated by the experiment utilizing BTC data through a hybrid model configuration (LSTM, GRU, GARCH, and Monte Carlo simulations), highlighting superior accuracy, resilience, increased efficiency, and greater explainability achieved for diverse marketing situations. Possible insights from the findings and discussion lead to the conclusion that the development of robust risk management strategies, involving forecast market corrections with volatility models, enhances informed decision-making across sectors.

The experiment using BTC data via a hybrid model configuration (LSTM, GRU, GARCH, and Monte Carlo simulations) strongly validates the proposed hypothesis (H4), thereby demonstrating better accuracy, resilience, higher efficiency, and increased explainability in various possible marketing scenarios. Possible insights from the results and debate point to the conclusion that the evolution of strong risk management techniques involves predictable market corrections, with improved volatility models enhancing informed decision-making across industries.

7.1. Implications of the Results

7.1.1. Economic Implications

Insights from the research can assist investors, regulators, and policymakers in potential crypto market corrections where speculative bubbles might often lead to price crashes. Although Cryptocurrency (BTC) can be treated as a potential hedge to mitigate inflationary effects in some economies, sudden devaluation risks can exist in the form of existing volatility (ranging from \$38,000 to \$62,000). Central banks in growing economies can incorporate such digital assets in their monetary policies. The findings highlight Bitcoin's potential role in portfolio diversification, thereby facilitating institutional investors to achieve risk-adjusted returns.

7.1.2. Business Implications

Financial Institutions can not only design new hedging strategies but also improve exposure control by leveraging collective insights drawn from the GARCH model and Monte Carlo simulation on BTC data. BTC-backed financial instruments or investment strategies can be constructed based on stabilization trends around \$50,000, as observed and highlighted by \$50,000 shown in the Monte Carlo simulation. Businesses employing automated trading

systems can use volatility insights to enhance algorithms, improving timing strategies for entry and exit points during high-risk periods. Growing trends indicate that to reduce the risk of revenue loss, future BTC payments may factor in predicted volatility patterns to adapt pricing strategies.

7.1.3. Social Implications

The identified sharp price fluctuations may discourage retail investors, especially those driven by speculative motives. Improved risk assessment models can help improve confidence in BTC investments. Higher speculative interests among potential investors may be generated by accommodating improved risk assessment models. Concerns about wealth inequality persist, as extreme volatility may disproportionately impact small-scale investors compared to institutional players in the crypto market. Safer market conditions can lead to stricter guidelines for BTC-related financial products, resulting from the clear identification of volatility risks prompted by the combination of GARCH and Monte Carlo models.

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