JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Hybrid Modeling for Cryptocurrency Volatility Prediction using Time-Series and Deep Learning

[1]Asif Ali Ansari, [2]Sarita Gulia, [3]Rashmi Gupta
[1]Research Scholar, [2]Assistant Professor, [3]Assistant Professor
[1]ASET,
[1]Amity University, Haryana, India

Abstract : The extreme volatility of cryptocurrency markets creates difficulties for traders, investors, and financial analysts due to their unpredictable nature. Traditional models like ARIMA and GARCH perform well for linear pattern detection whereas LSTM, GRU, and Transformer networks excel at modeling complex nonlinear dependencies. These models individually fail to deliver a complete and accurate depiction of cryptocurrency volatility. The research proposes a hybrid method that merges time-series forecasting models with deep learning methods to improve forecast precision. The analysis needs historical price data from CoinGecko while it evaluates technical indicators that include Simple and Exponential Moving Averages (SMA, EMA), Bollinger Bands, Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD) and volatility signals such as GARCH-based volatility, Average True Range (ATR), and rolling standard deviation. The study applies ensemble learning techniques to evaluate forecast reliability across different models including ARIMA, GARCH, LSTM, Transformer, and CNN-LSTM hybrid models. Metrics such as RMSE, MAE, MAPE, and the Sharpe Ratio are used in evaluating the models performance. Hybrid models produce better results than conventional statistical methods and deep learning techniques when forecasting short-term cryptocurrency volatility. The application of meta-learning and residual learning techniques alongside XGBoost as a meta-model leads to enhanced prediction accuracy. The study advances financial forecasting methods by demonstrating superior cryptocurrency volatility predictions with hybrid models to aid risk management and improve algorithmic trading and investment tactics.

Keywords - ARIMA, Cryptocurrency Volatility, Deep Learning, GARCH, GRU, Hybrid Modeling.

1. INTRODUCTION

The potential for high returns and the decentralized nature of cryptocurrency markets have attracted the attention of many investment people. However, they are very volatile as well and thus very unpredictable (Brauneis & Sahiner, 2024). The volatility of the stock markets poses a great challenge to traders, investors, and analysts, as investment decisions and trading strategies are more likely to involve high risk (Wang, Andreeva, & Martín-Barragán, 2023). However, the price movement of a cryptocurrency is very unpredictable and is influenced by the sentiment of the market, changes in the regulations surrounding it, the trading volume, and macroeconomic indicators (Seo & Kim, 2020). Finding the proper ways to showcase this volatility is essential to guarantee precise risk management, and algorithmic trading, and to help financial decision-making (Zahid, Iqbal, & Koutmos, 2022).

1.1 Problem Statement

Even though the progress in financial forecasting is advancing, the prediction of cryptocurrency volatility is a rather complicated problem. Most time series forecasting is done using conventional econometric models like ARIMA and GARCH but these models perform poorly in modeling the non-linear and chaotic nature of the cryptocurrency price fluctuations [1].These models rely solely on historical data and do not notice the sudden changes in market behaviour[2]. However, deep learning methods, including LSTM, GRU, and Transformer networks are much more adequate in identifying various complex patterns and dependencies in the financial data [3]. However, accounting for high-frequency financial data tends to produce models that are very sensitive to what they learn [4]. The standalone ML and DL models fail to offer a complete picture of volatility forecasting and hence are not reliable in volatility forecasting in a financial problem that requires high accuracy and adaptability [5]. The challenges of traditional econometric models reported above can be effectively addressed by a hybrid modeling approach that actively combines traditional econometric models along with deep learning architectures [6].A hybrid approach which combines the power of both methodologies offers to increase the accuracy and robustness of the volatility predictions [7]. The main focus of the research is to build an integrated framework for forecasting cryptocurrency volatility with statistical models, deep learning networks, and ensemble learning techniques [8].

1.2 Objectives

The purpose of the study is to develop a hybrid modeling strategy that is a mixture of Long short-term memory (LSTM), Transformer, GARCH and ARIMA so that it can enhance the prediction of cryptocurrency volatility. Specifically, it attempts to make use of existing technical indicators like Bollinger Bands, MACD, RSI, SMA, EMA, and ATR to expand its feature representation and supply much larger training datasets of predictive modeling. Also, various ensemble learning techniques will be applied such as Extreme Gradient Boosting which works as a meta-model for refinement of predictions and increasing forecast reliability. For the proposed models, we will evaluate their effectiveness using key performance metrics like Sharpe Ratio, MAE, MAPE, and RMSE to get accurate and Risk-adjusted returns. In addition, this research seeks to show how hybrid volatility forecasting could be used in financial risk-management, algorithmic trading, and investment decision-making in the real world.

2. LITERATURE REVIEW

Among the most outstanding features of the cryptocurrency market is that it is extremely volatile, which makes it even more challenging to trade for participants in its financial market [9]. Over the years, scientists have developed many methods for forecasting volatility patterns and variations in the value of cryptocurrencies. Conventional econometric models, ML models, DL architectures, and hybrid forecasting techniques are the categories into which human-made forecasting techniques fall. This section of the literature review examines research from a variety of fields, assessing the advantages and disadvantages of the technique and supporting the development of a hybrid model to enhance the forecast of bitcoin volatility.

2.1 Traditional Econometric Models for Volatility Prediction

Conventional econometric models, such as the GARCH and ARIMA, are mostly used for financial time-series forecasting [10]. ARIMA is utilized to effectively detect linear associations and time-series trends, while GARCH models perform better in the condition of conditional heteroscedasticity, which means that they can estimate the volatility fluctuations over time [11]. Models such as GARCH and ARIMA are widely used in the market for cryptocurrencies due to their interpretability and statistical strictness.

Despite that, hybrid versions of GARCH models such as GARCH-LSTM have been recently explored to fuse statistical volatility estimation with deep learning models for better versatility towards market fluctuations in real-time. Then this addresses one of the proverbial weaknesses of the GARCH models — their dependence on historical data and the inability to acknowledge the sudden structural change in the market [12].

2.2 Machine Learning Approaches for Volatility Prediction

Techniques used in machine learning have gained recognition as a result of their ability to learn complicated patterns and relationships that exist within financial data. For instance, Gradient Boosting Models (GBM), XGBoost, Random Forest, and SVM have shown a good outlook in predicting cryptocurrency volatility [3]. These particular models can take in more than one feature, such as technical indicators, sentiment analysis, and macroeconomic variables, to make the prediction performance better.

As proved recently by some studies, a combination of multiple base models with ensemble learning techniques like XGBoost and LightGBM is indeed able to produce better forecasting results compared to standard ML models alone. Specifically, the results obtained utilizing meta-learning strategies (when one model modifies another) have been unveiled to improve the error rate in volatility estimation. Additionally, the evolutionary algorithm based on selecting features improves the robustness of ML-based volatility predictions [8].

2.3 DL Models for Volatility Prediction

DL models have become solid tools in financial forecasting with their ability to take in large amounts of data and understand the smallest complex patterns [13]. LSTM networks and GRU are the foremost most applicable and generally used in time-series forecasting due to their great ability to handle long-term dependencies in sequential data [14]. These models have presented the best quality of accomplishment over traditional econometrical models and ML models in upholding the significance of cryptocurrency volatility [3].

In deep learning-based cryptocurrency forecasting, a gradient-specific optimization technique has been introduced. By dynamically adjusting the learning rate based on volatility clusters, this method makes the deep learning models better at adapting to a very fast-changing financial environment. Beyond that, CNN-BiLSTM models are also utilized to train short-term and long-term dependencies and are seemingly superior to conventional LSTM and Transformer models in high-frequency financial trading [15].

2.4 Hybrid Approaches for Cryptocurrency Volatility Prediction

Hybrid models combine the strengths of both ordinary methods and deep learning techniques to give precise and reliable forecasts. Latest investigations have aimed at merging ARIMA and GARCH models with LSTM, GRU, CNN-LSTM, and Transformer architectures in order to better predict the volatility [16]. The hybrid models can be grouped into two main categories.

- ***Residual Learning-Based Hybrid Models***: One possible way of proceeding is to first estimate the volatility using a traditional econometric model (for example, the ARIMA or GARCH model). The residual errors of the econometric model then go through a deep learning model (such as LSTM or CNN-LSTM) which is aimed to extract the models' missed patterns. Such an approach is beneficial in getting enhanced accuracy without sacrificing the inclusiveness of econometric models.
- ***Ensemble Learning and Meta-Learning Hybrid Models***: Another method to consider is to incorporate ensemble learning methods that utilize several models to achieve more accurate forecasting. The techniques like stacking, weighted averaging, and boosting have been the primary ones used in financial prediction to protect against unstable models [11]. In addition to contributing meta-learning strategies, some studies propose XGBoost to be a meta-model, which will refine the predictions of the other models in a process called stacking [17].

In a recent study, an LSTM-GARCH hybrid model was introduced, and the very successful result that it achieved lies in the fact that it combines the capability of pattern recognition of LSTM networks, with the interpretability of GARCH models, toward the prediction of volatility. According to this approach, this can minimize mistakes in extreme market conditions, where such models falter. Another study used hybrid GARCH-Transformer models more broadly, in that the attention that can be executed by transformer-based mechanisms can now be seen to improve the forecasting process when used in combination with statistical models like GARCH [7].

2.5 Technical Indicators and External Factors in Cryptocurrency Forecasting

Utilization of technical indicators to predict market movements or price changes is a very important part of stock market forecasting. The most common technical indicators in cryptocurrency volatility forecasting which are used are as follows:

- Moving Averages (SMA, EMA): It shows the price trend and eliminates price oscillations from the chart.
- Bollinger Bands: To understand the market volatility, move the other lines apart from the mean line for a clear indication.
- Relative Strength Index (RSI): The RSI model helps traders to potentially spot highs and lows in the market, thus RSI is an important tool even in the forex trading market.
- MACD: Although it is used for better visualization of the trend, in fact, MACD also helps estimate the direction of the price movement.
- Average True Range (ATR): It is calculated at any given time while the ATR takes into account data at the end of the predetermined period [5].

Predicting cryptocurrency volatility is an important and growing area of research that has paid much attention to the role of macroeconomic indicators, as well as investor sentiment analysis. The use of Google search trends, Twitter sentiment, and blockchain network activity has enabled researchers to make better short-term forecasting accuracy. Moreover, automatic feature selection in the framework of deep learning has been developed, wherein the most pertinent technical indicators are isolated using feature extraction methods based on deep learning [15].

2.6 Summary and Research Gap

These researches paints a clear picture of the steps made in cryptocurrency volatility forecasting using the most commonly used methods through traditional econometric models, ML, and DL technologies. In the midst of this, it should be noted, that traditional models, which offer statistical rigor, are not able to adequately represent complex nonlinear dependencies. Machine learning models can secure a higher forecasting accuracy while they usually require large amounts of feature engineering selection [10]. Deep learning systems enhance the precision of forecasting but face difficulties with interpretability and overfitting [1].

Despite the proposal of hybrid models to address the problem, there remains an issue of defining the best balance of ML and DL approaches to enable the models to arrive at an optimal point. In addition, the performance of hybrid models is not well examined under extreme volatility circumstances such as market crashes [18]. There still exist some challenges, and this research intends on doing through integrate them using sentiment analysis and real-time market indicators to increase predictive performance.

3. METHODOLOGY

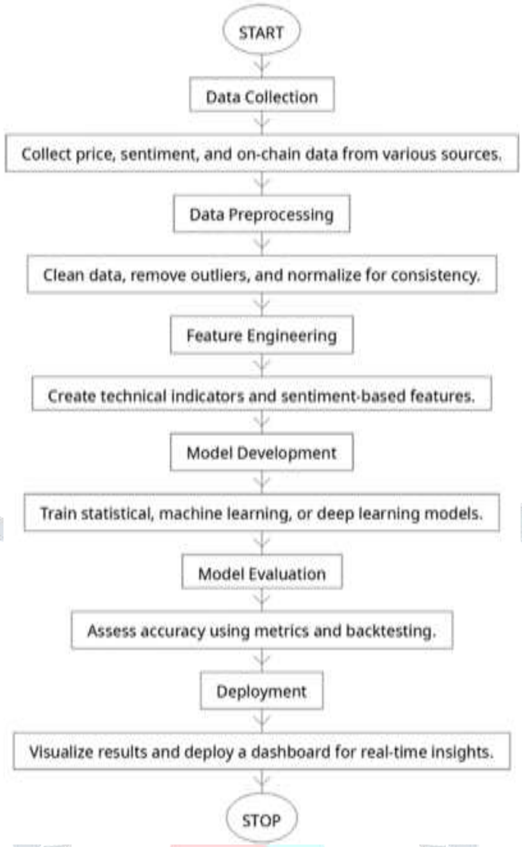

Fig 1: Cryptocurrency Prediction Pipeline: From Collection to Deployment

3.1 Data Collection

A comprehensive dataset has been built for volatility prediction by collecting data from several sources. CoinGecko offers cryptography price data such as the Open, High, Low, Close, trading volume, and transaction volume, from Glassnode and Coin Metrics. Public sentiment is extracted from Google Trends, Reddit discussions, and the Fear & Greed Index. Calculation of technical indicators, values such as Bollinger Bands, MACD, RSI, SMA, EMA, and ATR are calculated with the help of price data. Along with this, we obtain external macroeconomic indicators like interest rates, inflation, and stock indices from Yahoo Finance and FRED.

3.2 Data Preprocessing

The dataset is cleaned and structured to improve the accuracy of the model. Interpolation or forward fill is used to handle missing values. Statistical methods such as Z-score or Interquartile Range are used to remove the outliers. Min-max scaling or Z-score normalization has been applied in feature scaling. Temporal dependencies are captured by using time series transformation techniques such as lag features, and rolling statistics. This is done purely by time-based splitting, i.e., 75% training, 15% validation, and 10% testing to avoid data leakage.

3.3 Feature Engineering

Through the incorporation of feature engineering, we are able to unlock novel insights from the dataset, thereby enhancing model performance. Specifically, technical indicators like RSI, Bollinger Bands, and MACD are utilized to capture the nuances of price trends. Further analysis involves leveraging the Log of the returns, rolling standard deviation, and volatility derived from the Generalized Autoregressive with Conditional Heteroscedasticity model to generate volatility signals. Notably, Natural Language Processing techniques are employed to extract sentiment features from Reddit content, as well as relevant Google Trends, providing a more comprehensive view. Given these findings, we introduce external features of stock market indices and commodity prices, to contextualize our analysis within the broader market landscape.

3.4 Model Development

Several forecasting models from statistical zones alongside machine learning and deep learning methods are constructed and evaluated throughout this project.

- **Statistical Models:** ARIMA models can model the trends and seasonality, GARCH models model volatility fluctuations.

- **Machine Learning Models:** Random Forest finds the Non linear structure and XGBoost takes one step at a time to obtain the best values for parameters.
- **Deep Learning Models:** The LSTM and GRU DL Models are processed on long term dependencies, Transformer Models handle complex time-series relationships, and CNN-LSTM is extracted on both spatial and sequential patterns.
- **Hybrid Models:**
    - **Residual Learning:** Deep learning models build their training through the combination of residuals obtained from ARIMA/GARCH models.
    - **Ensemble Learning:** The method combines three approaches namely stacking, weighted averaging and the XGBoost meta-model for merging unpredicted model outcomes.

3.5 Model Training and Hyperparameter Tuning

Finally, time series cross-validation is used to train independent models, that ensure robust performance. Grid Search, Random Search, and Bayesian Optimization are done for hyperparameter tuning. To cope with a similar problem, dropout, batch normalization, and learning rate scheduling are used in DL models.

3.6 Model Evaluation

The model evaluation uses the following performance metrics:

- **Regression Metrics:** MAE, RMSE, and MAPE measure prediction accuracy.
- **Directional Accuracy:** Measures the percentage of correct up/down trend predictions.
- **Risk-Adjusted Metrics:** Measures risk-adjusted performance (useful for trading strategies).
- **Backtesting:** By using backtesting methods enables users to check how well the model performs with historical data to determine its practical application potential.

3.7 Visualization and Deployment

Historical trends, predicted vs actual volatility, and confidence intervals are visualized using some of the visualization tools which include Matplotlib, Seaborn, and Plotly. The real-time interactive visualization of cryptocurrency price trends and volatility forecasts is implemented in a Streamlit dashboard.

4. COMPARISON

4.1 Traditional Econometric Models

Table 4.1: Comparison of Papers with Traditional Models

Study Reference	Methodology Used	Key Findings	Limitations
A 2016 study comparing GARCH and Stochastic Models	Utilizes GARCH, Stochastic Volatility Models	GARCH models outperformed the traditional methods for Bitcoin Price Volatility	Limited ability to capture non-linear dependencies
Research conducted in 2017 on GARCH based modeling	Uses and Compares of GARCH Variants	GARCH models can effectively estimate Bitcoin volatility but the performance varies	Does not incorporates external factors like sentiment analysis

4.2 Machine Learning Models

Table 4.2: Comparison of Papers with ML Models

Study Reference	Methodology Used	Key Findings	Limitations
In 2018 a study employed DL techniques	Deep Learning (LSTM, CNN)	LSTM outperformed traditional models for crypto predictions	Models interpretability is low
In 2022 a research was conducted which used news sentiments	Neural Network- Based Sentiment Analysis	Sentiment Analysis enhances the ML- Based volatility predictions	Sentiment data is noisy and difficult to interpret
In 2023 research was conducted which used ML on crypto data	Machine Learning (XGBoost, Random Forest)	Incorporating external factors improves the volatility predictions	Computationally its very expensive
In 2023 research was done which combined sequence and attention based models	LSTM, Transformer	Transformer-based models are effective in the volatility forecastings	High risk of overfitting
In 2024 multiple ML models were compared	HAR, Machine Learning	Different ML models improves the cryptocurrency volatility forecasting	Feature Selection is a challenge
In 2024 comparative study of Deep Neural Models	Deep Learning (Comparative Study)	Compared various deep learning algorithms for crypto price prediction	No hybris models were tested
In 2023 a study which utilized Graph based deep models	Graph Neural Networks	Graph-based models improved the forecasting accuracy	Computational complexity is high
In 2023 a simulation based research on Crypto forecasting	Monte Carlo Simulations	Stochastic approaches improved the Bitcoin price forecasting	Less effective for Short term Volatility

4.3 Hybrid Models

Table III: Comparison of Papers with Hybrid Models

Study Reference	Methodology Used	Key Findings	Limitations
In 2020 DL study on Bitcoin Volatility	Hybrid Neural Networks	Hybrid forecasting were promising	Overfitting remains an issue due to high model complexity
A 2022 study combined econometric and ML Models	Hybrid GARCH-ML Models	GARCH models integrated with ML improves accuracy	Requires extensive feature engineering
In 2023 researchers explores Hybrid forecasting	Hybrid GARCH-Deep Learning	Hybrid deep learning models outperformed standalone GARCH models	High computational cost
In 2023 work focusing on combining LSTM and GARCH	LSTM-GARCH Hybrid Model	Integrating LSTM with GARCH improves accuracy	Data preprocessing is crucial for success
A comparative study happened in 2023	Statistical and ML Methods	Comparative study of statistical and Machine Learning approaches for crypto volatility	ML models require feature engineering
In 2024 investigation of DL optimizations	Hybrid Deep Learning Models	Gradient-specific optimization improves forecasting	High computational demand
In 2024 study utilizing attention based neural models and indicators	Transformer and Technical Indicators	Enhanced price prediction with neural networks and market indicators	Computational intensity is high
In 2024 Hybrid Forecasting study happened	Hybrid GARCH-Deep Learning	Hybrid models improve forecast robustness	Requires optimized hyperparameter tuning
In 2025 framework for crypto forecasting using graph models	Multiscale Graph Neural Network	Proposed a novel framework integrating graph networks for crypto forecasting	Requires significant historical data
In 2025 ensemble Hybrid models in risk management	Hybrid ML Models	Ensemble learning improves volatility predictions	Model complexity increases significantly

4.4 Insights from Comparison

- **Conventional Econometric Techniques** successively generate results in linear market conditions yet struggle to interpret the difficult non-linear chaotic patterns that characterize cryptocurrency markets.
- **Machine Learning Models** present complex predictive features although they encounter three vital problems by creating overfitting issues while generating high computational complexity and lacking adequate comprehension.
- **Hybrid Models** are the most effective method for predicting outcomes which integrates standard techniques and learning methods to generate substantial results. The deployment of these prediction models needs proper configuration together with significant computing capabilities.

5. CONCLUSION

Cryptocurrency volatility Prediction has remained a wide area of interest in financial research, mainly due to the complexity and instability of digital currency markets.

ARIMA and GARCH are the traditional econometric time series forecasting models have been widely used and are strong at capturing past trends and conditional volatility. Unfortunately, these models offer limited capability in explaining the complex nonlinear dependencies and intermittent behavior in cryptocurrency markets.

On the other hand, learning approaches such as ML or DL, using, for instance, GRU, LSTM or Transformer algorithms, proved to be rather successful in predicting complex patterns of financial time series data. While more predictive, these approaches pose additional problems surrounding overfitting, computational complexity, and interpretability. Hybrid modeling approaches that intelligently combine traditional statistical models and ML and DL techniques have been emerging as a promising direction in the area of recent studies to address these problems.

A review of the existing literature presents the benefits of using hybrid models in cryptocurrency volatility forecasting, which are more accurate and robust than standalone models. The use of technical indicators such as Bollinger Bands, MACD, RSI, SMA, EMA, and ATR also renders a much stronger lead for representing features. Apart from that, ensemble learning and meta-learning, such as Extreme Gradient Boosting (XGBoost), help stabilize the model better.

However, there are several research gaps in the advancements of hybrid modeling. Even now there remains an ongoing exploration of the challenge of achieving the right level of model interpretability while maintaining accuracy, the ability to be real-time adaptable, and the need for external macroeconomic integration. In future works, the computational efficiency to be optimized, further hybrid methodologies, and the alternatives of deep learning architectures should be paired with alternative deep learning architectures to increase the reliability of cryptocurrency volatility predictions.

Currently, the cryptocurrency market is taking turns, where traditional econometrics, machine learning, deep learning, and ensemble learning will correspondingly shape the future of financial forecasting. This review collects the gathered insight to be used as a start to make further progress in this area and to provide a roadmap for future researchers to develop more robust and adaptable predictive equations.

REFERENCES

[1] Mostafa, F., Saha, P., Islam, M. R., and Nguyen, N. 2021. GJR-GARCH volatility modeling under NIG and ANN for predicting top cryptocurrencies. *Journal of Risk and Financial Management*, 14(9): 421.

[2] Chen, C., Liu, L., and Zhao, N. 2020. Fear sentiment, uncertainty, and Bitcoin price dynamics: the case of COVID-19. *Emerging Markets Finance and Trade*, 56(10): 2298–2309.

[3] Mazinani, A., Davoli, L., and Ferrari, G. 2024. Deep learning algorithms for cryptocurrency price prediction: a comparative analysis. *Deleted Journal*, 4(1): 1–38.

[4] McNally, S., Roche, J., and Caton, S. 2018. Predicting the price of Bitcoin using machine learning. *IEEE Conference Proceedings*, 339–343.

[5] Amirshahi, B. and Lahmiri, S. 2023. Hybrid deep learning and GARCH-family models for forecasting volatility of cryptocurrencies. *Machine Learning With Applications*, 12: 100465.

[6] García-Medina, A. and Aguayo-Moreno, E. 2023. LSTM–GARCH hybrid model for the prediction of volatility in cryptocurrency portfolios. *Computational Economics*, 63(4): 1511–1542.

[7] Dudek, G., Fiszeder, P., Kobus, P., and Orzeszko, W. 2023. Forecasting cryptocurrencies volatility using statistical and machine learning methods: a comparative study. *Applied Soft Computing*, 151: 111132.

[8] Brauneis, A. and Sahiner, M. 2024. Crypto volatility forecasting: mounting a HAR, sentiment, and machine learning horserace. *Asia-Pacific Financial Markets*.

[9] J. B. and Selmi, R. 2016. Bitcoin price volatility: GARCH vs. stochastic volatility models. *ideas.repec.org*. Available: https://ideas.repec.org/a/ebl/ecbull/eb-16-00372.html

[10] Katsiampa, P. 2017. Volatility estimation for Bitcoin: a comparison of GARCH models. *Economics Letters*, 158: 3–6.

[11] Araya, H. T., Aduda, J., and Berhane, T. 2024. A hybrid GARCH and deep learning method for volatility prediction. *Journal of Applied Mathematics*, 2024(1).

[12] Singh, A., Jha, A. K., and Kumar, A. N. 2024. Prediction of cryptocurrency prices through a path dependent Monte Carlo simulation. *arXiv preprint*. Available: https://arxiv.org/abs/2405.12988

[13] Zhou, Y., Xie, C., Wang, G.-J., Gong, J., and Zhu, Y. 2025. Forecasting cryptocurrency volatility: a novel framework based on the evolving multiscale graph neural network. *Financial Innovation*, 11(1).

[14] Ladhari, A. and Boubaker, H. 2024. Deep learning models for Bitcoin prediction using hybrid approaches with gradient-specific optimization. *Forecasting*, 6(2): 279–295.

[15] Seo, M. and Kim, G. 2020. Hybrid forecasting models based on neural networks for the volatility of Bitcoin. *Applied Sciences*, 10(14): 4768.

[16] Kumar, S., Rao, A., and Dhochak, M. 2025. Hybrid ML models for volatility prediction in financial risk management. *International Review of Economics & Finance*: 103915.

[17] Zahid, M., Iqbal, F., and Koutmos, D. 2022. Forecasting Bitcoin volatility using hybrid GARCH models with machine learning. *Risks*, 10(12): 237.

[18] Wang, Y., Andreeva, G., and Martin-Barragan, B. 2023. Machine learning approaches to forecasting cryptocurrency volatility: considering internal and external determinants. *International Review of Financial Analysis*, 90: 102914.

[19] Khaniki, M. A. L. and Manthouri, M. 2024. Enhancing price prediction in cryptocurrency using transformer neural network and technical indicators. *arXiv preprint*. Available: https://arxiv.org/abs/2403.03606

[20] Sapkota, N. 2022. News-based sentiment and Bitcoin volatility. *International Review of Financial Analysis*, 82: 102183.

[21] Penmetsa, S. and Vemula, M. 2023. Cryptocurrency price prediction with LSTM and transformer models leveraging momentum and volatility technical indicators. *IEEE Conference Proceedings*.