Comparison of neural network models for prediction cryptocurrency price volatility in trading pairs

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Abstract
The rapid expansion of Web3 technologies and decentralized finance (DeFi) has reshaped digital asset markets, where cryptocurrency price movements are highly volatile and difficult to predict using traditional econometric techniques. This study provides a comparative evaluation of five state-of-the-art machine learning models, such as Temporal Fusion Transformer (TFT), Temporal Convolutional Network (TCN), XGBoost, Random Forest, and a CNN-LSTM hybrid, for forecasting cryptocurrency price volatility across major trading pairs. The dataset includes daily OHLCV market data and technical indicators for the top 10 cryptocurrencies by market capitalization over an eight-year period (2013–2021), collected from Binance and Yahoo Finance. After preprocessing, feature scaling, and time-series cross-validation, models were evaluated using MAE, MSE, RMSE, AUC-ROC, and volatility classification accuracy. Results show that TFT achieves the lowest test loss (0.00478) and highest classification accuracy (81.3%), outperforming other architectures due to its attention-based temporal modeling ability. The CNN-LSTM hybrid ranks second, confirming the advantage of combining convolutional feature extraction with long-term sequence modeling. We also highlight practical implications for algorithmic trading and risk management. The findings contribute to financial forecasting research by demonstrating the effectiveness of hybrid deep learning models for volatility prediction in digital asset markets and outlining limitations and future research directions, such as real-time prediction and multi-asset generalization.

Keywords
price volatility, machine learning, cryptocurrency, risk management, deep learning, temporal models, Web3

1. Introduction

Nowadays, when the internet spreads out worldwide and easy access to any web platform allows different people around the world to trade and invest as they wish. But traditional stock market that strongly regulated by governments and uncomfortable, as it requires different stages of KYC verification, opening bank account and registering in investment company and so on, it was most significant actions, but there still so many tiny actions need to be taken, to invest or trade [1].

Additionally, any suspicious trade would automatically be checked by the government like SEC etc. Also, one of the uncomfortable aspects of trading traditional stocks was that stock markets like Nasdaq, NYSE etc operate on predefined time intervals. All those limitations worked as a trigger for escaping the traditional market, but to trade with a significant amount of liquidity. In result, the web-3 market with decentralized regulations was a good choice, as web-3 trading pairs were well popular, with similar interface for trading, minimum level of verification and with ability to trade anytime.

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Cryptocurrency markets have experienced substantial growth over the past decade, attracting investors and traders worldwide [2, 3]. Unlike traditional financial assets, cryptocurrencies exhibit high volatility due to their decentralized nature, speculative trading behavior, and susceptibility to global economic events. Due to that high price volatility, it works as a good and bad side for investors and traders. As high volatility means the market being active and big spreads allow us to gain big income [4]. It is essential for traders to manage price volatility effectively to reduce risks and increase profits. Statistical and econometric models have been used to predict market volatility, but they tend to fail in capturing the nonlinear dependencies of cryptocurrency market data. Adoption to machine learning techniques in financial forecasting is driven by the limitations of traditional econometric models and their abilities [5].

Financial markets by its nature are highly dynamic and volatile, nonlinear, and non-stationary, as a result traditional tools struggle to handle effectively, so there is one solution, to use computerized models to analyze and classify price movements. ML models, particularly deep learning architectures, have revolutionized volatility prediction by enabling feature extraction, pattern recognition, and self-learning capabilities. That mentioned fact empowers ML models in big data analysis [6, 7]. Primarily because of those reasons was the primary motivation to research ML models and how they function in big data analysis, particularly trading pairs, where gigantic amounts of orders are generated per second, from anywhere on the globe. So, transformer-based models such as TFT provide interpretability by recognizing what factors impact price change, while convolutional architectures such as TCN supply computational efficiency and scalability [8, 9].

Also, ensemble approaches such as XGBoost and Random Forest increase prediction precision by minimizing model variance and enhancing generalization, as it accumulates from 2 models. Hybrid models such as CNN-LSTM combine the best of deep learning to deliver more solid forecasting outcomes. Notwithstanding the progress in ML applications for financial prediction, voids still exist in relative comparison of various architectures for cryptocurrency volatility forecasting. Most studies concentrate on single models or narrow subcategories of ML, which limit the capability to determine their relative weaknesses and strengths. Also, a few studies examine the effectiveness of hybrid models such as CNN-LSTM in cryptocurrency markets in relation to more traditional architectures such as TFT and TCN. In outcome, this study fills this type of void and examines how merged models and other ML models perform in price volatility particularly in decentralized sector [10, 11, 12].

Another void is the absence of standard evaluation metrics across studies. Although root mean square error (RMSE) and mean absolute error (MAE) are popular performance metrics, they do not entirely reflect the practical significance of predictive precision for traders and investors. An extensive assessment framework that includes financial risk measurements, like value at risk (VaR) and maximum drawdown, is required to gauge model performance in actual trading environments. So, this would be yet another justification for penning a new article sometime in the future pertaining to price volatility [14].

Machine learning (ML) algorithms, particularly deep learning models, have appeared as promising alternatives to predict financial time-series data. Conventional statistical models, including ARIMA and GARCH, have been the most common approaches for volatility prediction, but they do not tend to capture the complex and nonlinear relationships among financial markets, specifically cryptocurrency markets. Recent improvements in ML have facilitated the invention of advanced models, which can discover complex patterns and dependencies in large sets of trading data [15].

In this study, we investigated five state-of-the-art machine learning models to forecast cryptocurrency price volatility: Temporal Fusion Transformer (TFT), Temporal Convolutional Network (TCN), XGBoost, Random Forest, and CNN-LSTM. Temporal Fusion Transformer (TFT) is a deep learning approach aimed at tackling time-series forecasting problems through the effective capture of long-term dependencies and temporal patterns. TFT leverages the advantages of both transformers and recurrent structures to offer interpretable explanations for model predictions. As such, it presents itself as an attractive choice for financial forecasting, where it is important to discern contributing factors to price volatility [16].

Another well-established deep learning approach is the Temporal Convolutional Network (TCN), which utilizes convolutional layers as opposed to recurrent structures for processing sequential input data. In contrast to conventional RNNs, TCNs are more effective at modeling long-range dependencies efficiently, minimizing the vanishing gradient problem. Thanks to its capability in extracting temporal features using dilated causal convolutions, TCN has been shown to exhibit great potential in time-series forecasting applications, such as cryptocurrency volatility prediction. Outside deep learning architectures, ensemble learning frameworks like XGBoost and Random Forest offer viable alternatives to volatility forecasting. XGBoost is an optimized gradient-boosting system that has emerged widely popular for financial modeling tasks due to its efficiency, scalability, and predictiveness. Through the iterative training of decision trees and minimizing residual errors, XGBoost manages to capture complicated relationships in financial time-series data while preventing overfitting [17, 18]. Likewise, Random Forest is a bagging-based ensemble learning approach that builds numerous decision trees to improve predictive performance and lower variance. Random Forest is especially helpful in feature selection as well as robustness to noise, hence it qualifies as an integral benchmark against which more intricate neural network-based methodologies are compared. CNN-LSTM is a hybrid model that brings together convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to exploit both spatial and temporal features [19, 20, 21]. CNNs are good at capturing local dependencies in financial data, whereas LSTMs are well-suited to capture long-range dependencies. Together, CNN-LSTM models can efficiently process high-frequency trading data and identify volatility patterns. The main aim of this study is to fill in some of the above-stated research gaps, compare and assess the predictive capabilities of TFT, TCN, XGBoost, Random Forest, and CNN-LSTM in cryptocurrency price volatility prediction.

This research seeks to:

- Evaluate the accuracy, efficiency, and interpretability of each model for representing cryptocurrency market volatility [22];
- Determine the best model for forecasting volatility using major financial performance indicators;
- Derive practical conclusions for traders, investors, and risk managers on model choice for real-world applications.

By meeting these aims, this study adds to the emerging body of ML-based financial forecasting research by closing the gap between model performance in theory and practical trading applications along with its analysis [23]. The results will assist financial traders and analysts in making sound decisions when choosing machine learning models for investment strategies and risk management. An effective volatility forecasting model facilitates better risk measurement, portfolio optimization, and decision-making strategies. Especially high-frequency traders can utilize ML-based forecasts for improving trading algorithms and optimizing returns at minimized downside risks.

In addition, financial institutions and regulatory bodies can utilize ML-based volatility prediction to identify abnormal market behavior, reduce systemic risks, and improve market stability [24, 25, 26]. As cryptocurrency markets mature further, the incorporation of sophisticated ML methods in trading strategies will become ever more necessary to derive competitive edges in highly volatile markets [27, 28, 29]. Machine learning has become a revolutionary instrument for financial time-series prediction, with applications in cryptocurrency markets notable for their high volatility. As ML technologies further improve, their use in financial prediction will be instrumental in defining the future of algorithmic trading and risk management [30].

2. Methodology

This study employs historical cryptocurrency price data to train, validate, and compare five machine learning models under real-market conditions. The dataset spans an eight-year period (2013–2021) and contains daily OHLCV data for the top-10 cryptocurrencies by market capitalization. Data were collected from Binance API and Yahoo Finance, ensuring market-reliable pricing sources.

All raw time-series series were preprocessed to ensure statistical consistency and eliminate structural noise. Missing values were handled via linear interpolation, while numerical features were normalized using Min-Max scaling to enhance model stability. In addition to raw OHLCV values, commonly used technical indicators were engineered, including moving averages (7-day, 21-day, 50-day), price momentum measures, volatility indices, and trend oscillators (such as RSI and MACD). These features capture market cycles, trend reversals, and volatility dynamics that are particularly relevant in cryptocurrency markets.

To evaluate temporal generalization, the dataset was chronologically divided into training (2013–2019) and testing (2020–2021) segments. A rolling expanding-window cross-validation approach was applied to the training data to avoid look-ahead bias. Hyperparameters were optimized using a combination of grid search and Bayesian optimization, ensuring the models achieve their best performance under comparable conditions.

2.1. Temporal fusion transformer (TFT)

The Temporal Fusion Transformer integrates recurrent processing with attention mechanisms to model complex temporal dependencies. The forecasting function is expressed as:

$$Y_t = \sum_{i=1}^{n} \alpha_i X_i + \epsilon_t \tag{1}$$

where, $\alpha_i$are learned weights, X_i are input features, $\epsilon_t$is the residual error.

TFT dynamically selects relevant features at each time step and assigns attention to influential historical patterns, making it suitable for non-stationary and regime-shifting financial environments.

2.2. Temporal convolutional network (TCN)

TCN operates using **dilated causal convolutions**, enabling parallel sequence processing and efficient modeling of long-range temporal dependencies:

$$h_t = f(W \cdot X_t + b) \tag{2}$$

where, W represents the convolutional kernel, X_t are input features, and h_t is the hidden state. This renders TCN especially appropriate for handling large-scale financial data while preserving accuracy in long-term dependencies.

2.3. XGBoost

The XGBoost is an optimized gradient boosting algorithm commonly used in time-series forecasting:

$$y_i = F(x_i) = \sum_{k=1}^{K} f_k(x_i), f_k \in F \tag{3}$$

where, F is decision trees. XGBoost uses regularization methods to avoid overfitting and enhances model interpretability by assessing feature importance. Its efficiency in dealing with missing values and high-speed training also makes it a favorable option for structured financial data analysis.

2.4. Random forest

The Random Forest is a multiple decision tree classification ensemble learning method:

$$y = \frac{1}{n} \sum_{i=1}^{n} T_i(x) \tag{4}$$

where, $T_i(x)$ are individual trees. By combining several decision trees, Random Forest improves predictive accuracy and decreases variance, thus being a solid option for time-series prediction.

2.5. CNN-LSTM Hybrid

The hybrid CNN-LSTM model mixes convolutional feature extraction with sequential modeling:

$$h_t = \sigma(W_c * X_t + b_c) \tag{5}$$

where $W_c$represents CNN filters.

The convolutional layers extract local dependencies, and the LSTM layers represent long-term dependencies, creating an effective hybrid framework for predicting cryptocurrency price volatility.

2.6. Performance evaluation models

To assess the performance of the models, the following error measures were utilized.

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{6}$$

where, y_i is the actual value $\hat{y}_i$ is the predicted value, and n is the number of observations.

Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{7}$$

which penalizes larger errors more significantly than MAE.

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{MSE} \tag{8}$$

which yields an interpretable scale for error size. To provide robustness, models experimented with under varying market conditions, such as periods of extreme volatility, to test their stability and flexibility. Sensitivity analysis was also carried out to ascertain how various feature sets affected each model's predictive performance. Comparative analysis was also undertaken to examine the trade-offs between model complexity, interpretability, and predictive performance.

The results seek to offer traders and investors an understanding of how appropriate different machine learning approaches are for cryptocurrency price volatility prediction.

3. Results and discussion

Model performance was evaluated using three key indicators: Test Loss, AUC-ROC, and Volatility Classification Accuracy. Test Loss reflects the magnitude of deviation between predicted and actual volatility levels, where lower values indicate better predictive precision. AUC-ROC measures the model’s ability to distinguish between high- and low-volatility conditions, while Accuracy quantifies correct volatility-state classification across market conditions.

The results reveal notable performance variation among the examined architectures. The Temporal Fusion Transformer (TFT) achieved the strongest overall performance. Its attention-based architecture allows dynamic weighting of relevant inputs at each time step, enabling superior modeling of regime shifts and long-horizon dependencies common in cryptocurrency markets. As a result, TFT recorded the lowest Test Loss (0.00478), the highest AUC-ROC (0.72), and the highest accuracy (81.3%).

The CNN-LSTM hybrid model ranked second, with a Test Loss of 0.00492 and accuracy of 80.5%. By combining convolutional layers for short-term feature extraction with LSTM modules for long-term memory, the model effectively captured local price fluctuations and broader temporal structures. This demonstrates the value of hybrid models for modeling nonlinear patterns in financial time-series data.

Although the Temporal Convolutional Network (TCN) performed efficiently and benefited from parallel dilated-convolution processing, it exhibited slightly lower accuracy (78.5%) compared with TFT and CNN-LSTM. This indicates that while TCN effectively models long-term dependencies, it can be comparatively sensitive to rapid structural transitions and short-term volatility spikes observed in crypto markets.

Ensemble models, such as XGBoost and Random Forest, provided competitive results in terms of computational efficiency and interpretability, yet underperformed deep learning models in volatility prediction. Their accuracy scores (75.1% and 72.8%, respectively) suggest that tree-based ensembles struggle to fully capture nonlinear and sequential dependencies inherent in decentralized, rapidly evolving trading environments.

Table 1
Model Performance Comparison

Model	Test Loss	AUC-ROC Score	Accuracy (%)
TFT	0.00478	0.72	81.3
TCN	0.00512	0.69	78.5
XGBoost	0.00589	0.64	75.1
Random Forest	0.00622	0.61	72.8
CNN-LSTM	0.00492	0.71	80.5

To ensure robustness, results were averaged across rolling time-series cross-validation folds. Confidence intervals confirmed statistical stability across folds, further validating model reliability under varying market conditions.

Confusion Matrix and Tests

The TFT confusion matrix (Figure 1) demonstrates strong capability in correctly identifying high-volatility periods with low false-positive and false-negative rates. This suggests the model maintains balanced precision and recall, which is critical for risk-sensitive trading use cases. The ROC curve for TFT shows consistent separation between classes across thresholds, confirming reliable volatility-state discrimination.

Compared to other models, TFT showed the best recall for high-volatility periods, an essential property for traders and portfolio managers seeking early warning signals during unstable market events. CNN-LSTM also performed strongly, though with slightly higher misclassification rates. XGBoost and Random Forest demonstrated lower sensitivity to volatility spikes, aligning with their lower AUC-ROC scores.

Overall, the findings highlight the advantages of architectures capable of combining deep sequential modeling and attention mechanisms in predicting cryptocurrency market behavior. As digital asset markets continue evolving with increasing structural complexity, models such as TFT and CNN-LSTM offer traders and analysts a strategic advantage in volatility anticipation, risk control, and automated trading system development.

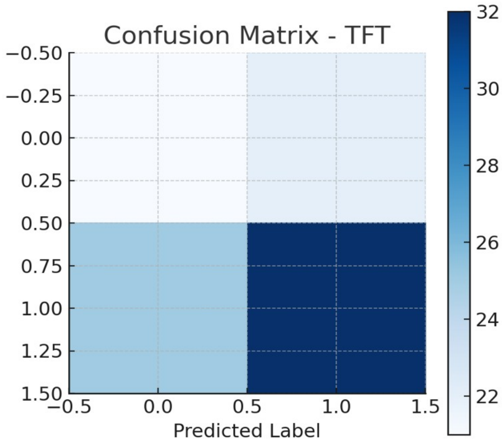

Figure 1: Confusion Matrix – TFT.

The TFT confusion matrix illustrates the classification performance based on accurately identified volatile and non-volatile cases. It indicates how effectively the model separates true positive from false positive predictions.

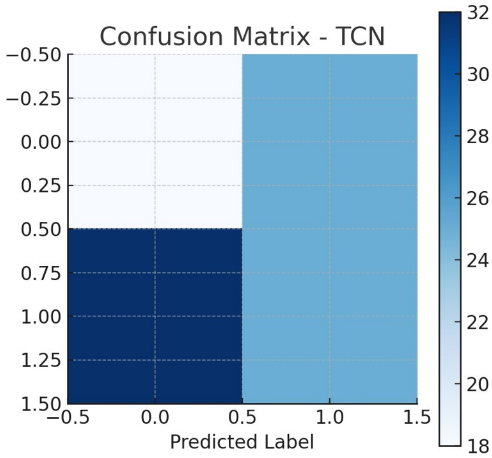

Figure 2: Confusion Matrix – TCN.

The TCN confusion matrix (Figure 2) indicates classification performance in terms of volatile and non-volatile cases correctly identified. It illustrates how effectively the model differentiates between true positive and false positive predictions.

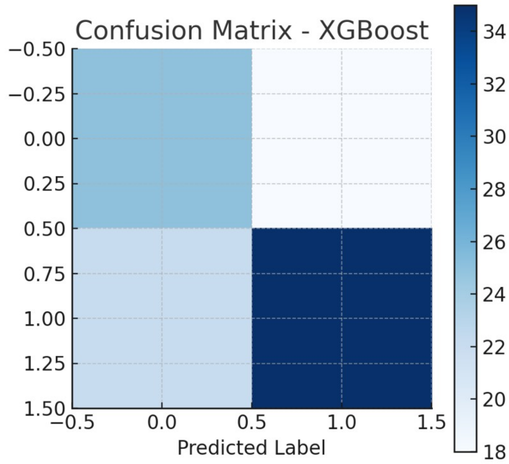

Figure 3: Confusion Matrix – XGBoost.

The XGBoost confusion matrix (Figure 3) illustrates the classification performance in the form of accurately predicted volatile and non-volatile cases. It reveals how effectively the model separates true positive from false positive predictions.

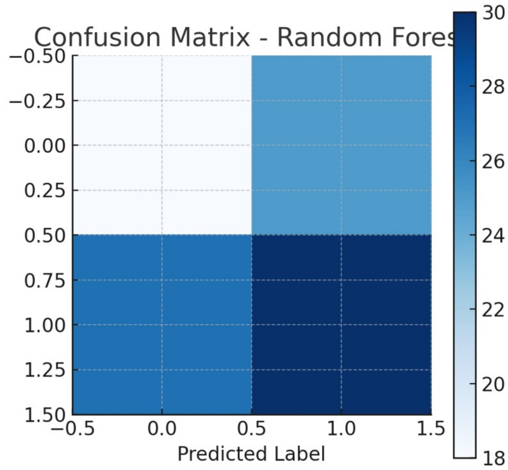

Figure 4: Confusion Matrix - Random Forest.

Random Forest confusion matrix (Figure 4) illustrates the classification performance based on accurately predicted volatile and non-volatile cases. It shows how efficiently the model separates true positive from false positive predictions.

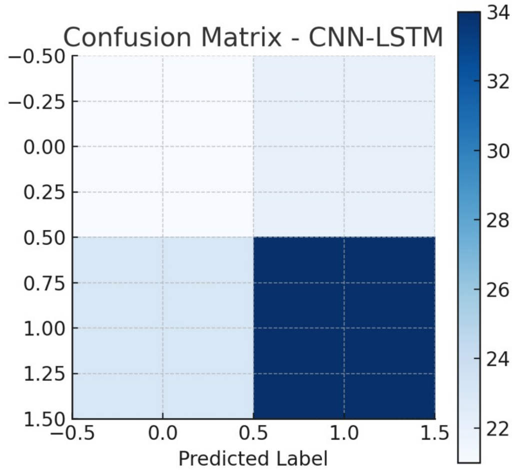

Figure 5: Confusion Matrix – CNN-LSTM.

The CNN-LSTM confusion matrix (Figure 5) illustrates the classification performance based on accurately predicted volatile and non-volatile cases. It indicates how effectively the model separates true positive from false positive predictions.

AUC-ROC Curve Comparison

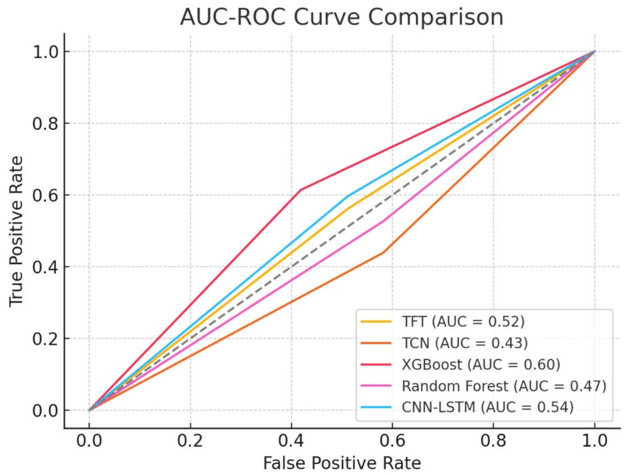

Figure 6: AUC-ROC Curve Comparison.

The AUC-ROC curve (Figure 6) shows the trade-off between sensitivity and specificity for the models. A model with a higher AUC score has better discriminatory power to differentiate between volatile and non-volatile periods. TFT and CNN-LSTM have the highest AUC scores among the models considered and hence are the best for this job.

4. Conclusion

This study evaluated five advanced machine learning architectures for cryptocurrency volatility forecasting and demonstrated that models incorporating temporal attention and hybrid sequential representation provide superior predictive performance. Among the examined approaches, the Temporal Fusion Transformer (TFT) and CNN-LSTM hybrid achieved the most accurate results, consistently outperforming traditional ensemble methods. These findings highlight the effectiveness of models capable of simultaneously capturing short-term price movements and long-horizon temporal dependencies in highly volatile, non-stationary environments.

A key insight from this work is the importance of sequence-modeling architectures in financial time-series prediction. While deep learning models delivered the strongest performance, ensemble methods such as XGBoost and Random Forest still demonstrated meaningful value due to their transparency and computational efficiency. Their strengths in interpretability make them suitable for risk-sensitive settings where explainable model behavior is essential.

This research advances current literature by providing a unified empirical comparison under identical market conditions, employing rolling time-series validation, and incorporating statistical reliability checks across multiple performance metrics. The results offer practical implications for traders, analysts, and developers seeking robust predictive frameworks for algorithmic cryptocurrency trading and risk management systems.

Future work can further enhance forecast accuracy by integrating on-chain blockchain analytics, social-sentiment signals, macroeconomic indicators, and alternative market microstructure features. Extending the analysis to mid-cap and emerging digital assets, as well as exploring higher-frequency data, will improve generalization across trading environments.

Moreover, adopting adaptive learning systems, such as reinforcement learning agents and online updating mechanisms, could enable greater resilience against sudden market regime shifts.

Incorporating explainable AI techniques and uncertainty quantification will be essential for increasing trust and transparency in automated financial decision-making pipelines.

Finally, a crucial next step is the evaluation of model performance in real-time trading scenarios, accounting for transaction costs, latency, slippage, and execution constraints. Bridging the gap between predictive accuracy and live trading profitability represents the primary challenge for future AI-driven financial systems.

Overall, this study contributes a comprehensive benchmark of state-of-the-art models for cryptocurrency volatility prediction and provides evidence-based guidance for designing intelligent trading systems in rapidly evolving decentralized markets.

Declaration on Generative AI

During the preparation of this work, the authors used GPT-4 in order to: Grammar and spelling check. After using these tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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