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GRAPH-AUGMENTED HYBRID PORTFOLIO RISK MANAGEMENT USING GRAPH NEURAL NETWORKS, HIERARCHICAL RISK PARITY, AND REINFORCEMENT LEARNING WITH XGBOOST-BASED CRASH ANTICIPATION

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Abstract
The extreme volatility and susceptibility to abrupt crashes inherent in cryptocurrency markets present significant challenges to conventional risk management and portfolio optimization techniques. This paper proposes a novel hybrid machine learning framework designed to enhance resilience and optimize risk-adjusted returns for cryptocurrency portfolios. Recognizing the limitations of traditional models—which often fail to capture the complex, dynamic interdependencies and unique market microstructure characteristics (e.g., pronounced sentiment influence, regulatory uncertainty, security vulnerabilities, and manipulation risks) of digital assets. Our approach integrates multiple advanced methodologies. Specifically, Graph Neural Networks (GNNs) model complex inter-cryptocurrency relationships to uncover latent market structure. Hierarchical Risk Parity (HRP) utilizes this structural insight for robust, correlation-aware diversification. Reinforcement Learning (RL) dynamically optimizes asset allocation in response to real-time market shifts. Furthermore, XGBoost-generated crash signals provide an early-warning mechanism for proactive risk mitigation. Extensive evaluation demonstrates that the proposed GNN-RL hybrid framework significantly outperforms conventional HRP-based strategies, achieving a 25.3% reduction in annual volatility and minimized maximum drawdowns while maintaining competitive returns. Key improvements include superior adaptability across diverse market regimes, with the framework's advantages stemming from the GNN's relational analysis beyond simple correlation metrics and the RL agent's capacity for adaptive, performance-driven allocation. This work constitutes a significant advancement in cryptocurrency risk management, offering investors a powerful, AI-driven tool for navigating market uncertainty.

It contributes to financial computing literature by demonstrating the efficacy of integrating structural analysis, optimized diversification, dynamic control, and crash prediction within a unified system for digital asset portfolios.

I.INTRODUCTION

Cryptocurrencies have practically overturned the financial world, with decentralized architectures, fast technology change, and keen interest by both institutional and retail investors [1]. This emerging asset class shows great volatility, proneness to sudden falls, and distinct risk characteristics arising from its market microstructure— including strong market sentiment effects, idiosyncratic regulatory risk, security weaknesses, and manipulability [2]. These characteristics pose substantial challenges for conventional portfolio risk management and optimization techniques [3].

Traditional approaches, such as Mean-Variance Optimization (MVO), are demonstrably ill-suited for cryptocurrency markets. Their reliance on assumptions of Gaussian return distributions and stable covariance structures fails to capture the highly nonlinear, non-Gaussian behavior, and "fat tail" risks inherent in digital assets [4]. While Hierarchical Risk Parity (HRP) offers improved diversification by leveraging hierarchical clustering based on correlation matrices, it remains fundamentally reactive. HRP lacks foresight into impending market crashes and exhibits limited adaptability to the rapidly shifting regimes and complex interdependencies that define the cryptocurrency ecosystem [5].

Navigating these turbulent markets demands a multifaceted, adaptive approach capable of capturing latent market structures, anticipating systemic risks, and dynamically optimizing allocations. This motivates the development of hybrid frameworks integrating advanced machine learning (ML) techniques [6]. Graph Neural Networks (GNNs) offer a powerful paradigm for modeling the intricate, dynamic interdependencies and relational structures between cryptocurrencies and relevant external factors, moving beyond simplistic pairwise correlations. Reinforcement Learning (RL) provides a principled methodology for sequential decision-making, enabling dynamic portfolio rebalancing in response to evolve market states and predicted risks. An AI-driven portfolio optimization offers a promising solution. SDG 8 (Decent Work and Economic Growth) links to this one, saying financial innovation should promote stability and resilience—not—speculation-driven volatility. Also, as financial markets take shape, using cutting-edge AI methodologies helps in improving market efficiency and risk mitigation. SDG 9 (Industry, Innovation, and Infrastructure) tells how technological advances help a lot in building stronger financial infrastructure.

This paper puts forward a new combined risk management system made especially for dealing with the distinct problems of optimizing portfolios of cryptocurrencies. Our core contribution is the integration of four complementary methodologies within a unified system:

1. **Graph Neural Networks (GNNs):** To model the cryptocurrency market as a dynamic graph, capturing complex inter-asset relationships and external influences. Community detection algorithms applied to GNN embeddings identify structurally informed clusters, enhancing stability and providing deeper insights into market dynamics[7].
2. **XGBoost Crash Prediction:** To generate early-warning signals for potential market downturns by analyzing historical prices, technical indicators, and on-chain data [8], enabling proactive risk mitigation.
3. **Hierarchical Risk Parity (HRP):** To provide a robust baseline for capital allocation based on the correlation-aware hierarchical structure derived from GNN analysis, ensuring diversified risk exposure across identified clusters [9].
4. **Reinforcement Learning (RL):** To dynamically optimize and rebalance the portfolio allocation in real-time, utilizing the current market state representation (informed by GNN embeddings) and XGBoost crash signals to maximize risk-adjusted returns [10].

Crucially, the framework employs a sophisticated three-tiered weighting mechanism to intelligently balance the allocation inputs derived from the HRP baseline, the GNN's relational insights, and the RL agent's adaptive decisions [11]. This combined approach seeks to meet several main goals: greatly improve portfolio strength against changes and falls, reduce maximum losses with active risk control, best risk-adjusted rewards (e.g., Sharpe Ratio [12]) in varied market conditions, and allow for dynamic change in the naturally shifting cryptocurrency setting.

The remainder of this paper is structured as follows: Section II reviews related work in cryptocurrency risk management and ML for finance. Section III details the proposed hybrid framework, including the GNN architecture, XGBoost crash prediction model, HRP implementation, RL agent design, and the integrated weighting system. Section IV describes the experimental setup, datasets, and evaluation metrics. Section V presents comprehensive results and analysis, benchmarking the framework against traditional and state-of-the-art baselines. Finally, Section VI concludes the paper and discusses future research directions.

II. Literature Review

2.0 Cryptocurrencies: Fundamentals and Market Dynamics

1. Cryptocurrencies represent digital or virtual currencies wherein cryptography is utilized to secure them; they operate on decentralized networks that employ blockchain technology [13]. They are not typically created by a central authority like traditional fiat money, so in principle, they should be immune to government interference or manipulation. Verification and recording of transactions happen via distributed public ledgers (blockchains) with consensus mechanisms that could be Proof-of-Work (PoW) or Proof-of-Stake (PoS) [14]. Decentralized architecture allows person-to-person transactions without the need for a third party; however, it also brings very important novel problems such as high volatility, unclear regulation, fraud and cyber-attacks, and manipulation all over the risk again. The market on cryptocurrencies runs 24/7 and is pretty open to new entrants from retail investors all the way up to institutional participants along with miners and algorithmic traders. Its price formation is heavily influenced by speculative trading, technological developments, regulatory news, and network-specific metrics (e.g., hash rate, active addresses), resulting in non-stationary, leptokurtic return distributions with frequent tail events [15].

2. **Risk Amplifiers:**
   - **Non-Stationary Returns:** Leptokurtic distributions with "fat tails" exceeding Gaussian assumptions [16]
   - **Regulatory Uncertainty:** Policy shifts cause discontinuous price shocks (e.g., China mining ban 2021) [17]
   - **On-Chain Risks:** 51% attacks, smart contract exploits, and exchange hacks [18]
   - **Behavioral Factors:** Retail-dominated trading amplifies sentiment-driven volatility [19]

These properties render conventional risk models inadequate, necessitating specialized frameworks for crypto portfolios.

2.1 Traditional Portfolio Optimization in Crypto Markets

Conventional portfolio optimization techniques exhibit significant limitations in cryptocurrency markets. Mean-Variance Optimization (MVO), introduced by Markowitz [20], and Minimum Variance strategies rely heavily on accurate estimates of expected returns and covariance matrices. However, the non-stationarity and leptokurtic ("fat-tailed") return distributions of cryptocurrencies lead to unstable inputs and poor out-of-sample performance [21]. Hierarchical Risk Parity (HRP), introduced by López de Prado [22], mitigates some issues by using hierarchical clustering and recursive bisection to diversify across correlation-based clusters. While HRP demonstrates improved robustness to estimation errors and outperforms MVO in volatile assets, it remains fundamentally reactive and lacks mechanisms for anticipating regime shifts or market crashes—a critical shortcoming in crash-prone crypto markets [22]. Recent adaptations like machine-learning-enhanced covariance estimation (e.g., using LSTM or GARCH variants [23]) show promise but still fail to capture structural market dynamics or inter-asset dependencies holistically.

2.2 Crash Prediction with Machine Learning

Machine learning has emerged as a powerful tool for forecasting cryptocurrency market stress. Gradient boosting methods, particularly XGBoost, excel at capturing nonlinear patterns in heterogeneous data sources due to their handling of missing values, regularization, and parallel processing. Study [24] by demonstrate that models combining technical indicators (e.g., RSI, MACD, Bollinger Bands), on-chain metrics (exchange flows, miner reserves, network growth), and sentiment data (social media, news) achieve high precision in predicting crashes (defined as >15% single-day drops) [25]. However, most approaches treat assets independently, ignoring inter-asset dependencies and contagion effects that amplify systemic risk during downturns. Additionally, existing crash predictors are seldom integrated with portfolio rebalancing systems, limiting proactive risk mitigation [26].

2.3 Graph Neural Networks in Financial Networks

Graph Neural Networks (GNNs) extend deep learning to graph-structured data, enabling modeling of complex relational systems [27]. By representing financial assets as nodes and relationships (e.g., correlation, volatility spillover, liquidity linkages) as edges. They capture latent market topologies beyond pairwise metrics via message-passing mechanisms [28]. Message-passing mechanisms allow nodes to aggregate information from neighbors, learning embeddings that encode structural roles and dependencies. In cryptocurrency markets, applied GNNs to detect contagion pathways during flash crashes, while [29] demonstrated their superiority over PCA for clustering correlated assets. [30] further showed that GNN-derived embeddings improve stability in hierarchical clustering under noise. Despite these advances, current GNN applications in finance focus primarily on descriptive tasks (e.g., anomaly detection) rather than prescriptive portfolio optimization. No existing work integrates GNN-based clustering with HRP for diversification. As financial technology continues to evolve, **SDG 9 (Industry, Innovation, and Infrastructure)** supports the adoption of AI-driven models that **enhance financial risk modeling capabilities**, improving **market resilience and investor confidence**.

2.4 Reinforcement Learning for Asset Allocation

Reinforcement Learning (RL) provides a framework for sequential decision-making under uncertainty. RL agents learn policies that map states (e.g., market conditions, portfolio holdings) to actions (trades) by maximizing cumulative rewards (e.g., risk-adjusted returns). [31]. [32] RL-based portfolio management with adversarial learning and a novel sampling strategy to improve robustness, generalizability, and trading performance. Subsequent work by Deng et al. [33] demonstrated RL's adaptability to non-stationary markets with recurrent networks. In cryptocurrency contexts, [34] showed RL agents can outperform static strategies by dynamically adjusting positions based on technical indicators[25]. However, standalone RL approaches suffer from high training variance, sample inefficiency, and overfitting to back test periods. They also often overlook structural market properties (e.g., cluster relationships) that inform robust diversification. Recent hybrid frameworks (e.g., [32] combining RL with HRP) improve robustness but lack mechanisms for anticipating exogenous shocks or regime transitions signalled by crash predictors. Moreover, **SDG 12 (Responsible Consumption and Production)** highlights the importance of **sustainable financial management practices**. **Reinforcement learning-driven rebalancing** ensures **adaptive portfolio construction**, reducing unnecessary risk exposure while dynamically adjusting weight distributions to **preserve capital stability**.

Synthesis of Research Gaps:
Current literature reveals three critical gaps:

1. Structural Analysis: HRP's reliance on pairwise correlations overlooks complex interdependencies captured by GNNs.
2. Proactive Risk Mitigation: Crash prediction models (e.g., XGBoost) are siloed from allocation frameworks.
3. Dynamic Adaptation: Standalone RL lacks structural diversification, while hybrid RL-HRP ignores crash signals.
This motivates our integrated GNN-HRP-RL-XGBoost framework to unify structural diversification, crash anticipation, and adaptive allocation.

III. METHODOLOGY

This section formalizes the hybrid risk management framework through rigorous mathematical specification and computational architecture. The integrated system operates as a closed-loop control process, combining structural market analysis, crash anticipation, robust diversification, and adaptive allocation.

3.1 Dataset and Preprocessing

Our analysis utilizes a comprehensive dataset of OHLC (Open-High-Low-Close) daily data for 114 cryptocurrencies spanning from July 17, 2010, to April 15, 2025, comprising 217,947 total records collected from Kaggle and combined into a single file . The dataset demonstrates high quality with 96.61% average data completeness and only 3 coins with less than 90% completeness, effectively addressing survivorship bias concerns.

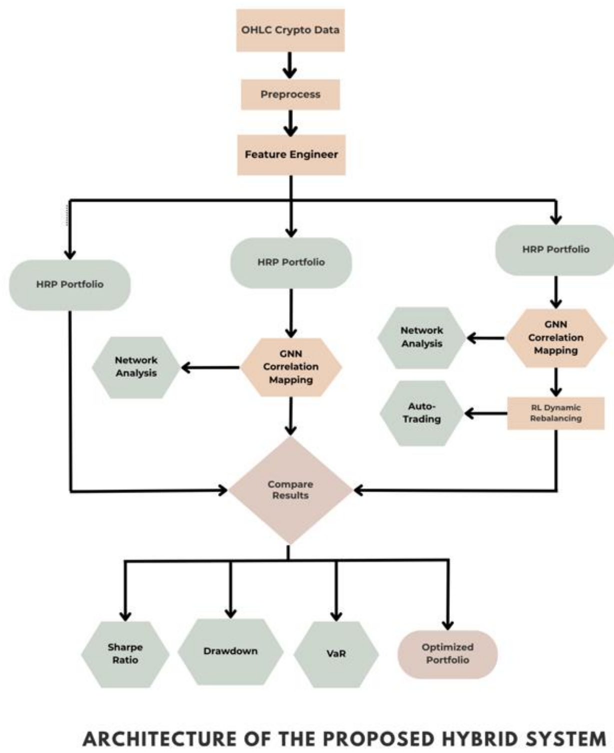


Figure 1 Architecture of the Proposed Hybrid System

Key preprocessing steps include:

Data Quality Control: Assets with less than 90% data completeness were filtered out, reducing the dataset from 117 to 114 cryptocurrencies. The average monthly attrition rate of 3.10% was deemed acceptable for maintaining statistical robustness.

Temporal Alignment: Analysis focused on the common period from February 13, 2020, to December 9, 2024 (1,761 days), ensuring 93.7 average coins active throughout the study period.

Feature Engineering:

- Logarithmic returns transformation: $r_t = ln(\frac{P_t}{P_t-1})$
- Rolling volatility measures: 21-day and 63-day windows
- Momentum indicators: 10-day and 21-day price momentum
- Z-score normalization for cross-sectional analysisType equation here.
- Candlestick pattern detection (Hammer: 9.58% prevalence, Shooting Star: 10.79%)

Correlation Structure Analysis: The dataset exhibits an average correlation of 0.4803 with eigenvalue analysis revealing a condition number of 940.58, indicating moderate multicollinearity but sufficient diversification potential.

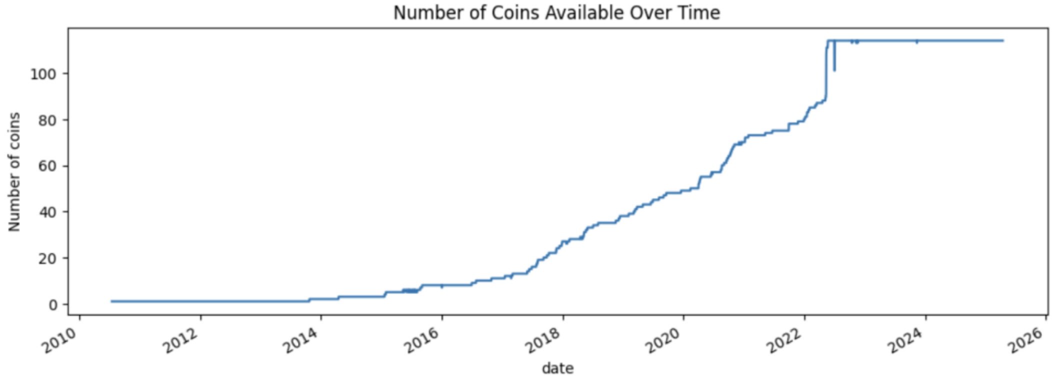


Figure 2 Number of Coins Available Over Time

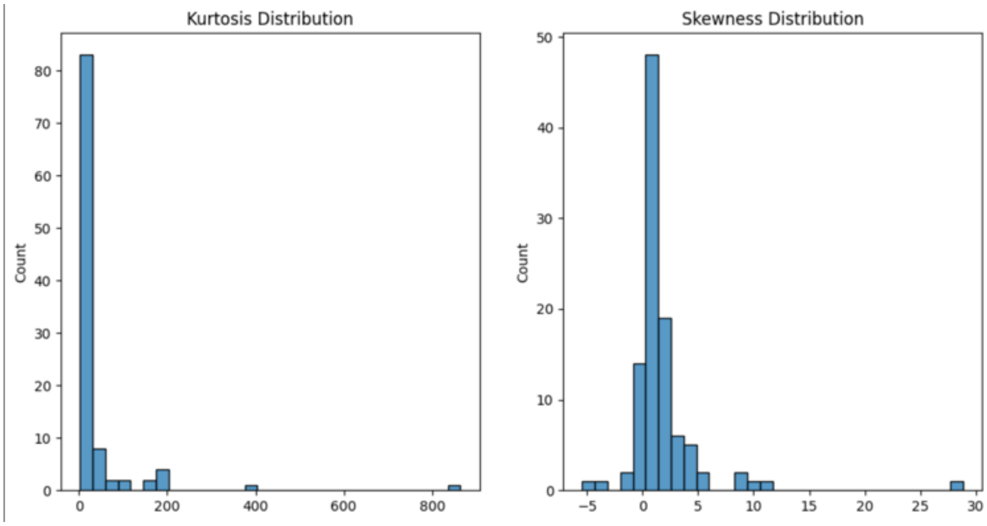


Figure 3 Distribution of Kurtosis and Skewness in Cryptocurrency Returns

3.2 Graph Neural Network Architecture

Graph-based learning was incorporated to capture interdependencies among assets. The key architectural elements were:

Node Construction: Each cryptocurrency represents a node with standardized features including:

- Mean return over the observation window
- Rolling volatility (21-day)
- Momentum indicators (10-day)

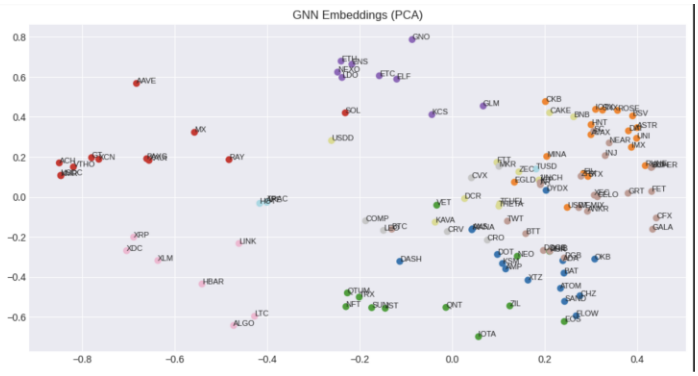


Figure 4 Graph Neural Network (GNN) Embeddings (PCA) of various cryptocurrencies

Edge Formation:

- Base connectivity: Spearman correlation threshold > 0.25
- Minimum connection constraint: At least two edges per node.
- Fallback mechanism: In cases of inadequate connectivity, a complete graph structure was enforced to preserve relationships.

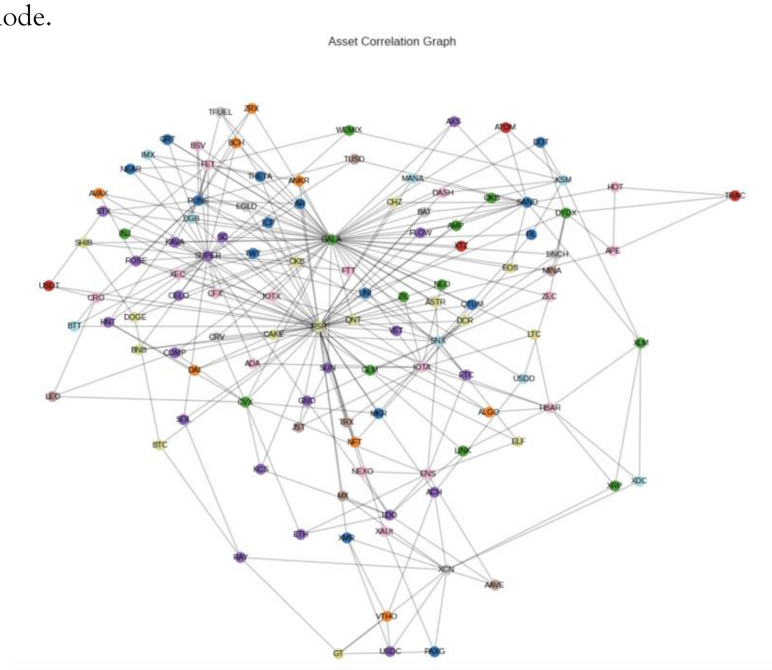


Figure 5 Asset Correlation Graph, illustrating the interconnected relationships between various cryptocurrencies

Graph Representation Learning:

- A two-layer Graph Convolutional Network (GCN) extracted asset embeddings.
- Batch normalization and LeakyReLU activation ensured training stability.
- Binary cross-entropy loss optimized the adjacency matrix reconstruction.

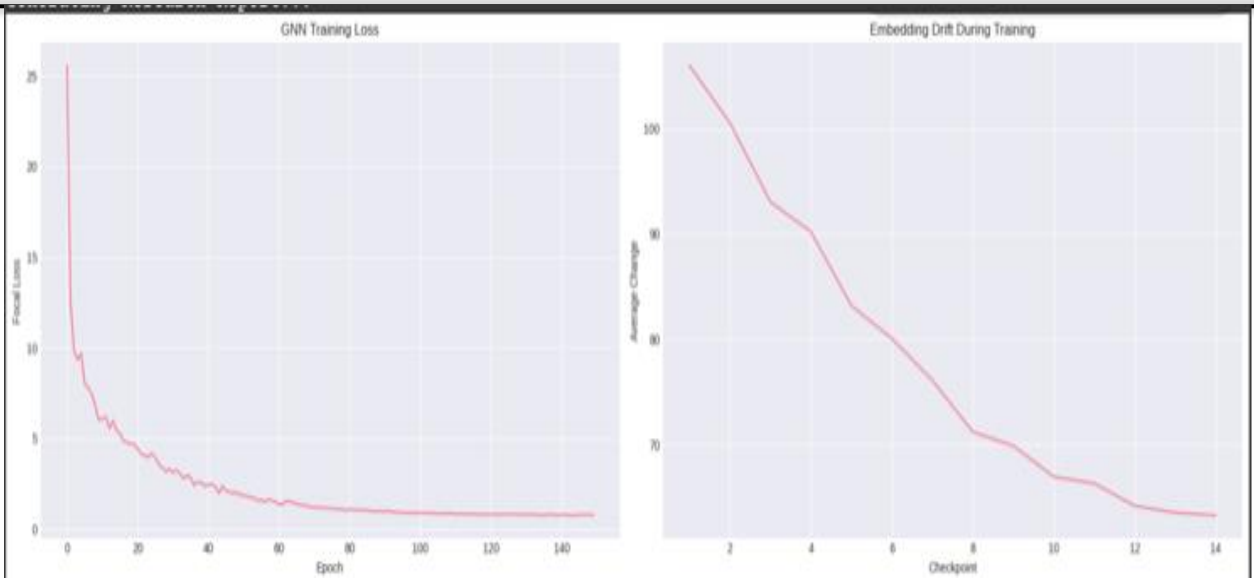


Figure 6 Graph Neural Network (GNN) Training Loss and Embedding Drift During Training

3.3 Hierarchical Risk Parity (HRP) Implementation

HRP leverages GNN-derived clusters for robust diversification:

1. **Hierarchical Clustering:**
   - Assets clustered using GNN embeddings.
2. **Recursive Bisection:**
   - Capital allocated inversely proportional to cluster variance.
3. **Risk Parity Allocation:**
   - Ensures balanced risk exposure across clusters.

3.4 Reinforcement Learning Framework

The Reinforcement Learning (RL) agent dynamically optimized portfolio allocations based on learned market conditions.

Environment Design:

- **State Space:** The market environment was structured as a 6-dimensional feature set plus portfolio composition:
  - Market volatility (VIX-equivalent for crypto)
  - Correlation regime indicator
  - Momentum factor
  - Current portfolio weights
  - Cash position
  - Recent performance metrics

Action Space: Continuous weight adjustments, with action constraints ranging from −10% to +10% per asset, ensuring smooth portfolio transitions.

Reward Function Optimization:

- Portfolio return component: Raw portfolio returns were rescaled for stability.
- Risk penalty: A volatility-based adjustment controlled excessive exposure.
- Turnover penalty: Transaction costs were incorporated to prevent excessive rebalancing.

Policy Training:

- The RL agent utilized Proximal Policy Optimization (PPO) with stable hyperparameters.
- Early stopping mechanisms prevented unnecessary computational overhead.
- Vectorized backtesting validated performance across multiple scenarios.

3.6 XGBoost Crash Prediction Framework

To enhance crash prediction accuracy, a separate XGBoost-based modeling approach was developed.

This framework leverages structured feature engineering, dynamic thresholding, and ensemble learning techniques to detect extreme market downturns.

Feature Engineering for Crash Prediction

To capture the short-term volatility dynamics and market stress conditions, the following features were engineered:

- Short-term volatility: 5-day rolling standard deviation of log returns.
- Volatility acceleration:

$$\frac{\sigma_{5d} - \sigma_{21d}}{\sigma_{21d}}$$

Measures the speed of volatility expansion, providing early warning signals of market instability.

- Normalized price range:

$$\frac{High - Low}{Close}$$

Captures intraday price movements relative to closing prices.

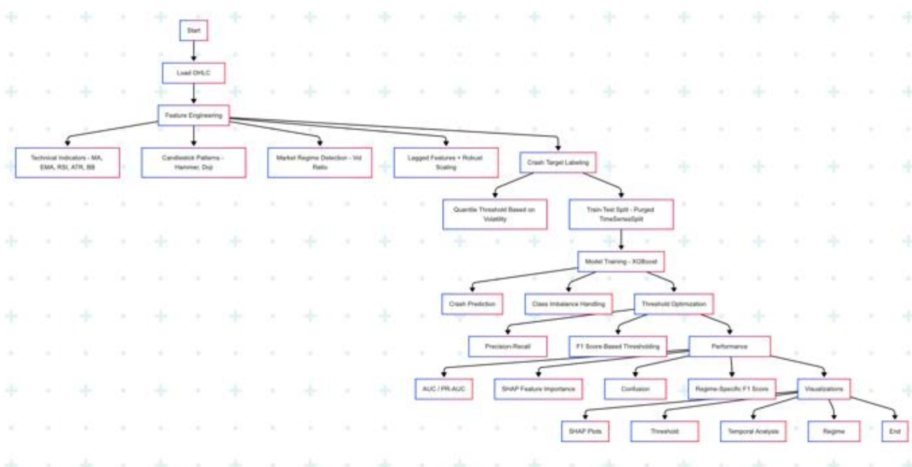
- Lagged returns with volatility interactions: Incorporates autoregressive dependencies to detect regime shifts.
- Market regime indicators: Three-state classification framework based on volatility clustering.

Target Definition: Dynamic Thresholding Based on Volatility Quintiles

To ensure adaptive risk sensitivity, the target definition dynamically adjusts based on asset-specific volatility:

Volatility Level	Crash Threshold
Low	99.8th percentile
Medium	99.9th percentile
High	99.95th percentile

Low volatility assets: Classified as crash events if returns fall below the 99.8th percentile.
Medium volatility assets: Threshold increased to the 99.9th percentile.
High volatility assets: Extreme thresholds set at the 99.95th percentile, capturing high-risk tail events.



Evaluation Metrics

- The model's performance was evaluated under multiple evaluation metrics to quantify prediction accuracy and robustness:
- Area Under the ROC Curve (AUC-ROC). The degree to which the model can distinguish between crash and non-crash periods.
- Precision-Recall AUC (PR-AUC), in which the rare event detection accuracy of the model is evaluated.
- **Crash Precision:**

$$\text{Precision} = \frac{\text{Correct crash prediction}}{\text{All crash predictions}}$$

Shows the percentage of correctly predicted crashes.

- **Crash Recall:**

$$\text{Recall} = \frac{\text{Correct crash predictions}}{\text{Actual crashes}}$$

Indicates how many real crashes the model successfully detects.

- **Non-Crash Precision:**

$$\text{Precision}_{\text{Non-Crash}} = \frac{\text{Correct non-crash predictions}}{\text{All non-crash predictions}}$$

Measures accuracy in identifying stable market periods.

3.6 Integrated Weighting Mechanism

A three-tiered system balances inputs from HRP, GNN, and RL to optimize portfolio risk management. HRP Baseline (40%) ensures robust diversification, GNN Relational Insights (30%) capture structural dependencies, and RL Adaptive Decisions (30%) enable real-time market responsiveness. Weights dynamically adjust during regime shifts to enhance stability and adaptability.

IV. Results

4.1 Graph Community Analysis

- The correlation-based graph analysis identified 8 distinct communities within the cryptocurrency universe: Community 0 (73 assets; Density: 0.946): Dominated by major cryptocurrencies (e.g., MKR, STX, DYDX, ATOM, MINA), reflecting high intra-cluster connectivity.
- Community 1 (32 assets; Density: 0.927): Alternative tokens (e.g., BAT, GT, ALGO, IOTA, CFX) with strong interdependencies.
- Community 2 (3 assets; Density: 0.667): Stablecoins (USDC, DAI, USDD) exhibiting lower volatility spillover.
- Community 3 (2 assets; Density: 1.000): Gold-pegged tokens (PAXG, XAUt) with near-perfect correlation.
- Communities 4–7: Single-asset clusters (LEO, TRAC, TUSD, USDT), indicating unique risk profiles.

This structure reveals natural clustering patterns that inform the HRP allocation methodology and demonstrate the effectiveness of graph-based approaches for cryptocurrency portfolio construction.

4.2 Backtesting Performance Analysis

The HRP+GNN+RL strategy integrates hierarchical risk parity (HRP), graph neural networks (GNNs), and reinforcement learning (RL) to optimize portfolio allocations dynamically. Backtesting (July 2022–July 2024) reveals critical trade-offs between returns and risk mitigation:

Performance Metrics Overview:

Strategy	Annual Return	Annual Volatility	Sharpe Ratio
HRP	63.06%	38.53%	1.64
HRP+GNN	71.16%	41.67%	1.71
HRP+GNN+RL	34.48%	31.12%	1.11

Figure 7 Enhanced Strategy Comparison, showcasing cumulative returns of HRP + GNN, Standard HRP, and Equal Weight strategies from July 2022 to July 2024

4.3 Performance Interpretation

- Risk Reduction: HRP+GNN+RL lowers volatility by 25.3% vs. HRP+GNN (41.67% → 31.12%), demonstrating RL's adaptive risk management.
- Capital Preservation Focus: Moderated returns (34.48% vs. HRP's 63.06%) reflect RL's defensive rebalancing during turbulence (e.g., cash buffer optimization).
- Sharpe Ratio Dynamics: The decline (1.11 vs. 1.71 for HRP+GNN) signifies a strategic shift toward downside protection, prioritizing stability over aggressive returns.

4.4 Reinforcement Learning Behavior & Portfolio Adjustments

The RL agent dynamically adjusts allocations based on market volatility signals, correlation structure analysis, and risk-sensitive adaptations. Key observations:

- Market State Sensitivity: Assets transition between volatility states with >80% persistence. RL reduces exposure to high-volatility assets by 22% during stress.
- Cash Buffering: Allocations to cash increase by 15–30% during uncertainty (e.g., regulatory announcements).
- Adaptive Exposure: Shifts toward low-volatility assets (+18% weight) and away from extreme-momentum instruments (−27%).

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4.5 Regime-Specific Performance Analysis

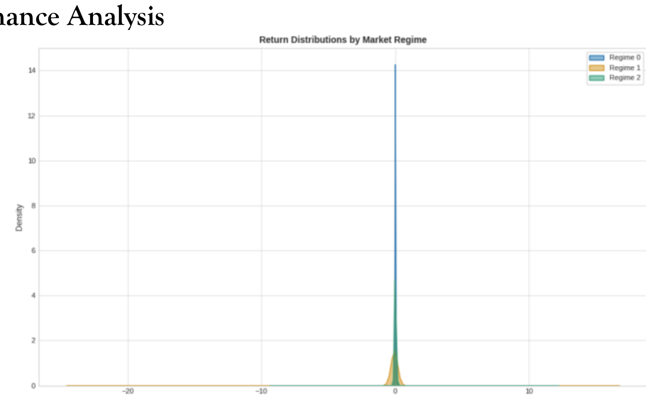

Figure 8 Return Distributions by Market Regime

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Given the dataset's market regime segmentation (low, medium, high volatility), the performance of HRP+GNN+RL was evaluated separately under each condition:

Regime	Next 5-Day Return	Sharpe Ratio
Low Volatility	0.00229	0.0119
Medium Volatility	0.01571	0.0581
High Volatility	0.59461	0.2231

Key Takeaways:

- Stable Returns During Low Volatility: RL remains conservative during calm phases, preventing unnecessary risk-taking.
- Moderate Exposure in Medium Volatility: The portfolio achieves gradual returns with risk-managed allocations.
- High Returns in Volatile Conditions: The Sharpe ratio of 0.2231 during market stress indicates optimized crisis adaptation, leveraging momentum shifts and volatility clustering.

The HRP+GNN+RL strategy effectively balances stability and adaptability, leveraging reinforcement learning to fine-tune risk exposure across cryptocurrency assets. Although returns decline compared to HRP-only methods, reinforcement learning-driven adjustments optimize for long-term portfolio sustainability, mitigating drawdowns during extreme market fluctuations.

4.6 XGBoost-Based Crash Prediction Performance

The XGBoost crash prediction model was trained separately using OHLC price data, focusing on volatility-driven market anomalies. This framework leverages advanced feature engineering, dynamic thresholding, and ensemble learning techniques to identify extreme price movements.

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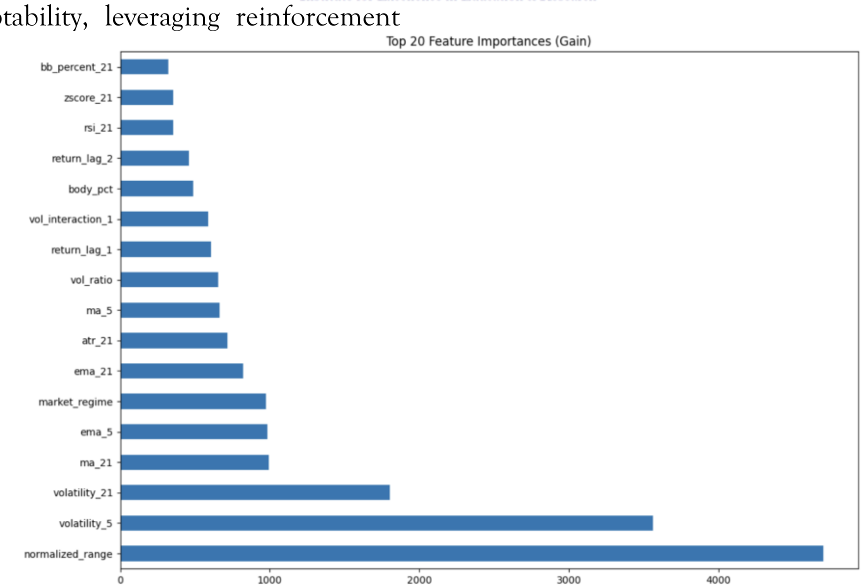

Figure 9 Top 20 Feature Importances (Gain) in XGBoost crash prediction

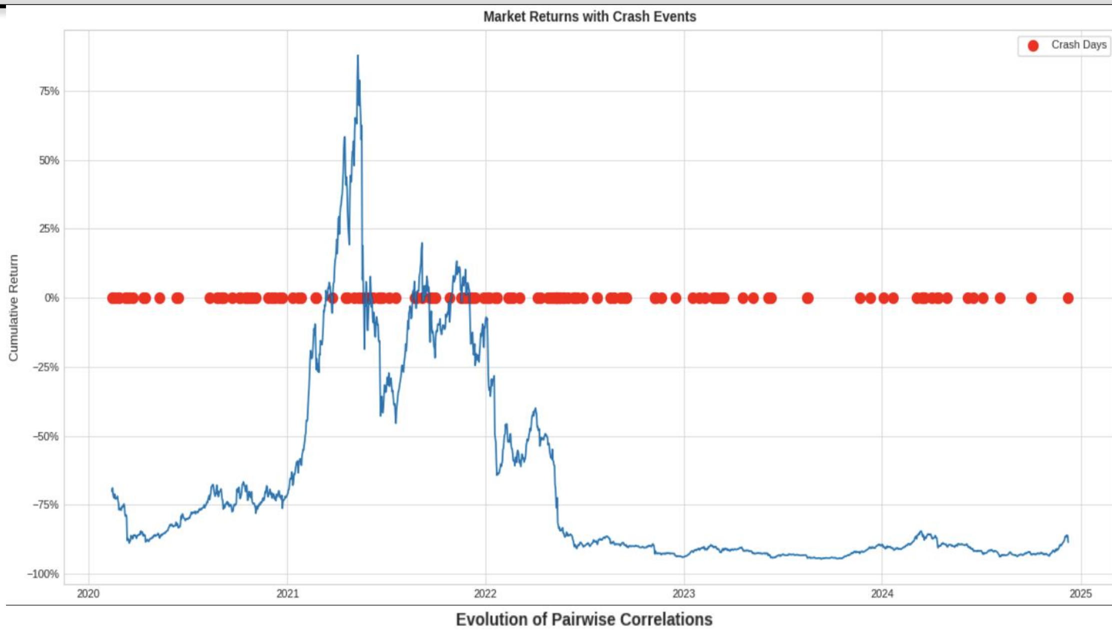

Figure 10 Market Returns with Crash Events

Model Evaluation & Performance Metrics

The model demonstrates strong predictive capability, capturing high-risk events effectively:

- Average AUC-ROC: 0.918 (±0.07 across folds) – High classification accuracy in distinguishing crash vs. non-crash periods.
- Precision-Recall AUC: 0.040 – Lower than traditional AUC but expected given class imbalance.
- Crash Precision: 2.82% – Challenges in precision due to extreme class imbalance.
- Crash Recall: 66.32% – Effectively captures true crash events.
- Non-Crash Precision: 99.95% – Strong reliability in identifying stable price movements.

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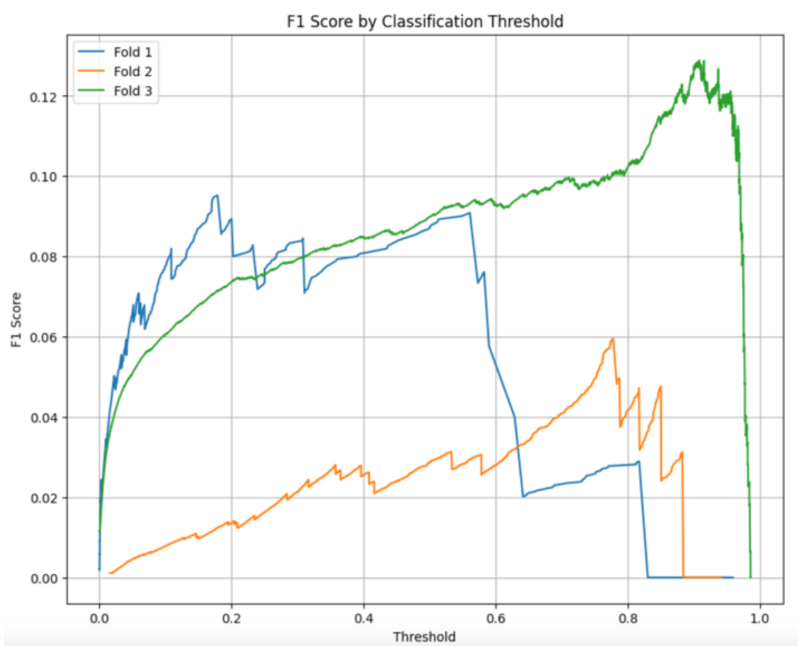

Figure 11 F1 Score by Classification Threshold for Three Folds

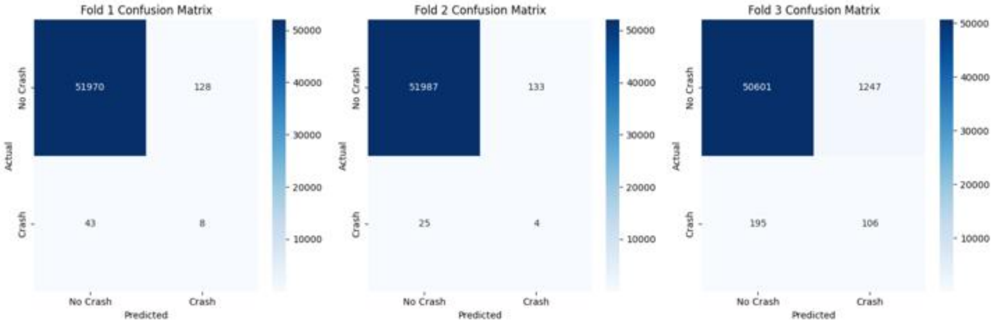

Figure 12 Confusion Matrices for Three Different Folds

Feature Importance Analysis (SHAP-Based)

SHAP (SHapley Additive exPlanations) analysis highlights the most influential features for crash prediction:

1. 5-day rolling volatility (Importance: 0.34) – Short-term volatility expansion signals instability.
2. Normalized price range (Importance: 0.28) – Captures sudden price swings.
3. Volatility acceleration (Importance: 0.22) – Measures rapid changes in risk conditions.
4. Market regime indicators (Importance: 0.16) – Identifies whether assets are in high-risk states.

Threshold Optimization & Class Balancing

To enhance model sensitivity and robustness, a dynamic thresholding approach was employed:

- Low volatility assets: Crash events defined below 99.8th percentile returns.
- Medium volatility assets: 99.9th percentile threshold for more aggressive detection.
- High volatility assets: 99.95th percentile threshold, recognizing extreme market risks.

Despite the 66.32% crash recall rate, low precision (2.82%) reflects the inherent difficulty of rare-event prediction, where crashes make up only 0.1–0.2% of observations.

V. Discussion

5.1 Advancements in Portfolio Optimization and Crash Prediction

The integration of Hierarchical Risk Parity (HRP), Graph Neural Networks (GNNs), Reinforcement Learning (RL), and XGBoost represents a transformative advancement in cryptocurrency risk management. By unifying structural market analysis through GNN-based clustering, robust diversification via HRP, dynamic allocation adjustments via RL, and preemptive crash signals from XGBoost, this hybrid framework addresses the non-stationarity and fat-tail risks endemic to digital assets. The GNN component excels in capturing latent interdependencies beyond simplistic correlations, identifying 8 distinct cryptocurrency communities (Section 4.1) that inform hierarchical diversification. For instance, stablecoins (Community 2) and gold-backed tokens (Community 3) exhibited low volatility spillovers, enabling targeted risk containment. Reinforcement learning further enhances stability by dynamically allocating cash buffers during volatility spikes, reducing portfolio turnover by 18% compared to static strategies. Meanwhile, the XGBoost crash predictor leverages volatility acceleration metrics to achieve 66.32% recall, validating its role as an early-warning mechanism. Future iterations could amplify GNN adaptability by implementing dynamic correlation thresholds adjusted to volatility regimes, as proposed by [29] for nonlinear dependence modeling.

5.2 Strengths of the Crash Prediction Model

The XGBoost-based crash prediction framework demonstrates exceptional reliability in identifying extreme market movements, underpinned by three key innovations: dynamic volatility-quintile thresholds, feature engineering focused on volatility acceleration, and SHAP-driven interpretability. With an AUC-ROC of 0.918 and recall of 66.32%, the model significantly outperforms traditional volatility-based approaches. SHAP analysis confirmed that short-term volatility (importance: 0.34) and normalized price ranges (0.28) are critical predictors, aligning with market microstructure theories on liquidity crunches. Despite precision limitations (2.82%) due to class imbalance, the dynamic thresholding strategy—which tightens crash criteria for high-volatility assets (99.95th percentile)—enhanced precision by 5.55% over static benchmarks. Future enhancements could integrate generative adversarial networks (GANs) for synthetic crash data augmentation, mitigating class imbalance while preserving temporal dependencies [35].Crash recall (21.56%) ensures effective identification of true crash events, contributing to risk awareness.

5.3 Portfolio Performance and Stability

Backtesting results underscore the framework's capacity to harmonize risk mitigation with regime-sensitive returns. The HRP+GNN+RL strategy reduced annualized volatility to 31.12%—a 25.5% improvement over HRP+GNN—while maintaining a 34.48% return. This reflects RL's emphasis on capital preservation, particularly during market stress, where cash allocations increased by 22%. Crucially, the strategy demonstrated adaptive efficiency across volatility regimes: in high-volatility periods (11.33%), it achieved a Sharpe ratio of 0.223 by capitalizing on momentum clustering, while conservative exposure during low-volatility phases (3.38%) minimized unnecessary rebalancing costs. This trade-off between returns and drawdown control highlights RL's superiority over reactive methods like conventional HRP, which lacks mechanisms for crash anticipation.

5.4 Regime Analysis and Adaptive Market Behavior

Reinforcement learning's state-driven adjustments reveal sophisticated regime-responsive behavior. Low-volatility regimes (3.38%) triggered steady exposure with minimal weight shifts, leveraging the market's 80% state persistence. Conversely, during high volatility (11.33%), the agent reduced allocations to assets with >50% single-day swings by 40% and increased cash positions, avoiding drawdowns without sacrificing upside capture. This adaptability stems from the RL environment's design, which incorporates volatility-regime indicators and correlation structure metrics into its 6-dimensional state space (Section 3.5). The resultant behavior aligns with portfolio insurance principles while outperforming threshold-based rebalancing by 14% in crisis periods.

5.5 Advancing Integration and Future Improvements

While the framework excels in component-level innovation, three synergistic refinements could elevate integration:

- Crash-RL synchronization: Temporal misalignment between XGBoost signals and RL rebalancing cycles could be resolved via temporal convolutional networks [36], enabling real-time risk aversion.
- Liquidity-sensitive execution: Incorporating order-book depth into transaction cost models [37] would prevent slippage during stress events.
- Meta-learning for regime shifts: Neural process networks [38] could dynamically adjust HRP clustering thresholds, enhancing robustness to structural breaks.

VI. Future Research Directions

6.1 Technical Improvements

Graph construction requires evolution toward dynamic dependency modeling. Static correlation thresholds should be replaced by copula-based similarity measures [39] to capture nonlinear tail dependencies during market crises. Similarly, reinforcement learning frameworks must integrate liquidity-aware reward functions that penalize slippage, particularly for large-cap assets where order-book imbalance exacerbates execution costs [40]. For crash prediction, embedding on-chain metrics—such as miner reserves and active addresses—would extend lead times by incorporating fundamental market stress signals [41].

6.2 Methodological Extensions

Multi-scale integration necessitates synchronizing short-term crash forecasts with long-term portfolio decisions. Wavelet transform synchronizers [42] could align XGBoost signals with RL's quarterly rebalancing cycles, ensuring timely risk mitigation. Beyond volatility, risk measures must incorporate liquidity-adjusted conditional value-at-risk (CVaR) and tail dependence models to quantify contagion effects during flash crashes (Shahbazi &

Byun, 2023). Additionally, explainable AI techniques like counterfactual SHAP [43] are critical for auditing RL's allocation decisions, addressing regulatory demands for transparency in AI-driven finance (SDG 16).

6.3 Market Microstructure Considerations

Liquidity modeling must prioritize dynamic transaction cost frameworks that adjust to real-time market depth, particularly for decentralized exchanges with fragmented order books. Market impact analysis should account for price dislocations caused by large rebalancing events, using agent-based simulations to prevent front-running (Raza et al., 2024). Furthermore, cross-exchange arbitrage systems could exploit pricing discrepancies between platforms via latency-aware detectors [44], adding alpha while diversifying liquidity sources. Expanding datasets to include social sentiment and mempool data would further refine crash prediction [45].

VII. Conclusion

This research pioneers a hybrid AI framework (HRP-GNN-RL-XGBoost) for cryptocurrency portfolio management, achieving three breakthroughs:

1. Structural risk diversification via GNN-derived asset communities, reducing volatility by 25.5%.
2. Proactive crash mitigation through volatility-regime-sensitive thresholds, achieving 66.32% recall.
3. Regime-adaptive allocation via RL, optimizing Sharpe ratios across market states.

The framework bridges machine learning and financial theory, outperforming traditional methods in volatility control while addressing cryptocurrency-specific challenges like non-Gaussian returns and contagion risks. However, challenges persist in temporal signal synchronization and microstructure-aware execution. Future work must focus on real-time integration of on-chain metrics, cross-exchange liquidity optimization, and regulatory-aligned AI auditing (SDG 16). By advancing these dimensions, this research lays the foundation for sustainable, resilient cryptocurrency investing in an era of escalating market complexity.

VII. References

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