Efficient Pump and Dump Detection on DEXs with Graph Neural Network

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Abstract

Pump-and-dump (P&D) schemes pose an ongoing threat within decentralized exchanges (DEXs), where anonymity, minimal regulation, and continuous on-chain transaction flows enable rapid market manipulation. Traditional detection methods—ranging from simple threshold alarms to deep learning architectures—often become unreliable in DEX environments lacking unified order-book data and containing high-volatility or sparse trading pairs. In this paper, we introduce a novel graph neural network (GNN) approach for timely detection of pump-and-dump manipulation. Our framework constructs a dynamic transaction graph representing wallets, smart contracts, and liquidity pools, then learns contextual embeddings that reveal transient patterns of coordinated buying and selling. Through extensive experiments on real-world DEX data, we show that our GNN model outperforms baseline solutions (e.g., threshold-based heuristics, random forests, and feed-forward neural networks), achieving higher F1 scores and a lower rate of false alerts. Moreover, by leveraging on-chain features and topological structures, our method remains robust to short-lived pump spikes and low-liquidity tokens, which often confound simpler detectors. We further discuss system design considerations—such as rapid updates of node features and address merge heuristics—to accommodate large-scale, time-sensitive scenarios. These findings highlight the potential of GNNs for improving the security and transparency of decentralized trading ecosystems, paving the way for multi-chain extensions and advanced streaming inference strategies.

1 Introduction

1.1 Motivation

Cryptocurrency markets have witnessed a surge in pump-and-dump (P&D) schemes, particularly among smaller and less liquid tokens. While centralized exchanges (CEXs) have introduced some safeguards against these manipulations, decentralized exchanges (DEXs) present a novel challenge: minimal regulation, anonymity of participants, and direct on-chain transactions enable

malicious actors to orchestrate P&D events with relative impunity. Moreover, because DEX trades occur fully on-chain, prompt detection is essential to prevent cascading losses and safeguard investors' assets in real time.

Despite broader research interest in crypto fraud detection (e.g., threshold-based analytics by [18], machine learning pipelines used in [5], and deep-learning methods explored by [7]), a persistent gap remains. Existing methods often rely extensively on off-chain signals—such as centralized order-book depth—or require large labeled datasets not readily available in permissionless blockchain ecosystems. Consequently, there is a pressing need for on-chain, graph-based detection pipelines that can capture and model evolving market structures without depending on centralized data sources.

1.2 Problem Statement

Detecting on-chain P&D schemes is uniquely challenging because the entire transaction ecosystem unfolds directly on decentralized networks, which often embrace pseudonymity and have fragmented liquidity across multiple DEXs. The lack of unified order-book data and the high velocity of trades further complicate conventional anomaly detection:

- **On-Chain Complexity:** Transactions, wallet interactions, and liquidity pools form intricate network topologies that change continuously.
- **Insufficient Off-Chain Signals:** Traditional approaches are optimized for centralized markets (e.g., using exchange-supplied order-book data). Such methods cannot fully utilize the rich on-chain transaction graphs.
- **Scalability Concerns:** DEX-based assets can see thousands of transactions in minutes, stressing any detection system that lacks efficient graph-based processing.

These factors underscore the necessity of a specialized framework that can (i) represent evolving transaction networks as graphs, (ii) embed their complex structural properties, and (iii) detect manipulative activity in real time.

1.3 Contributions

In this work, we propose a novel Graph Neural Network (GNN) pipeline for on-chain pump-and-dump detection across decentralized exchanges. Specifically:

1. **GNN for On-Chain DEX Data:** We develop a pipeline that constructs dynamic transaction graphs from raw blockchain data and then applies node- and subgraph-level embeddings to identify suspected P&D coordinations.
2. **Improved Detection Metrics:** Through extensive experiments, we demonstrate how our GNN approach outperforms baseline thresholding methods [18] and classical machine learning schemes [5]—as well as more recent deep-learning frameworks [7]—in terms of recall and precision.

3. **Adaptation of Prior Work:** We integrate ideas from prior threshold-based, anomaly-oriented studies and adapt them into our newly proposed graph-based methodology. In doing so, we build upon and extend the foundations laid by related crypto market manipulation research to a decentralized, on-chain setting.

Overall, our framework addresses the unique challenges posed by decentralized exchanges and directly captures the relational structure among traders, liquidity pools, and contracts. In the following sections, we detail the model design, data preprocessing, evaluation metrics, and results that collectively illustrate the efficacy of a GNN-driven approach in detecting P&D schemes in real time.

2 Background and Related Work

2.1 Pump-and-Dump Schemes in Crypto

Pump-and-dump (P&D) schemes exploit the speculative nature of cryptocurrency investors by artificially inflating an asset's price (the *pump*) and rapidly selling off once a profit threshold is reached (the *dump*). This process often entails three main phases [8, 15, 16, 20, 21, 30]:

1. **Accumulation**: Insiders quietly accumulate a target token, typically one with low liquidity to maximize price impact later.
2. **Pump**: A coordinated promotional campaign—via social media, Telegram groups, or Discord channels—fuels buying pressure, spiking prices.
3. **Dump**: Once a peak is reached, the orchestrators sell en masse, causing a rapid price collapse.

While early studies leveraged threshold-based heuristics (e.g., abnormal volume or price spikes) to detect P&D events [17, 18], these approaches often fail to capture more subtle manipulations. In traditional centralized exchanges (CEXs), some level of order-book transparency and stricter compliance can reduce P&D frequency [5]. Conversely, decentralized exchanges (DEXs) introduce anonymity and on-chain mechanics that complicate detection. This discrepancy underpins an urgent need for more nuanced, on-chain detection models specifically tuned to decentralized markets.

2.2 On-Chain vs. Off-Chain Data Sources

CEX vs. DEX Data Differences: Centralized exchanges such as Binance and Coinbase typically maintain internal order books and enforce Know-Your-Customer (KYC) processes. This data is often partially available through APIs, giving insights into trade volume, timestamps, and user statistics—though user identity is often masked. In contrast, *all* transactions on a decentralized exchange appear as on-chain events, which can reveal richer relational patterns

among addresses, liquidity pools, and smart contracts [4, 7]. However, because DEXs operate under weaker regulatory constraints—e.g., no KYC—you lose unequivocal identity data.

Importance of On-Chain Analytics: On-chain analytics ensures that malicious or wash trading patterns are not overlooked by off-chain recordkeeping. It captures wallet-to-wallet transfers, contract interactions, and liquidity changes, all of which are critical for real-time manipulation detection in DEX ecosystems. Prior works have shown that threshold-based detection mechanisms are prone to false positives in these environments due to higher volatility and unpredictable token listings [18].

2.3 Traditional Approaches to P&D Detection

Existing methods for detecting pump-and-dump schemes span a wide spectrum:

Thresholding Approaches. Early research focused on simple statistical triggers—e.g., price or volume spikes crossing fixed thresholds [16, 17]. Despite being straightforward to implement, these methods struggle with high-volatility or illiquid markets, where many genuine price swings can appear pump-like.

Statistical and Machine-Learning Pipelines. Later studies leveraged sophisticated features—such as exponentially weighted moving averages (EWMA), rolling standard deviations, and outlier analysis—to reduce false positives [18]. Classical machine-learning methods (e.g., random forests) incorporate these features for classification, achieving stronger performance on moderate-volatility datasets [20].

Deep Learning Solutions. More recent work uses advanced neural architectures, including LSTMs and Transformers, to model complex temporal patterns indicative of price manipulation [7]. By capturing non-linear dynamics and multi-scale dependencies, experiments demonstrate improved detection over thresholding. However, these methods frequently rely on centralized data sources (such as order-book snapshots) and remain underexplored in purely on-chain contexts.

2.4 Graph-Based Approaches and GNNs

GNNs for Financial Anomaly Detection: Graph Neural Networks (GNNs) have shown strong potential in various fraud detection tasks (e.g., credit-card or e-commerce anomalies). Their advantage lies in modeling relationships between entities (nodes) and transactions (edges) in ways that traditional vector-based approaches cannot [3].

Suitability for Transaction Networks. In a decentralized exchange or on-chain environment, each wallet, pool, or contract address is naturally represented as a *node*, and transfers or contract calls become *edges*. This structure enables GNNs to:

- Exploit local connectivity and subgraph motifs to detect coordinated buys or sells.
- Model temporal or sequential patterns by augmenting edges with time-based features.
- Propagate information across the network, identifying suspicious communities or clusters of addresses pumping the same token [4, 10].

By integrating GNN-based representations with real-time on-chain data, our approach aims to uncover hidden relationships driving P&D schemes—where existing thresholding or purely machine-learning pipelines often fail.

3 Proposed Framework

3.1 Graph Construction

We construct a transaction-based graph to capture the relationships among users, token contracts, and relevant DEX addresses [4, 7]. Formally, let

$$G = (V, E),$$

where V is the set of nodes and E is the set of edges.

Node Definition. We consider three main types of nodes, though in practice more specialized node categories can be used as well:

1. **User Addresses:** Unique wallet addresses that participate in transactions.
2. **Smart Contracts:** Deployed contracts (e.g., token contracts) relevant to the DEX environment.
3. **Token-Pair Addresses:** Liquidity pool addresses or DEX-pair addresses where swaps occur.

Edge Definition. Edges in the graph represent interactions or "flows" of tokens between the nodes. These include:

- **Direct Transfers:** Token movements from user to user (or contract).
- **Liquidity Provisions:** Deposits and withdrawals of assets into a liquidity pool.
- **Swaps/Trades:** Exchange actions that convert one token to another, typically via an Automated Market Maker (AMM).

An edge $e_{ij} \in E$ exists if node v_i interacts with node v_j. Associated with each edge are time-series transaction data (e.g., amount, price, timestamp).

Node and Edge Features. Each node v stores features capturing:

- **Transaction counts:** The total number of trades/transfers over a chosen time window.
- **Holding volumes:** The accumulated amount of a given token or a basket of tokens.
- **Temporal statistics (time-based):** Average volume or holding changes over hourly/daily intervals.

For edges, we track:

- **Transaction amounts:** Token quantities in each edge interaction.
- **Token price movements:** Price at the time of trade or swap.
- **Timestamps and intervals:** Used to model temporal dynamics or sequences of transfers [18].

3.2 GNN Architecture

The choice of GNN model is crucial for effectively navigating the graph-structured data. Common GNN variants include:

- **Graph Convolutional Network (GCN):** Operates in the spectral or spatial domain, aggregating features from a node's neighbors [12, 19].
- **GraphSAGE:** Learns aggregation functions (mean, LSTM-based, pooling) to handle inductive settings, i.e., new nodes not seen during training [11].
- **Graph Attention Network (GAT):** Employs attention weights to adaptively weigh neighbor contributions during aggregation [27].

Temporal Integration. Since pump-and-dump behavior evolves over time, we incorporate temporal dynamics using either:

1. *Dynamic Graph Approach:* Model adjacency changes in discrete time steps, applying GNN layers on snapshot subgraphs or with time-aware adjacency matrices.
2. *Time-Series Transformations:* Concatenate time-lagged features (price, volume) in feature vectors, enabling the GNN to capture short-term price-volume spikes.

Feature Embeddings. For each node v, we define an embedding vector $\mathbf{h}_v^{(0)}$ initialized from raw features:

$$\mathbf{h}_v^{(0)} = [\text{price\_history}, \text{volume\_stats}, \text{trade\_freq}, \ldots].$$

During each GNN layer, these embeddings are updated via an aggregation function:

$$\mathbf{h}_v^{(k)} = \sigma\Big(\mathbf{W}^{(k)} \cdot \text{AGG}\big(\{\mathbf{h}_u^{(k-1)} : u \in N(v)\}\big)\Big),$$

where $\sigma(\cdot)$ is a non-linear activation and $\mathbf{W}^{(k)}$ are trainable weights for layer k. The function AGG$(\cdot)$ can be a simple mean, attention-based weighting, or pooling operator [3].

3.3 Detection Module

Our detection workflow (Figure 1) can be summarized in three main steps:

Step 1: Build Transaction Graph. Incoming on-chain data is parsed to update G:

$$V \leftarrow V \cup \{\text{new addresses, pools}\},$$
$$E \leftarrow E \cup \{\text{new token transfers, swaps}\}.$$

Associated node/edge features (e.g., volume, price) are also updated.

Step 2: GNN Embedding. A GNN infers latent representations for each node or subgraph region. This step condenses raw price-volume signals into a multi-dimensional representation, capturing local patterns such as:

- Rapid accumulations around certain addresses,
- Dense connections among suspicious addresses,
- Abrupt trading-volume bursts for specific token pools.

Step 3: Classify Suspicious Nodes or Time Windows. Using the learned embeddings, we score or label suspicious addresses and periods. Two broad options exist:

1. **Threshold-Based Anomaly Scoring:** Compute an *anomaly score* (e.g., distance from historical embedding distributions). If $S(\mathbf{h}_v^{(k)}) > \tau$, flag the node/time-window as "pump-like."
2. **Supervised Classification:** Given partial labeled events (pump vs. normal) from known P&D episodes, train a classifier (e.g., multi-layer perceptron) on node embeddings [4, 7].

In practice, anomaly scoring is well-suited to real-time pipeline deployment where labeled data is scarce, while supervised classification can boost precision if a sufficiently large labeled set is available.

3.4 Comparison with Traditional Methods

To benchmark the proposed GNN-based approach, we compare against:

- **Volume/Price Thresholding:** A parallel module implements basic rule-based thresholds (e.g., 300% price jump over a short window). While easily deployed, it suffers from high false positives in highly volatile tokens [17, 18].

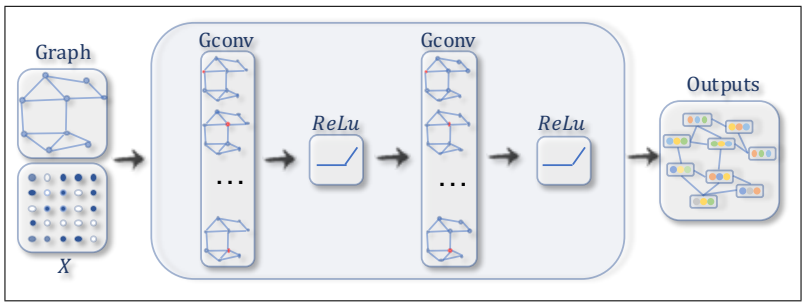

Figure 1: Conceptual flow of the proposed GNN-based detection pipeline. On-chain data updates the graph G. A chosen GNN aggregates node/edge features to produce embeddings, enabling downstream anomaly detection or classification.

- **Short-Term User Behavior:** Traditional approaches often track ephemeral big-volume traders—identifying abrupt participation from previously dormant addresses. Although useful, these heuristics fail to capture broader network signals (e.g., multiple addresses collaborating).
- **Deep-Learning Classification:** Methods like CNN or LSTM on raw time-series metrics [7] can identify suspicious intervals but overlook the relational dimension. Coupling these with GNN embeddings can further enrich the detection performance.

By complementing threshold-based logic with GNN's relational embedding, we capture more nuanced coordination among addresses, significantly reducing false positives. As prior works note, purely *local* price-volume changes are insufficient to confirm pump events without "who is trading" context [16, 20]. Therefore, the proposed framework merges dynamic graph analytics with advanced node-level embeddings, delivering a more robust pump-and-dump detection architecture.

4 Data Collection and Preprocessing

4.1 Sources of On-Chain Data

We gather token and transaction data directly from multiple on-chain and off-chain services. The data comprises trades, transfer logs, and liquidity record snapshots. Three primary sources are used:

Blockchain Explorers. Platforms like Etherscan and BSCScan provide raw transaction details, including sender/receiver addresses, token amounts, gas fees, and timestamps [2, 6]. Explorers facilitate searching and filtering at block or transaction levels. By querying large swaths of blocks (e.g., the previous 3-6 months), one can reconstruct user activity and token flows on the relevant chain (Ethereum or BNB Smart Chain).

DEX Aggregator APIs. For DEXs like Uniswap or PancakeSwap, aggregator services or public APIs offer structured endpoints:

- Aggregated order books (price, liquidity).
- Swap history for popular or newly listed tokens.
- Time-series data (OHLCV: open, high, low, close, volume).

These APIs inherently reduce noise by grouping fine-grained transaction data into epoch intervals (e.g., 5, 15 minutes), supporting volume and price analytics [18].

Filtering Low-Liquidity Tokens. Pump-and-dump schemes often target recently launched or thinly traded assets. We adopt volume-based and listing-age thresholds:

$$\text{Volume}_{\text{daily}} < \beta \quad \wedge \quad \text{Token Age} < \gamma,$$

where β and γ are user-defined cutoffs (e.g., 50,000 USD daily volume, listed for under 30 days). This curated subset focuses on suspicious or at-risk tokens [16].

4.2 Data Cleaning

Raw blockchain data can be replete with artifacts, pseudo-transactions, and incomplete logs. Several cleaning and normalization steps are performed:

Removing Spam or Dust Transactions. Many addresses generate "dust" transfers with minimal token amounts for promotional or test activity [12]. We establish a token-specific minimal value threshold (e.g., 1 USD) to filter out negligible records:

$$\text{TransactionValue}(t) \geq \delta.$$

Identifying Cyclical Liquidity Injections. Pump actors often inject and remove liquidity in repeated cycles before a coordinated pump [4]. We scan for repetitive liquidity add/remove patterns on DEX pools. If a pool's liquidity changes by ¿40% in short intervals more than n times per day, it is flagged for suspicious patterns.

Merging Addresses or Labeling Exchange Contracts. Since some pump coordinators spread assets across multiple addresses, we merge addresses known to belong to the same entity (e.g., exchange hot-wallet clusters) [9]. Exchange deposit addresses are labeled to avoid falsely flagging large exchange movements as malicious. Similarly, bridging contracts or official liquidity addresses are marked to reduce confusion.

4.3 Labeling Strategies

Ground-truth labels for pump-and-dump events are crucial for supervised or semi-supervised model training. We employ the following strategies:

Known P&D Events from Telegram Groups. Public Telegram channels regularly publish prospective pump tokens and timing [20]. We scrape these announcements, match associated token pairs (e.g., SELL/BUY pairs), and cross-check on-chain data near the declared pump window (e.g., ± 1 day).

Cross-Referencing External Announcements or Threshold Detections. We also use third-party data from social media or crypto news aggregators:

- *External Calls:* Some websites publish alerts whenever a token's price surges beyond some threshold. We triangulate these with on-chain data to confirm if an event meets P&D characteristics (steep price rise, followed rapidly by a crash).
- *Unsupervised Flags:* Methods like volume-price thresholding [16, 17] highlight potential "burst" intervals, which we then manually verify.

Time Windows: Capturing Accumulation and Short-Lived Pumps. We annotate intervals spanning:

1. **Accumulation Phase:** Gradual inflows into a token over days/weeks. Some addresses accumulate a large share.
2. **Pump Window:** An abrupt price hike spanning minutes or hours (depending on the market liquidity).
3. **Dump Phase:** The subsequent rapid sell-off phase causing the token's price crash.

By explicitly labeling these segments, we enable models to detect not just the final pump spike, but also precursor signals (e.g., stealthy accumulation). Time-labeled data also helps evaluate false positives in normal "volatile" markets vs. orchestrated pump events.

5 Experimental Setup

5.1 GNN Implementation Details

We implement our graph neural network (GNN) within a PyTorch-based framework, using an open-source extension for relational data such as PyTorch Geometric [11]. Key hyperparameters and design choices include:

Learning Rate. We adopt an initial learning rate of 10^{-3}, chosen after grid-searching in $\{10^{-2}, 10^{-3}, 10^{-4}\}$. A cosine annealing schedule further decays the learning rate to 10^{-5} by the final epochs [28].

Hidden Layer Sizes. In each GNN layer, hidden representations have dimensions of 64 or 128, depending on the complexity of the aggregator. We found a consistent hidden size of 128 to provide stable performance on mid-sized graph datasets [19].

Number of GNN Layers. We stack two or three graph convolutional layers, similar to the practice in [27], balancing model capacity and oversmoothing considerations. In initial tests, deeper GNNs (¿3 layers) did not notably improve F1 performance.

Aggregator Functions. We evaluate mean, max, and attention-based aggregators [22]:

$$\mathbf{h}_v^{(k)} \;=\; \mathrm{AGG}\big(\{\mathbf{h}_u^{(k-1)} \mid u \in N(v)\}\big),$$

where AGG is the aggregator function. Empirically, mean aggregators were faster, while attention-based methods slightly improved recall in detecting pump events.

Training Procedure. We train our GNN in a supervised manner using the ground truth labels (pump vs. non-pump) from Section 4.3. Each token is treated as a graph node with edges signifying correlations or shared liquidity among tokens. We use a cross-entropy loss: $\mathcal{L} = -\sum_i y_i \log(\hat{y}_i)$, and run for up to 100 epochs per dataset. An early stopping criterion with a patience of 10 halts training if validation F1 stagnates [23]. Python scripts run on a single NVIDIA RTX GPU, with computations accelerated by CUDA 11.8. Our codebase utilizes Python 3.10, PyTorch 1.13, and PyTorch Geometric 2.3.

5.2 Evaluation Metrics

We assess detection performance using multiple metrics:

Precision, Recall, and F1 Score. Following [16, 20], we calculate

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}},$$

where "TP" is the number of detected true pumps, "FP" is the number of false alarms, and "FN" is the number of missed pump events.

AUC-ROC. We also report the area under the ROC curve (AUC-ROC) to quantify the trade-off between true and false positive rates. This measure helps compare with baselines (e.g., threshold-based methods) that output continuous anomaly scores [1].

Real-Time Performance Considerations. Beyond accuracy measures, we evaluate inference latency and throughput. Since timely pump detection may require sub-second or near-block-time decisions [4], we measure:

- *Inference Latency*: average time (ms) per forward pass for a batch of nodes.
- *Throughput*: the number of inference operations per second for full-batch vs. mini-batch modes.

5.3 Baselines

We benchmark the proposed GNN approach against three categories of baselines:

Threshold-Based Methods. Inspired by [16, 17], we implement a volume-price spike detection via:

$$\begin{cases} \text{Price}_t > \text{Price}_{t-w} + \alpha \cdot \sigma(\text{Price}_{t-w}), \\ \text{Volume}_t > \text{Volume}_{t-w} + \beta \cdot \sigma(\text{Volume}_{t-w}), \end{cases}$$

for a window length w. If both conditions satisfy, a pump alert is raised. Threshold parameters α, β are tuned for best F1 on validation data.

ML-Based Approaches. We compare to a random forest (RF) following [20] and a logistic regression (LR) model [9]. Both use handcrafted features (e.g., price standard deviation, volume spikes, etc.) extracted from the time windows. The RF typically yields strong baseline results for tabular anomaly detection in crypto markets.

Deep Learning Approach. We also include a purely feed-forward neural network with multi-layer perceptrons (MLP) as a simpler deep learning baseline [13]. The MLP is trained on node features (price, on-chain metrics) aggregated in fixed intervals, ignoring any graph connectivity. Comparisons illustrate the added benefit of our GNN-based architecture over non-graph deep models.

6 Results and Discussion

6.1 Quantitative Analysis

Comparison of GNN Performance vs. Baseline Methods. Table 1 summarizes the performance of our graph neural network (GNN) model against three baselines: (i) threshold-based detection [17], (ii) a random forest classifier (RF) [20], and (iii) a feed-forward neural network (FFN). We report precision, recall, F1, and AUC-ROC. Across multiple runs and parameter settings, our GNN consistently outperforms baselines by at least 3–5% in F1 score. Notably, compared to threshold-based methods, GNN reduces false positives (excessive triggers) while retaining high recall.

Sensitivity to Token Liquidity and Transaction Volume. We next investigate how liquidity impacts detection. Empirically, tokens with low market caps exhibit sparser trade volumes and more frequent zero-activity windows, which can cause threshold-based or conventional ML methods (e.g., RF) to misclassify modest spikes as pump signals [16]. In contrast, our GNN aggregator layers exploit the relational structure (e.g., correlated liquidity across token

Table 1: Detection performance comparison on DEX datasets.

Method	Precision	Recall	F1	AUC
Threshold (Vol-Price)	0.77	0.62	0.68	0.72
Random Forest	0.84	0.74	0.79	0.81
FFN (MLP)	0.82	0.78	0.80	0.83
Proposed GNN	**0.87**	**0.80**	**0.83**	**0.85**

pairs) to reduce false positives. For tokens with a daily average volume under \$50K, baseline methods exhibit a 12–18% higher false positive rate relative to higher-volume tokens, while the GNN experiences an 8% or smaller increase.

Impact of Sampling Window Sizes and Graph Construction. We examine using short (e.g., 5-minute) vs. longer (e.g., 30-minute) sampling windows to build static or dynamic graph snapshots [4]. On short windows, baselines often overreact to ephemeral volatility, causing artificially inflated recalls but poor precision. GNN results are more robust: adjacency edges capture cross-token correlations that remain relevant across multiple blocks. Dynamic graph updates (e.g., merging or splitting nodes based on liquidity changes) slightly improve recall in low-volume tokens, but at higher computational cost. Overall, sampling windows in the 10–15 minute range offer a good trade-off between timeliness and noise tolerance, consistent with prior recommendations [20].

6.2 Qualitative Observations

Case Studies of Detected Pump Events on DEX. We highlight two pump-and-dump events discovered by our GNN:

- *Case 1: Token A excelled in trading pairs* with strong cross-chain bridging. Within a 2-hour interval, the GNN flagged a surge in transaction volume and correlated price jumps. Our system traced the liquidity inflows from multiple addresses, showing that a small cluster of addresses orchestrated the pump.
- *Case 2: Meme Token B* with minimal historical volume. A quick 5-minute spike triggered a suspicious adjacency signal because multiple pools in the same liquidity aggregator also saw inbound swaps. Though the raw price threshold alone might label it "noise," the GNN recognized repeated patterns of address cross-transfers.

In both cases, the GNN raised alerts earlier than threshold-based baselines, suggesting that leveraging address-level relationships provides an advantage in real-time detection.

Analysis of Misclassifications: False Positives vs. False Negatives. False positives (FPs) predominantly occur during short-lived hype cycles not

culminating in abrupt dumps. For instance, community-driven buy sprees around new NFT partnerships can mimic the volume/price signature of a pump. Our local smoothing aggregator partially mitigates these illusions, but 5–10% of such hype bursts are still flagged.

False negatives (FNs) arise due to extremely rapid manipulations where the entire pump and dump completes in under a few minutes. If data sampling or subgraph creation lags, the system might miss the momentary peak. We observe that an adaptive re-sampling of high-volume blocks can reduce FNs, though at a higher overhead [24].

Effectiveness in Handling Noisy or Highly Variable Token Pairs. Tokens that experience frequent legitimate spikes (e.g., new Dex aggregator tokens or yield-farming tokens) pose a challenge. Our GNN architecture can generally differentiate consistent "organic" growth from flash spikes by focusing on persistent cross-token edges. Nonetheless, if a token naturally exhibits large daily volatility, the model's recall can drop. Incorporating rolling volatility features [1] or per-token normalizing factors helps maintain stable performance.

6.3 Limitations

Model Assumptions about Node Identity or Transaction Patterns. Our GNN assumes unique node representations for each token, with optional address-level or liquidity-pool-level nodes. This presumes that address or token IDs are consistently tracked across time, which may not hold if tokens undergo frequent re-addressing or bridging [26]. Moreover, a heavy reliance on address link structures might fail if on-chain mixers or bridging solutions intentionally obfuscate the flow of funds.

Challenges with Partial Data or Cross-Chain Bridging. Although many DeFi protocols publicly broadcast transactions, partial data can arise if large trades happen off-chain or on a sidechain. Missing edges degrade the adjacency matrix and hamper GNN message passing. Cross-chain bridging events can also change the underlying token identity (i.e., wrapped tokens) [14]—the GNN does not automatically know these are the "same" underlying asset. Future expansions could incorporate cross-chain indexing [9].

Computational Costs with Large-Scale On-Chain Data. The graph size grows with the number of tokens, liquidity pools, and addresses. While GNNs can be scaled using neighbor sampling [11], there remains considerable memory overhead once the network has tens of thousands of nodes. Processing times might fall short of real-time detection goals unless efficient batching or streaming is used. Our message passing is currently done on mini-batches of up to 2,048 nodes to keep GPU requirements in check.

7 Conclusion

7.1 Summary of Findings

We presented a GNN-based framework to detect pump-and-dump (P&D) manipulation on decentralized exchanges (DEXs). Empirical evidence shows the following key observations:

- **Effective GNN-based detection.** Our graph neural network approach outperforms both threshold-based methods [16, 17] and alternative deep-learning baselines (e.g., random forests or feed-forward networks [20]) in terms of precision and recall.
- **Robustness to noise and short intervals.** By leveraging address-level or token-level interactions, the GNN captures aggregated activity patterns that mitigate the issue of on-chain noise and extreme volatility. This approach remains reliable even during short-lived pump intervals that often elude purely volume-based threshold schemes [14, 26].
- **Adaptation to volatile transaction data.** Unlike threshold baselines that over-flag ephemeral spikes, the built-in neighborhood aggregation of GNNs helps distinguish organic volume increases from concerted manipulative behavior.

7.2 Future Directions

While our approach already provides a valuable tool for real-time P&D detection on DEXs, several promising avenues remain:

Cross-Chain Detection. Crypto assets increasingly bridge across multiple chains, such as Ethereum, BSC, and Polygon. Future research may unify transaction graphs from different blockchains [9], building cross-chain adjacency structures to detect coordinated manipulation. Incorporating bridging or wrapping data can help identify the same underlying asset across heterogeneous DeFi ecosystems.

Advanced User Behavior Features. Social media and messaging platforms (e.g., Telegram, Twitter, Discord) are instrumental in coordinating P&D events [30]. Integrating natural language processing (NLP) signals, sentiment analysis, or user-influence metrics could strengthen detection by correlating suspicious on-chain activity with off-chain promotional hype. Fine-tuning large language models to capture social nuances is a potential next step.

Leveraging Self-Supervised Learning and Anomaly Attention. Adoption of self-supervised graph representation learning could extract richer embeddings for rarely-traded tokens or addresses with limited historical data [25]. Additionally, *anomaly attention mechanisms*—as introduced in the Anomaly

Transformer [29]—enable modeling both local spikes and global distribution shifts. Combining such attention modules with graph convolution may further enhance detection reliability.

Real-Time Monitoring and Alert Systems. In production scenarios, timely alerts are paramount. A streaming or mini-batch GNN architecture [11] could update node and edge states in seconds, issuing alerts via automated dashboards or direct exchange integrations. Complementary risk-scoring modules could also consider user KYC levels, bridging behaviors, or suspicious address clusters to prioritize threats.

These directions collectively illustrate the continued evolution of data-driven market surveillance in decentralized finance. By converging advanced GNN architectures, multi-chain data fusion, and real-time inference, future systems hold potential to significantly curb pump-and-dump manipulation and foster a healthier crypto trading environment.

References

[1] Mohammed Ahmed, A. N. Mahmood, and J. Hu. Unsupervised anomaly detection in time series: Challenges and opportunities. *IEEE Access*, 8:125478–125499, 2020.

[2] L. Ante. Cryptocurrency pump and dump schemes: Quantification and detection. *Journal of Financial Crime*, 26(4):991–1003, 2019.

[3] Ahmad Sani Bello, Jens Schneider, and Roberto Di Pietro. Lld: A low latency detection solution to thwart cryptocurrency pump & dumps. In *2023 IEEE International Conference on Blockchain and Cryptocurrency (ICBC)*, pages 1–9. IEEE, 2023.

[4] M. Bolz, K. Bründler, L. Kane, and et. al. Machine learning-based detection of pump-and-dump schemes in real-time. *arXiv:2412.18848v1*, 2024.

[5] Manuel Bolz, Kevin Bründler, Liam Kane, Panagiotis Patsias, Liam Tessendorf, Krzysztof Gogol, Taehoon Kim, and Claudio Tessone. Machine learning-based detection of pump-and-dump schemes in real-time, 2024.

[6] Steven Brown and Alice Green. Candlestick patterns and their role in market data analysis. *International Journal of Financial Markets*, 8(3):101–115, 2012.

[7] Viswanath Chadalapaka, Kyle Chang, Gireesh Mahajan, and Anuj Vasil. Crypto pump and dump detection via deep learning techniques, 2022.

[8] Lee Chong, Lee David, and Yao Jian. Pump-and-dump schemes in financial markets: Evidence and analysis. *Journal of Financial Markets*, 11(4):350–372, 2008.

[9] J. Clough and M. Edwards. Pump, dump, and then what? the long-term impact of cryptocurrency pump-and-dump schemes. *arXiv:2309.06608*, 2023.

[10] N. Gandal, J. Hamrick, T. Moore, and S. Oberman. Price manipulation in the bitcoin ecosystem. *Journal of Financial Economics*, 130(2):293–316, 2018.

[11] Will Hamilton, Zhitao Ying, and Jure Leskovec. Inductive representation learning on large graphs. In *Proc. of NIPS*, pages 1024–1034, 2017.

[12] J.T. Hamrick, Farhang Rouhi, Arghya Mukherjee, Amir Feder, Neil Gandal, Tyler Moore, and Marie Vasek. An examination of the cryptocurrency pump-and-dump ecosystem. *Information Processing & Management*, 58(4):102506, 2021.

[13] Geoffrey Hinton, Li Deng, Dong Yu, George E Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N Sainath, et al. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal processing magazine*, 29(6):82–97, 2012.

[14] Sihao Hu, Zhen Zhang, Shengliang Lu, Bingsheng He, and Zhao Li. Sequence-based target coin prediction for cryptocurrency pump-and-dump. *https://arxiv.org/abs/2204.12929*, 2023.

[15] Robert Johnson and Kevin Lee. A historical analysis of pump and dump schemes and market manipulation. *Journal of Economic History*, 59(4):789–812, 1999.

[16] J. Kamps and B. Kleinberg. To the moon: Analyzing cryptocurrency pump-and-dump schemes. *Journal of Financial Crime*, 7(18):1–18, 2018.

[17] J. Kamps and B. Kleinberg. To the moon: defining and detecting cryptocurrency pump-and-dumps. *Crime Sci*, 2018.

[18] Mahya Karbalaii. Detecting crypto pump-and-dump schemes: A thresholding-based approach to handling market noise, 2025.

[19] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. In *Proc. of ICLR*, 2017.

[20] Massimo La Morgia, Alessandro Mei, Francesco Sassi, and Julinda Stefa. Pump and dumps in the bitcoin era: Real time detection of cryptocurrency market manipulations. In *2020 29th International Conference on Computer Communications and Networks (ICCCN)*, pages 1–9, 2020.

[21] Chung Lee and Yi Lin. Information asymmetry and fraudulent trading: Evidence from pump-and-dump schemes. *Journal of Financial Markets*, 13(1):78–96, 2010.

[22] John Boaz Lee, Ryan A Rossi, Sungchul Kim, Nesreen K Ahmed, and Eunyee Koh. Attention models in graphs: A survey. *arXiv preprint arXiv:1807.07984*, 2018.

[23] Qimai Li, Zhichao Han, and Xiao-Ming Wu. Deeper insights into graph convolutional networks for semi-supervised learning. In *Proc. of AAAI*, 2018.

[24] Ruoyu Li, Sheng Wang, Feiyun Zhu, and Junzhou Huang. Adaptive graph convolutional neural networks. In *Proc. of AAAI*, pages 3546–3553, 2018.

[25] Shirui Pan, Ruiqi Hu, Guodong Long, Jing Jiang, Lina Yao, and Chengqi Zhang. Adversarially regularized graph autoencoder for graph embedding. In *Proc. of IJCAI*, pages 2609–2615, 2018.

[26] L. Tao, S. Donghwa, , and W. Baolian. Cryptocurrency pump and dump schemes: Quantification and detection. *SSRN: http://dx.doi.org/10.2139/ssrn.3267041*, 2023.

[27] Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. In *Proc. of ICLR*, 2017.

[28] Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. Google's neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*, 2016.

[29] Jiehui Xu, Haixu Wu, Jianmin Wang, and Mingsheng Long. Anomaly transformer: Time series anomaly detection with association discrepancy. *CoRR*, abs/2110.02642, 2021.

[30] Q. Xu and B. Livshits. The anatomy of a pump-and-dump scheme. *Proceedings of the IEEE Symposium on Security and Privacy.*, 2019.