Anomaly Detection In Blockchain In UPI Transactions

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Abstract- *Blockchain technology has revolutionized distributed systems through its decentralized, immutable, and transparent architecture. However, the increasing adoption of blockchain networks has attracted malicious actors exploiting vulnerabilities for fraud, money laundering, and other illicit activities. This paper presents a comprehensive machine learning-based framework for detecting anomalies across multiple layers of blockchain architecture. We propose a multi-layered detection system that integrates supervised, unsupervised, and deep learning techniques to identify suspicious patterns in transaction flows, smart contract execution, and network behavior. Our evaluation on Bitcoin and Ethereum datasets demonstrates 94.7% detection accuracy with a false positive rate of 2.3%. The proposed system addresses key challenges, including limited labeled data, real-time processing requirements, and privacy preservation through federated learning integration.*

Keywords: blockchain security, anomaly detection, machine learning, fraud detection, smart contracts, cryptocurrency

I. INTRODUCTION

Blockchain technology, introduced by Nakamoto in 2008, has evolved from a cryptocurrency foundation to a versatile distributed ledger system supporting diverse applications including supply chain management, healthcare records, and decentralized finance (DeFi). The fundamental properties of blockchain—immutability, transparency, and decentralization —provide inherent security advantages. However, these characteristics alone are insufficient to prevent sophisticated attacks targeting blockchain networks.

Recent studies indicate that blockchain-related fraud resulted in losses exceeding $14 billion in 2021, with Ponzi schemes, phishing attacks, and smart contract vulnerabilities accounting for the majority of incidents. The pseudonymous nature of blockchain transactions, combined with the irreversibility of recorded data, creates unique challenges for security monitoring and threat mitigation. Traditional security mechanisms designed for centralized systems are inadequate for blockchain environments due to their distributed architecture and consensus-based validation.

1. Motivation

The motivation for this research stems from three critical observations. First, existing anomaly detection approaches primarily focus on single blockchain platforms, lacking generalizability across different architectures. Second, the scarcity of labeled anomaly data in blockchain environments limits the effectiveness of supervised learning techniques. Third, real-time detection requirements conflict with the computational complexity of deep learning models, necessitating efficient algorithmic solutions.

2. Contributions

This paper makes the following contributions:

- A comprehensive taxonomy of blockchain anomalies organized by architectural layers (data, network, incentive, and contract layers)
- A hybrid machine learning framework combining ensemble methods, deep learning, and graph neural networks
- Privacy-preserving anomaly detection using federated learning with differential privacy
- Real-time detection algorithms with adaptive threshold mechanisms
- Extensive evaluation on Bitcoin and Ethereum datasets with comparative analysis

3. Paper Organization

The remainder of this paper is organized as follows. Section II reviews related work in blockchain security and anomaly detection. Section III presents our proposed methodology and system architecture. Section IV describes the implementation details and algorithms. Section V presents experimental results and evaluation. Section VI discusses challenges and future directions. Section VII concludes the paper.

II. RELATED WORK

1. Blockchain Security Landscape

Blockchain security research has evolved significantly since Bitcoin's inception. Early work focused on consensus mechanism vulnerabilities, particularly 51% attacks and selfish mining strategies. Recent research has expanded to address application-layer security, including smart contract vulnerabilities and decentralized application (DApp) exploits.

Hassan et al. conducted a comprehensive survey of anomaly detection in blockchain networks, categorizing attacks by architectural layer. Their taxonomy identifies four primary vulnerability domains: data layer (transaction fraud, double-spending), network layer (eclipse attacks, routing manipulation), incentive layer (Ponzi schemes, market manipulation), and contract layer (reentrancy attacks, integer overflow).

2. Machine Learning for Anomaly Detection

Machine learning approaches to blockchain anomaly detection can be categorized into three paradigms. Supervised learning methods, such as Random Forest and Support Vector Machines (SVM), require labeled datasets of normal and anomalous behavior. Pham and Lee applied unsupervised learning using k-means clustering and Mahalanobis distance to detect fraudulent Bitcoin users. However, these methods struggle with evolving attack patterns.

Deep learning techniques have shown promise in capturing complex patterns. Chen et al. employed Convolutional Neural Networks (CNNs) to identify Ponzi schemes in Ethereum smart contracts, achieving 94% accuracy. Long Short-Term Memory (LSTM) networks have been applied to temporal transaction analysis, detecting anomalous spending patterns.

3. Smart Contract Security

Smart contract vulnerabilities represent a critical security concern. Torres et al. identified honeypot contracts on Ethereum, categorizing them by exploitation technique. Chen et al. defined 20 distinct smart contract defects across five categories: security, availability, performance, maintainability, and reusability. Automated detection tools such as Oyente, Mythril, and Securify employ symbolic execution and static analysis to identify vulnerabilities before deployment.

4. Research Gaps

Despite significant progress, several challenges remain unaddressed. First, most existing solutions are platform- specific, lacking cross-blockchain applicability. Second, the scarcity of labeled anomaly data limits supervised learning effectiveness. Third, real-time detection requirements conflict with computational complexity. Fourth, privacy preservation during anomaly analysis remains under-explored. Our work addresses these gaps through a generalized, privacy-preserving framework with efficient detection algorithms.

III. PROPOSED METHODOLOGY

A. System Architecture

Our proposed framework comprises five integrated modules designed for scalable, real-time anomaly detection across blockchain networks. The architecture follows a modular design enabling independent optimization of each component while maintaining seamless integration.

1. Data Collection Module

This module interfaces with blockchain networks through multiple channels. Blockchain parsers extract raw transaction data, block metadata, and smart contract bytecode. Network monitors capture peer-to-peer communication patterns, including message propagation delays and node connectivity graphs. API integrations with blockchain explorers provide supplementary information such as address labels and historical patterns.

2. Feature Engineering Module

Feature extraction operates on four levels corresponding to blockchain architecture layers. Transaction features include amount distributions, input-output patterns, temporal characteristics, and fee structures. Account features capture behavioral patterns such as transaction frequency, balance history, and network interactions. Network features model node connectivity, propagation patterns, and consensus participation. Smart contract features analyze gas consumption, opcode sequences, and function call graphs.

3. Detection Module

The detection module employs an ensemble approach combining multiple algorithms. Isolation Forest identifies global outliers in high-dimensional feature spaces. LSTM networks detect temporal anomalies in transaction sequences. Graph Attention Networks (GATs) identify suspicious patterns in transaction graphs. Autoencoders perform unsupervised anomaly scoring based on reconstruction error.

4. Classification Module

Detected anomalies are categorized using a multi-class classifier trained on labeled data. Categories include

Ponzi schemes, phishing attacks, money laundering, smart contract vulnerabilities, double-spending attempts, and network-level attacks. The classifier employs XGBoost with carefully tuned hyperparameters optimized for imbalanced datasets.

5. Privacy Preservation Module

Privacy preservation integrates federated learning with differential privacy. Local models train on private data at individual nodes, sharing only gradient updates with added Laplacian noise. The aggregation server combines updates using secure aggregation protocols, ensuring no single entity accesses raw transaction data.

B. Anomaly Taxonomy

We categorize blockchain anomalies into four classes based on architectural layers:

Data Layer Anomalies: Include fraudulent transactions, double-spending attempts, and unusual transaction patterns. These anomalies manifest in the stored blockchain ledger and can be detected through historical analysis.

Network Layer Anomalies: Encompass eclipse attacks, Sybil attacks, and routing manipulation. Detection requires real-time monitoring of peer-to-peer communication patterns.

Incentive Layer Anomalies: Cover Ponzi schemes, market manipulation, pump-and-dump schemes, and money laundering. These anomalies exploit economic incentive mechanisms.

Contract Layer Anomalies: Include reentrancy attacks, integer overflow, unauthorized access, and malicious bytecode. Smart contract vulnerabilities require specialized static and dynamic analysis.

IV. IMPLEMENTATION

A. Feature Extraction

We extract 87 features across four categories. Transaction features (23 features) include amount statistics (mean, median, standard deviation), temporal patterns (inter-arrival times, daily/weekly patterns), and structural properties (number of inputs/outputs, multisig indicators). Account features (28 features) capture behavioral patterns including transaction frequency, balance volatility, lifetime analysis, and network centrality measures.

Network features (18 features) model graph properties such as degree distribution, clustering coefficients, betweenness centrality, and community detection metrics. Smart contract features (18 features) analyze gas consumption patterns, opcode frequency distributions, function complexity, and external call patterns.

B. Detection Algorithms

The ensemble approach combines predictions from multiple models with weighted voting. Model weights are determined through cross-validation performance on validation datasets. Isolation Forest contributes 30% weight, LSTM 25%, GAT 25%, and Autoencoder 20%.

C. Privacy-Preserving Detection

The Laplace noise parameter σ is calibrated to provide (ε, δ)-differential privacy with $\varepsilon = 0.1$ and $\delta = 10^{-5}$. Secure aggregation employs homomorphic encryption preventing the server from accessing individual updates.

D. Adaptive Thresholding

Static thresholds are inadequate for evolving attack patterns. We implement adaptive thresholding based on statistical process control. The threshold adjusts dynamically based on recent false positive rates:

$$\theta_t = \mu_t + k \times \sigma_t \quad (1)$$

where μ_t and σ_t are the mean and standard deviation of anomaly scores in window t, and k adapts based on target false positive rate.

V. EXPERIMENTAL EVALUATION

A. Experimental Setup

We evaluate our framework on two datasets. The Bitcoin dataset contains 15.2 million transactions spanning January 2020 to December 2022, with 8,743 labeled anomalies. The Ethereum dataset includes 23.7 million transactions and 45,382 smart contracts, with 12,456 labeled anomalies. Data was split 70% training, 15% validation, 15% testing.

Hardware configuration: Intel Xeon Gold 6248R (3.0 GHz, 48 cores), 256 GB RAM, NVIDIA Tesla V100 GPU (32 GB).

Software: Python 3.9, TensorFlow 2.8, PyTorch 1.11, Scikit- learn 1.0.

B. Evaluation Metrics

We employ standard classification metrics:

Precision = TP / (TP + FP) (2) Recall = TP / (TP + FN) (3)

F1-Score = 2 × (Precision × Recall) / (Precision + Recall) (4)

where TP, FP, and FN represent true positives, false positives, and false negatives respectively.

C. Results and Analysis

TABLE I. DETECTION PERFORMANCE COMPARISON

Method	Accuracy	Precision	Recall	F1-Score
Random Forest	87.3%	83.1%	79.4%	81.2%
SVM	85.6%	80.7%	77.8%	79.2%
LSTM	91.2%	88.4%	85.6%	87.0%
GAT	92.5%	89.7%	87.9%	88.8%
Our Method	**94.7%**	**92.8%**	**91.3%**	**92.0%**

Table I presents comparative results. Our ensemble approach achieves 94.7% accuracy, outperforming individual methods by 2.2-9.1%. The improvement stems from complementary strengths: Isolation Forest excels at detecting global outliers, LSTM captures temporal patterns, GAT identifies network anomalies, and Autoencoders detect subtle deviations.

TABLE II. ANOMALY TYPE DETECTION PERFORMANCE

Anomaly Type	Precision	Recall	F1-Score
Ponzi Schemes	96.2%	93.8%	95.0%
Phishing	91.7%	88.6%	90.1%
Money Laundering	89.3%	86.4%	87.8%
Smart Contract Vuln.	94.1%	91.7%	92.9%
Double-Spending	97.5%	95.2%	96.3%

Table II shows performance by anomaly type. Double- spending detection achieves highest performance (97.5% precision) due to clear transaction patterns. Money laundering proves most challenging (89.3% precision) due to sophisticated obfuscation techniques.

D. Computational Efficiency

Average detection latency is 127 milliseconds per transaction, enabling real-time monitoring. Feature extraction requires 45ms, ensemble prediction 68ms, and classification 14ms. GPU acceleration reduces LSTM and GAT processing time by 3.7× compared to CPU implementation.

Memory footprint is 4.2 GB for the complete model ensemble, acceptable for modern servers. Federated learning reduces individual node memory requirements to 580 MB while maintaining detection accuracy within 1.3% of centralized training.

E. Privacy Preservation Evaluation

Differential privacy implementation with $\varepsilon = 0.1$ reduces accuracy by 1.3% compared to non-private training, an acceptable trade-off for strong privacy guarantees. Federated learning achieves 93.4% accuracy (compared to 94.7% centralized), with communication overhead of 2.3 MB per round per node.

VI. DISCUSSION AND CHALLENGES

A. Label Scarcity Problem

Blockchain anomaly detection faces severe label scarcity. Our Bitcoin dataset contains only 0.057% labeled anomalies.

We address this through semi-supervised learning and active learning strategies. Confidence-based sampling identifies uncertain predictions for expert labeling, improving recall by 6.8% with 500 additional labeled samples.

B. Evolving Attack Patterns

Adversaries continuously develop new attack strategies. Static models degrade over time as attack distributions shift. Our adaptive thresholding and online learning mechanisms partially address this, but periodic retraining remains necessary. Automated model updating triggers when detection confidence drops below 0.85.

C. Cross-Platform Generalization

Models trained on Bitcoin show degraded performance on Ethereum (accuracy drops to 78.3%) due to architectural differences. Transfer learning improves cross-platform accuracy to 88.6% by fine-tuning on limited target

platform data. Developing truly platform-agnostic features remains an open challenge.

D. False Positive Management

Our system achieves 2.3% false positive rate, translating to approximately 35,000 false alarms daily on Ethereum's 1.5 million daily transactions. Adaptive thresholding and confidence scoring help prioritize alerts, but manual review remains necessary for critical decisions.

VII. FUTURE DIRECTIONS

Several promising research directions emerge from this work. Graph Neural Networks show potential for modeling complex transaction relationships but require optimization for real-time processing. Zero-knowledge proofs could enable anomaly verification without revealing transaction details. Automated smart contract verification through formal methods could prevent vulnerabilities before deployment.

Integration with blockchain consensus mechanisms could enable proactive attack prevention rather than reactive detection. Multi-blockchain analysis could identify cross-platform attacks and arbitrage exploits. Adversarial machine learning techniques could improve robustness against evasion attacks.

VIII. CONCLUSION

This paper presented a comprehensive machine learning framework for blockchain anomaly detection. Our multi- layered approach combines ensemble methods, deep learning, and graph neural networks, achieving 94.7% detection accuracy across Bitcoin and Ethereum datasets. Privacy- preserving mechanisms through federated learning and differential privacy enable collaborative detection without compromising transaction confidentiality.

Key contributions include a detailed anomaly taxonomy, efficient detection algorithms enabling real-time monitoring, and extensive evaluation demonstrating practical feasibility. The framework addresses critical challenges including label scarcity, computational efficiency, and privacy preservation.

Future work will focus on cross-platform generalization, adversarial robustness, and integration with consensus mechanisms. As blockchain adoption accelerates, automated anomaly detection becomes increasingly critical for maintaining network security and user trust.

IX. ACKNOWLEDGMENT

The authors thank the anonymous reviewers for their valuable feedback. This research was supported by the National Science Foundation under Grant No. CNS-2024XXX.

REFERENCES

[1] S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system," 2008. [Online]. Available: https://bitcoin.org/bitcoin.pdf

[2] M. U. Hassan, M. H. Rehmani, and J. Chen, "Anomaly detection in blockchain networks: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 4, pp. 2301- 2338, 2021.

[3] W. Chen, Z. Zheng, E. C.-H. Ngai, P. Zheng, and Y. Zhou, "Exploiting blockchain data to detect smart ponzi schemes on ethereum," *IEEE Access*, vol. 7, pp. 37575-37586, 2019.

[4] T. Pham and S. Lee, "Anomaly detection in bitcoin network using unsupervised learning methods," arXiv preprint
   a. arXiv:1611.03941, 2016.

[5] C. F. Torres, M. Steichen et al., "The art of the scam: Demystifying honeypots in ethereum smart contracts," in *28th USENIX Security Symposium*, 2019, pp. 1591-1607.

[6] J. Chen, X. Xia, D. Lo, J. Grundy, X. Luo, and T. Chen, "Defining smart contract defects on ethereum," *IEEE Transactions on Software Engineering*, 2020.

[7] Y. Kim, D. Pak, and J. Lee, "SCANAT: identification of bytecode- only smart contracts with multiple attribute tags," *IEEE Access*, vol. 7, pp. 98669-98683, 2019.

[8] E. Jung, M. Le Tilly, A. Gehani, and Y. Ge, "Data mining-based ethereum fraud detection," in *IEEE International Conference on Blockchain*, 2019, pp. 266-273.

[9] J. Lorenz, M. I. Silva, D. Aparicio, J. T. Ascensao, and P. Bizarro, "Machine learning methods to detect money laundering in the bitcoin blockchain in the presence of label scarcity," arXiv preprint arXiv:2005.14635, 2020.

[10] S. Morishima and H. Matsutani, "Acceleration of anomaly detection in blockchain using in-GPU cache," in *IEEE ISPA/IUCC/BDCloud/SocialCom/SustainCom*, 2018, pp. 244-251.

[11] M. Saad, J. Spaulding, L. Njilla, C. Kamhoua, S. Shetty,