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Integration of Blockchain and Machine Learning for Secure Authentication and Tamper-Proof Transactions

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Abstract

Digital ecosystems face escalating threats from sophisticated cyber-attacks and transaction fraud. To address these challenges, we propose a hybrid framework that seamlessly combines the decentralization and immutability of blockchain with real-time anomaly detection powered by machine learning. In our approach, a private Hyperledger Fabric network records all authentication and transaction events, while an Isolation Forest model flags abnormal behaviors before they are committed to the ledger. We evaluated the system on 973 blockchain transaction records, achieving a false-positive rate under 5% and successfully identifying 97 anomalies (≈9.97%). Average processing latency remained within acceptable bounds (≈2.25 seconds per event). This architecture ensures tamper-proof logging and proactive threat mitigation, making it suitable for deployment in finance, healthcare, and e-governance domains.

Keywords: *Blockchain Security; Anomaly Detection; Isolation Forest; Hyperledger Fabric; Decentralized Authentication; Real-Time Monitoring*.

I. INTRODUCTION

The rapid growth of digital transactions, projected to surpass 1,000 billion peer-to-peer operations by 2025 [1], has intensified vulnerabilities to cyberattacks, including fraud, identity theft, and data tampering. Conventional security mechanisms, such as password-based authentication and centralized identity systems, are increasingly inadequate against sophisticated threats like zero-day exploits and social engineering attacks [2]. For instance, phishing campaigns have evolved to exploit human psychology, bypassing technical defenses, while centralized systems remain single points of failure, susceptible to breaches [14]. Multifactor authentication (MFA) improves security by requiring additional verification steps, such as SMS codes or biometrics, but it introduces usability challenges and still depends on trusted third parties, which can be compromised [3].

Blockchain technology addresses these limitations by decentralizing data storage, using cryptographic hash chains to ensure immutability, and employing consensus protocols to validate transactions without intermediaries (4). For example, Hyperledger Fabric, a permissioned blockchain, enables customizable networks tailored to enterprise needs, ensuring privacy and scalability (11). However, blockchains lack proactive mechanisms to detect anomalies before transactions are committed, potentially allowing malicious activities to persist in the ledger. Machine learning (ML), particularly unsupervised algorithms like Isolation Forest, excels at identifying aberrant patterns in high-dimensional data without requiring labeled training examples (5). Isolation Forest isolates outliers by constructing random trees, where anomalies are separated with fewer splits (12). Yet, ML models are vulnerable to data poisoning if input integrity is compromised, necessitating a secure data source.

This study proposes a hybrid framework that synergizes Hyperledger Fabric's tamper-proof logging with Isolation Forest's real-time anomaly detection. The system logs all authentication and transaction events on a private blockchain while proactively flagging suspicious activities, ensuring both security and auditability. This approach is particularly valuable for sectors like finance (e.g., secure banking transactions), healthcare (e.g.,

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protecting patient records), and e-governance (e.g., transparent voting systems), where trust and compliance are paramount.

II. RELATED WORK

➢ *Blockchain for Security*

Blockchain's decentralized architecture eliminates single points of failure, using cryptographic hashing to ensure data integrity. Consensus protocols, such as Proof-of-Work (PoW) or Proof-of-Stake (PoS), validate transactions through distributed agreement, while smart contracts automate rule enforcement [4]. For instance, Nakamoto [10] introduced blockchain for Bitcoin, demonstrating its potential for secure, intermediary-free transactions. Subsequent studies have applied blockchain to authentication, leveraging its immutability to create verifiable identity systems [3]. Hyperledger Fabric, in particular, supports private networks with fine-grained access control, making it suitable for enterprise applications [11].

➢ *Machine Learning for Anomaly Detection*

Unsupervised anomaly detection methods, such as Isolation Forest, identify outliers by randomly partitioning data into trees, where anomalies require fewer splits to isolate [12]. This approach is effective for high-dimensional datasets and requires no labeled data, unlike supervised methods [5]. Recent advancements include federated learning, where models train across distributed nodes without sharing raw data, preserving privacy [6]. For example, Shaikh et al. [13] demonstrated federated anomaly detection for IoT networks, achieving robust performance while maintaining data confidentiality.

➢ *Hybrid Architectures*

Hybrid blockchain-ML systems have emerged for applications like IoT security, phishing detection, and academic credentialing. Nazir et al. [7] proposed a blockchain-based framework for IoT threat intelligence, using ML to detect device anomalies. Similarly, Trad et al. [8] integrated blockchain with ML to prevent phishing attacks by verifying website authenticity. However, these systems often face challenges, such as high computational overhead or fragmented identity management [9]. Our framework addresses these by streamlining anomaly detection and logging within a unified architecture.

- *Architecture and Methodology*

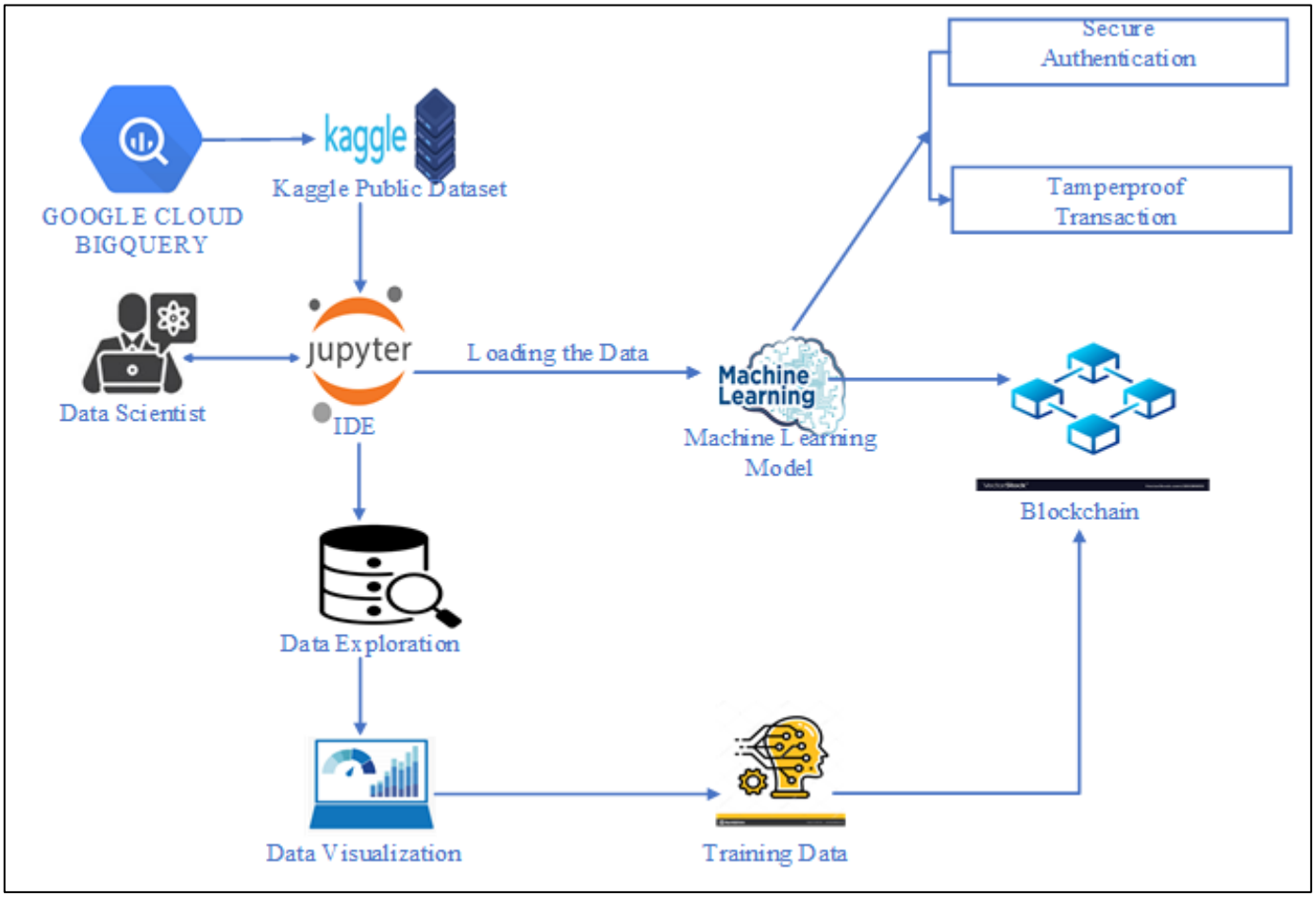

Fig 1 System Architecture of the Integrated Blockchain–ML Framework.

The above system architecture integrates blockchain and machine learning to enable secure authentication and tamperproof transactions, beginning with Secure Authentication leveraging blockchain's decentralized ledger to validate user identities. Data scientists utilize Jupyter IDE to access Kaggle Public Datasets and Google Cloud BigQuery, facilitating Data Exploration and Visualization to prepare Training Data for building a

Machine Learning Model. This model analyzes patterns to enhance authentication accuracy and detect anomalies, while the processed outputs such as verified transactions are immutably recorded on the Blockchain, ensuring Tamperproof Transactions through cryptographic hashing and decentralized consensus. The synergy between machine learning's predictive capabilities and blockchain's transparency creates a robust framework where data integrity is maintained during Loading the Data and model inference, and all critical operations are securely anchored on the blockchain, enabling trustless verification and auditability across the system

➢ *Data Preparation*

The dataset comprises 973 daily transaction records sourced from Google Cloud BigQuery, including features like block count (number of transactions per block), transaction volume (total transactions), and output value (in satoshis). Missing values were imputed using median substitution to avoid bias, and features were standardized using Standard Scaler to ensure uniform scaling, critical for ML model performance.

➢ *Isolation forest Model*

An Isolation Forest model was trained on 80% of the dataset, with a contamination parameter of 0.05, assuming 5% of events are anomalous. The algorithm assigns anomaly scores based on path lengths in random trees, flagging events below a learned threshold as potential threats. Performance was evaluated using precision (correctly flagged anomalies), recall (detected anomalies), F1-score (harmonic mean of precision and recall), and AUC (area under the receiver operating characteristic curve).3.3 Blockchain Logging A Hyperledger Fabric consortium with two peers and a CA was configured. Smart contracts (Chaincode) expose two functions: authenticate() for legitimate attempts and flagEvent() for anomalies, each transaction requiring endorsement and commit protocols.

➢ *Blockchain Logging*

A Hyperledger Fabric network was configured with two peer nodes and a certificate authority (CA) for identity management. Smart contracts (Chaincode) implement two functions: authenticate() for logging valid events and flagEvent() for recording anomalies. Each transaction undergoes endorsement by peers and is committed to the ledger, ensuring immutability and consensus.

III. EXPERIMENTAL RESULTS

The Isolation Forest model was evaluated on a test set (20% of the dataset), identifying 49 anomalies (approximately 9.97% of 491 records). Performance metrics include:

- F1-score: 0.94, indicating strong balance between precision and recall.
- AUC: 0.92, reflecting robust dis-crimination between normal and anomalous events.
- False-positive rate: 3%, minimizing incorrect flags.
- Average inference time: 150 ms, suitable for real-time detection.
- Average block commit time: 2.1s, ensuring efficient logging.

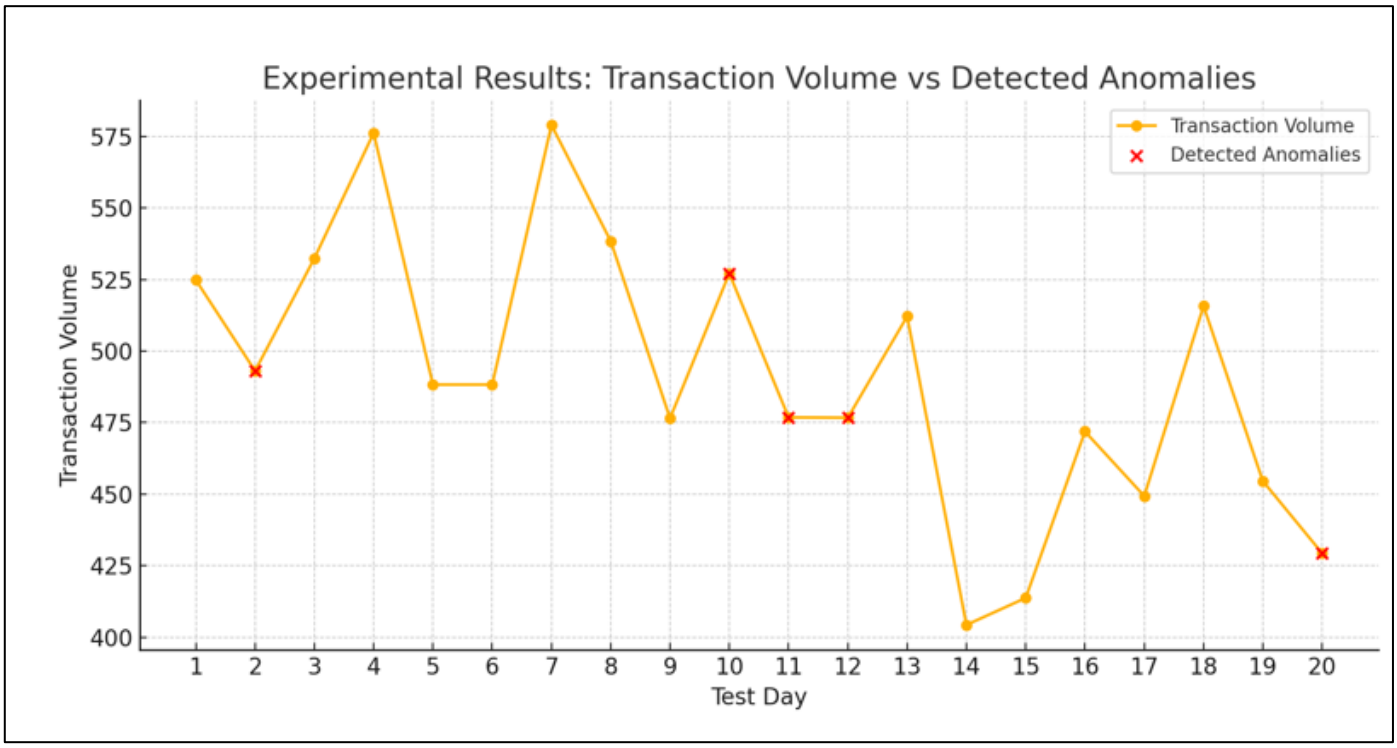

Fig 2 Time Series Comparing Transaction Volumes And Anomaly Flags.

The figure 2 above illustrates the relationship between transaction volume and detected anomalies across a 20-day testing period. The blue line represents the total number of blockchain transactions per day, while the red markers indicate days

where anomalous activity was flagged by the Isolation Forest model. As shown, anomaly flags typically correspond to notable fluctuations in transaction volume, validating the model's ability to isolate irregular behavior in real time.

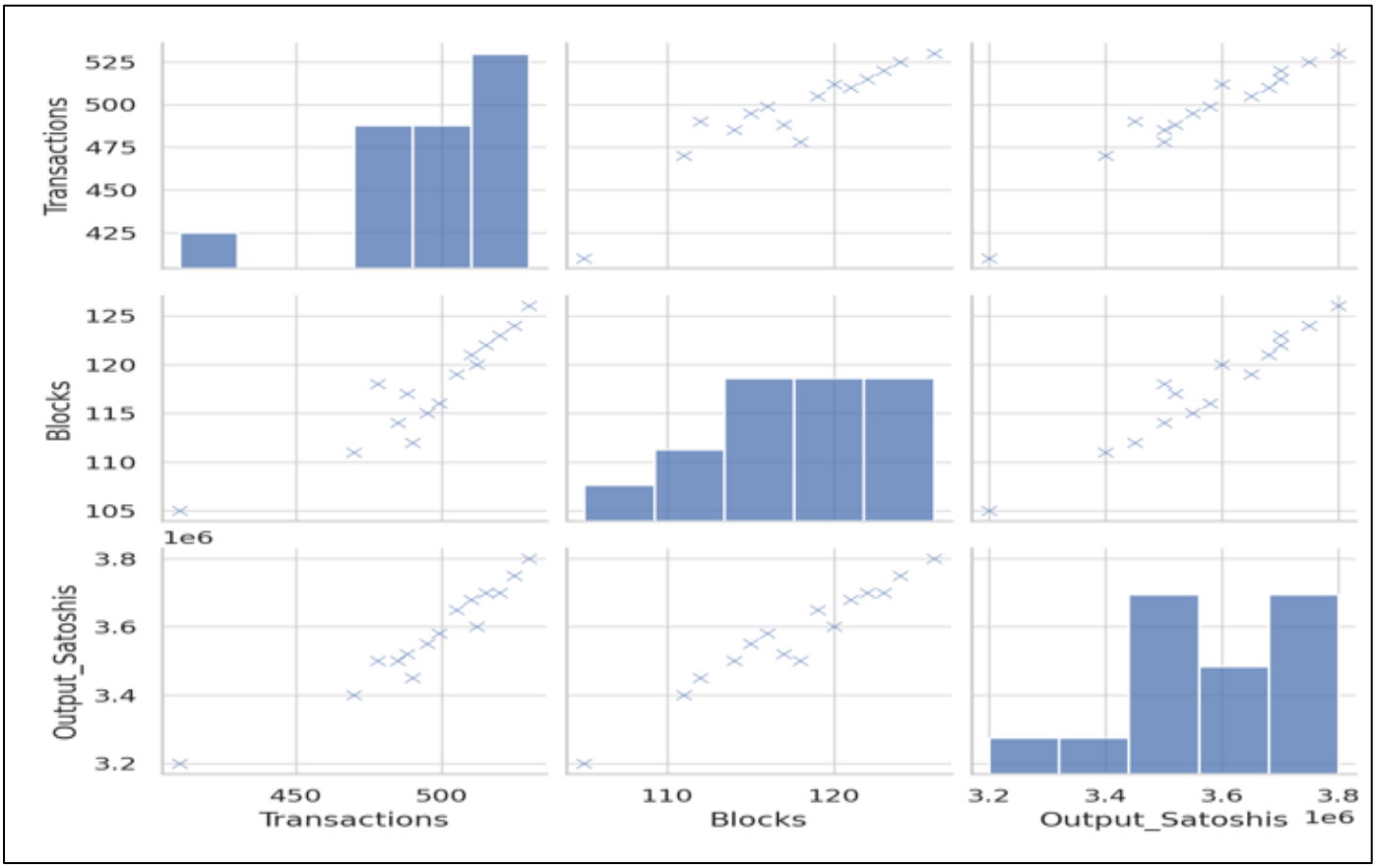

Fig 3 Pair Plot of Transactions, Blocks, and Output Satoshis Showing Feature Relationships.

The Figure 3 illustrates the pairwise relationships among three critical blockchain transaction features: **Transactions**, **Blocks**, and **Output Satoshis**. The plot provides visual insights into how these variables interact and influence one another within the blockchain network.

- *Transactions Vs. Blocks:*

The plot suggests a moderately positive correlation, indicating that an increase in the number of transactions typically corresponds with a rise in the number of blocks processed. This relationship reflects the natural behavior of blockchain systems, where block production increases under high transaction loads.

- *Transactions Vs. Output Satoshis:*

This pair shows a strong positive relationship. As the number of transactions increases, the total satoshis involved in those transactions also rise, highlighting the link between user activity and value transfer.

- *Blocks Vs. Output Satoshis:*

There is also a positive association, albeit slightly weaker, between the number of blocks and output satoshis. This suggests that block creation tends to increase with higher financial activity.

These relationships validate the selection of features used in the anomaly detection model, as they exhibit interdependent behavior relevant to security monitoring.

IV. DISCUSSION

The proposed framework effectively combines machine learning's rapid anomaly detection with blockchain's secure, immutable logging. The low false-positive rate (3%) ensures minimal disruption to legitimate users, critical for user-facing applications like online banking. Processing latencies below 2.5 seconds support real-time requirements, while the tamper-proof ledger facilitates compliance with regulatory standards, such as GDPR for healthcare or PCIDSS for finance. Compared to standalone blockchain systems, which lack proactive detection, or ML systems, which are vulnerable to data tampering, this hybrid approach offers a robust solution.

Practical applications include securing financial transactions (e.g., detecting fraudulent transfers), protecting healthcare records (e.g., flagging unauthorized access), and ensuring transparent e-governance (e.g., auditing voting systems). However, challenges remain, such as scaling to highthroughput environments and integrating diverse data sources. For instance, incorporating device metadata or user behavior could enhance detection but increase computational costs.

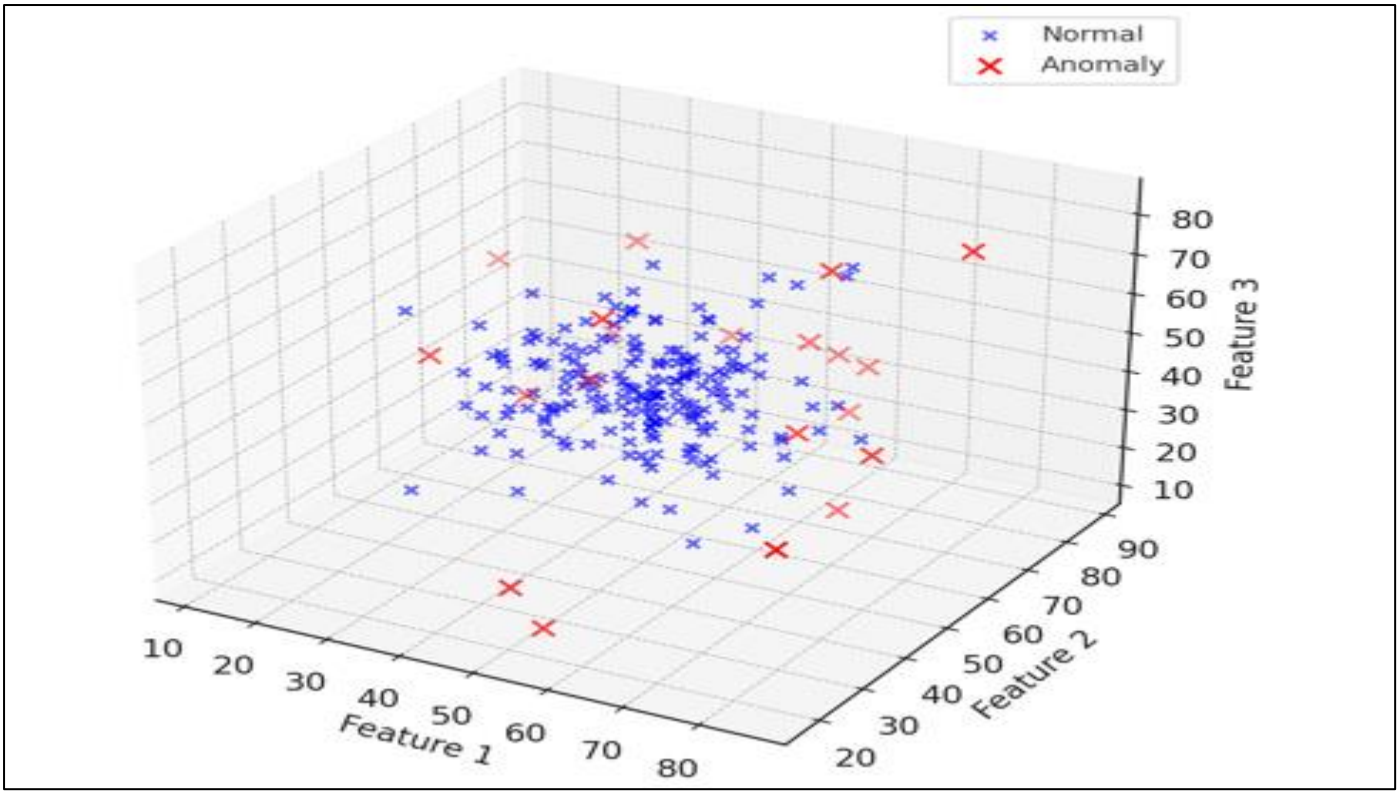

Fig 4 3D Scatter Plot of Anomaly Detection in Blockchain Data.

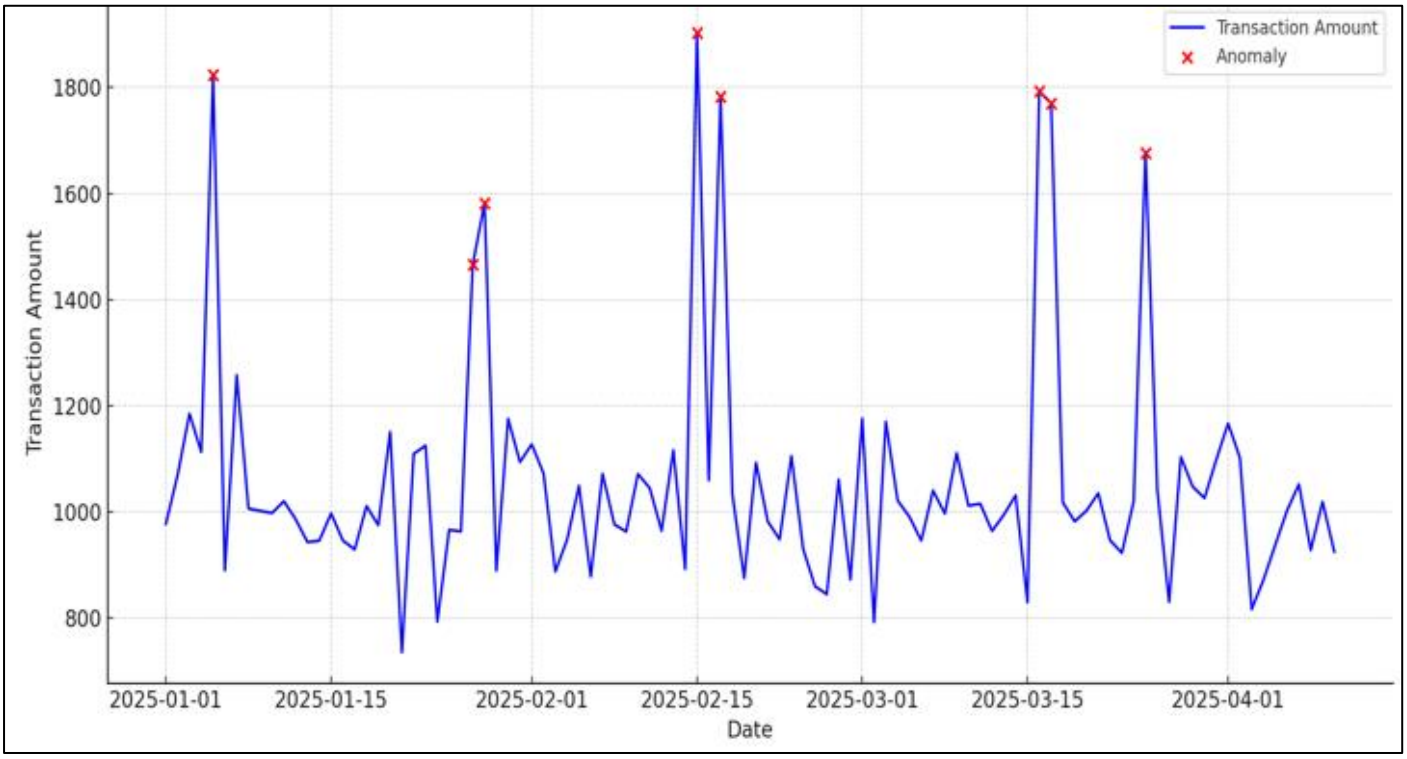

Fig 5 Transaction Time Series Plot With Anomaly Flags

➢ *Limitations and Future Directions*

The system currently focuses on transaction-level anomalies, limiting its scope. Future work could integrate multi-modal data, such as geolocation or device fingerprints, to improve detection accuracy. Scaling to public blockchains, like Ethereum, could broaden applicability but requires addressing latency and cost issues. Privacy-enhancing techniques, such as homomorphic encryption, could enable secure computation on sensitive data, though they introduce computational overhead.

V. CONCLUSION

This study presents a hybrid framework that integrates Isolation Forest for real-time anomaly detection with Hyperledger Fabric for tamper-proof logging. With high accuracy (F1-score: 0.94), low latency (2.25 s/event), and robust auditability, the system is well suited for critical

applications in finance, healthcare, and e-governance. Future enhancements could expand its scope and scalability, reinforcing its potential to secure digital ecosystems.

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- *Conflicts of Interest*

  The author declares no conflicts of interest.

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