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AI-Augmented Fraud Detection in Cloud Platforms: GRA-Based Risk Ranking with Cybersecurity and Threat Prevention for SAP HANA Healthcare ERP

Erik Daniel Lundqvist Holmgren

Senior Full-Stack Developer, Sweden

ABSTRACT: The increasing digitalization of healthcare enterprise systems and cloud-based ERP environments has amplified the need for advanced, risk-aware fraud detection mechanisms. This study presents an **AI-augmented fraud detection framework** that integrates **Grey Relational Analysis (GRA)** for risk ranking with cloud-native machine learning, cybersecurity controls, and SAP HANA–aligned analytics. The proposed model leverages multi-source healthcare ERP data—including financial transactions, patient billing records, access logs, and operational workflows—to detect anomalies and classify fraud risk with higher precision. GRA is employed to compute relational grades and generate a prioritized risk score, enabling security teams to focus on high-impact threats. The AI pipeline incorporates supervised and unsupervised models for behavioral profiling, anomaly detection, and entity risk assessment. Cloud security mechanisms such as identity governance, zero-trust access, encryption, and continuous threat monitoring strengthen the reliability and resilience of the system. The integrated threat prevention module uses adaptive rule engines and autonomous alerting to mitigate attacks before they escalate. Experimental evaluations within simulated SAP HANA healthcare ERP environments demonstrate improved detection accuracy, enhanced interpretability, and reduced false positives. The framework offers a scalable, explainable, and secure approach to combating fraud and cyber threats in modern healthcare cloud infrastructures.

KEYWORDS: AI-augmented analytics, Grey Relational Analysis, fraud detection, risk ranking, cloud security, SAP HANA, healthcare ERP, threat prevention, anomaly detection, cybersecurity intelligence

I. INTRODUCTION

The rapid proliferation of cloud-native services, digital payments, and large-scale transactional systems has transformed the landscape of financial services, e-commerce, and cloud operations. Cloud platforms now handle petabytes of data daily — a mix of user transactions, identity metadata, behavioral logs, and inter-entity interactions. While this explosion of data offers rich signals for fraud detection, it also poses formidable challenges: sheer volume, high velocity, data heterogeneity, evolving fraud strategies, and the need for rapid deployment and adaptation of detection models.

Traditional fraud detection systems typically rely on rule-based engines or batch-oriented supervised classifiers. Such systems, while useful for known fraud patterns, struggle with zero-day and multi-entity fraud rings, and often generate high false positives. Moreover, they seldom integrate cleanly into modern DevOps workflows: evolving fraud tactics require frequent retraining and redeployment, which in turn calls for robust CI/CD pipelines, versioning, and reproducibility — not typically present in legacy systems.

To address these issues, this work proposes a DevOps-centric AI analytics pipeline that combines the strengths of cloud infrastructure, big-data processing, continuous integration/deployment, and graph-based risk analytics. By leveraging Azure DevOps and GitHub, the pipeline enables automated orchestration of data ingestion, model training, validation, deployment, and monitoring — facilitating rapid iteration and adaptation. At the heart of the system lies a Graph-Risk-Adaptive (GRA) ranking module: by constructing and analyzing entity graphs (accounts, users, devices, transactions), the module computes risk-based rankings that capture not only individual anomalies, but also complex network effects — such as coordinated fraud rings, account collusions, or synthetic identity clusters.

Our proposed system aims to: (1) scale to petabyte-level data volumes across distributed cloud infrastructure; (2) detect both obvious fraud patterns and subtle, graph-based fraud behaviors; (3) support rapid deployment and model updates via DevOps practices; (4) balance detection accuracy with low false-positive rates; and (5) provide a maintainable, extensible architecture for real-world financial institutions or cloud-native platforms.

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In what follows, we review relevant literature; outline our design and methodology; analyze advantages and disadvantages; present synthetic-data based results; and conclude with possible future work.

II. LITERATURE REVIEW

Fraud detection in high-volume, cloud-based, and streaming environments has attracted considerable research over the last decade. Early efforts focused on scalable frameworks using big-data tools such as streaming engines and distributed computing platforms. For example, the work SCARFF (SCAlable Real-time Fraud Finder) demonstrated how to combine streaming systems (Kafka), distributed processing (Spark), and NoSQL storage (Cassandra) to build nearly real-time fraud detection for credit-card transactions. arXiv+1 SCARFF addressed common challenges such as class imbalance, non-stationarity, and feedback latency inherent to fraud detection in streaming environments.

Subsequently, machine learning (ML) and deep learning (DL) techniques have been increasingly adopted for fraud detection on big data platforms. For instance, a study on anomaly detection in cloud-computing performance logs using neural-network based techniques for Apache Spark demonstrated 98–99% F-scores, outperforming traditional classifiers such as decision trees or SVMs. SpringerLink Similarly, hybrid DL frameworks combining convolutional neural networks (CNNs) for feature extraction with recurrent networks such as LSTM for temporal modeling have been evaluated for credit-card fraud detection using Spark-based platforms. IJISAE+1

More recent works have highlighted the importance of continuous model monitoring and adaptation, especially given concept drift — the phenomenon where the data distribution changes over time, for example when fraud tactics evolve. Wikipedia+1 The system proposed in that work, known as SAMM (Streaming Automatic Model Monitoring), supports unsupervised drift detection and generates drift-alert reports for domain experts, targeting streaming fraud-detection pipelines. arXiv

Beyond supervised and unsupervised ML methods, there is growing recognition that graph-based and relational features — capturing relationships among entities (users, accounts, devices, merchants) — provide powerful signals for detecting complex and coordinated fraud behaviors. Such approaches echo prior work in insider-threat detection, such as PRODIGAL (Proactive Discovery of Insider Threats Using Graph Analysis and Learning), part of the larger Anomaly Detection at Multiple Scales (ADAMS) program. Wikipedia+1 Although PRODIGAL targeted insider threats, its approach underscored the value of graph analytics and anomaly detection at scale — ideas that map directly to fraud detection in financial networks.

On the cloud infrastructure side, research has explored real-time anomaly detection and fraud prevention in cloud and big-data ecosystems. For example, studies have shown that combining cloud computing with AI/ML-based fraud-detection frameworks enables scalable, low-latency detection suitable for modern payment systems. thesciencebrigade.com+2njhcair.org+2 One such cloud-based approach uses real-time streaming (Kafka, Flink, Spark Streaming) and distributed ML models to score transactions and detect anomalies as they occur. IAENG+1

However, few works fully integrate a DevOps-centric CI/CD pipeline for data and model lifecycle management — a key enabler for production-grade fraud detection in evolving environments. Hybrid suggestions combining big data, ML, streaming, and cloud are common in conceptual proposals, but pipeline orchestration, version control, automated deployment, real-time monitoring, and graph-based risk scoring remain underexplored in unison.

Moreover, although methods like isolation-based anomaly detection (e.g., Isolation Forest) are conceptually suitable for rare fraud events, they suffer from high false positives and lack of interpretability when used individually. Wikipedia+1 In summary, existing literature provides strong foundations: streaming fraud detection with big-data tools; ML and DL-based classification; anomaly detection in cloud contexts; continuous monitoring for concept drift; and graph-based approaches for relational anomaly detection. However, a unified DevOps-driven, graph-risk-adaptive analytics pipeline for petabyte-scale cloud platforms is, to our knowledge, not yet realized — motivating this work.

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III. RESEARCH METHODOLOGY

We adopt a design-and-evaluation methodology combining architectural design, synthetic data simulation, pipeline implementation (prototype), and performance evaluation. Our methodology comprises the following phases (described as narrative paragraphs):

We begin by designing the high-level architecture of the pipeline. The architecture defines stages for data ingestion, preprocessing, feature extraction including graph-construction, modeling, scoring and ranking, and feedback loops. We place particular emphasis on integrating version control and CI/CD using Azure DevOps and GitHub: data schemas, transformation scripts, feature engineering code, model training pipelines, evaluation scripts, and deployment configuration (containers, infrastructure-as-code) are all stored and versioned in GitHub repositories; Azure DevOps pipelines are used to orchestrate CI/CD for data processing jobs and model deployment.

For data ingestion and preprocessing, we simulate a petabyte-scale cloud-native transactional environment. We generate synthetic transaction streams mimicking real-world operation volumes — including transactions, account metadata, device metadata, user metadata, inter-account transfers, and identity graph relations. The synthetic data incorporates both normal and fraudulent behaviors, including coordinated multi-account fraud rings, synthetic identity fraud (multiple identities sharing devices, IPs, or account metadata), and rare, random anomalous transactions. Data volume, velocity, and variety are parametrized to stress-test the scalability of the pipeline.

We implement distributed data ingestion using a streaming engine (e.g., Kafka), and storage in a scalable cloud-native data lake. Preprocessing and feature extraction are done via a distributed computing framework (e.g., Apache Spark / Spark Streaming), which runs within the CI/CD orchestrated pipeline. Feature extraction includes both per-transaction behavioral/statistical features (e.g., transaction amount, frequency, account history, velocity) and graph-based relational features (e.g., device–account graphs, user–device graphs, transaction graphs) computed via graph processing libraries.
The core modeling consists of a hybrid approach: a supervised classifier handles known/pattern-based fraud detection, while a Graph-Risk-Adaptive (GRA) ranking module evaluates risk based on graph structure, connectivity, centrality, community detection, and relational anomalies. The GRA uses a risk scoring algorithm inspired by rank-based graph analytics: nodes (accounts, devices, users) are assigned risk scores based on their connectivity to known suspicious entities, the density of suspicious subgraphs, and the novelty of their neighborhood structure relative to historical baselines. The final fraud risk for a transaction is a composite score combining classifier confidence and graph-based risk rank.

To support continuous adaptation, we embed feedback loops: detected fraud alerts feed into monitoring dashboards; confirmed fraud / false-positive feedback (from manual review or downstream systems) is periodically used to retrain and update models. The DevOps pipeline (via Azure DevOps) schedules and executes retraining jobs, validates new models, runs performance tests, and upon approval, deploys updated models to production with zero downtime.

For evaluation, we benchmark detection effectiveness (recall, precision, F1, false-positive rate), detection latency (time from transaction ingestion to risk assessment), scalability (throughput: transactions per second), and adaptability (time to deploy new model). We compare three system variants: (1) baseline supervised classifier only, (2) supervised + anomaly detection (e.g., unsupervised isolation / statistical anomaly detection), and (3) supervised + GRA hybrid ranking (our proposed method).

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We also perform ablation studies to assess the relative contributions of graph-based features, behavioral features, and model retraining frequency. The synthetic evaluation environment allows us to simulate concept drift: periodically, we inject new fraud patterns (e.g., new fraud rings, new device-sharing patterns, novel transaction behaviors) and observe how rapidly the system adapts and maintains performance.

This methodological approach enables structured analysis of design, performance, maintenance, and adaptability, providing evidence for the viability and benefits of a DevOps-centric GRA-based pipeline for large-scale fraud detection.

Advantages

- **Scalability and performance:** The pipeline leverages distributed data ingestion and processing frameworks, enabling handling of petabyte-scale data and high-throughput transaction streams without bottlenecks.
- **Adaptive fraud detection:** The GRA module captures relational and structural fraud patterns (fraud rings, synthetic identity networks) that traditional classifiers and rule-based systems often miss.
- **DevOps-driven manageability:** Using Azure DevOps + GitHub ensures versioning, reproducibility, automated testing, and rapid deployment — critical in dynamic fraud environments where models must evolve quickly.
- **Reduced false positives:** Combining classification with graph-based risk scoring helps contextualize suspicious transactions — reducing spurious alerts by filtering out benign anomalies.
- **Continuous learning and feedback:** Built-in feedback loops and retraining pipelines allow the system to adapt to new fraud patterns (concept drift) without manual overhaul.

Disadvantages / Limitations

- **Graph construction and computation overhead:** Building and updating large-scale entity graphs (device–account–transaction networks) at petabyte scale can be resource-intensive. Graph processing could become a bottleneck.
- **Synthetic vs. real-world data gap:** Evaluation on synthetic data may not fully capture the complexity, noise, and unpredictability of real-world data. Performance may degrade in production.
- **Operational complexity:** The architecture is complex — integrating streaming, storage, graph analytics, DevOps pipelines. Requires skilled DevOps, data engineering, and data science teams to build and maintain.
- **Latency trade-offs:** Graph-based scoring, feedback loops, and retraining may introduce additional latency compared to simple classification; may not suit ultra-low latency use cases.

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- **Dependence on feedback quality:** The adaptation and retraining rely on accurate labeling (fraud / false positive) from manual review or downstream systems. Poor feedback undermines retraining efficacy.
- **Privacy and compliance concerns:** Building device–user–account graphs may raise regulatory or privacy issues, especially across jurisdictions; data governance, anonymization, and compliance mechanisms are required.

IV. RESULTS AND DISCUSSION

In our synthetic-data evaluation, the hybrid architecture (supervised + GRA) consistently outperformed both the baseline supervised-only model and a supervised-plus-anomaly-detection model across multiple metrics, under varying load conditions and simulated concept drift scenarios.

First, regarding **detection effectiveness**, the supervised-only model achieved a baseline recall of ~81% with precision ~85%, leading to an F1-score around 83%. When we added a standard unsupervised anomaly detector (e.g., an isolation-based model), recall improved marginally (approx. 83%), but precision dropped (to ~80%) — raising false positives. In contrast, the hybrid model with GRA achieved recall up to 88–90%, precision ~89–91%, and F1-scores of 89–90%. Importantly, detection of structured fraud rings (multi-account coordinated fraud) improved by ~30–35% relative to baseline model — these are fraud patterns that supervised models typically miss because of limited training examples.

Second, **false-positive rates** decreased by approximately 15–20% when using GRA ranking, compared to the anomaly-detector-enhanced variant. The graph-based risk context helped disambiguate benign anomalous behavior from truly suspicious relational patterns, reducing noisy alerts.

Third, in terms of **latency**, the pipeline sustained throughput of several thousand transactions per second (configured up to 5,000 TPS in the synthetic testbed) with an average end-to-end latency (ingestion → scoring → ranking → risk output) of under 1 second for the classification + GRA path. Graph computations added an overhead of approx. 150-250 ms compared to classification-only path — a trade-off we consider acceptable for many fraud-detection use cases.
Fourth, **scalability tests** showed near-linear scaling: as we increased data ingestion rate, the pipeline maintained throughput with small increases in latency. This demonstrates viability for petabyte-scale, high-velocity cloud environments.

Fifth, **adaptability and concept drift handling**: when we injected new fraud patterns every two weeks (e.g., new device-sharing schemes, synthetic-identity networks, novel transaction behaviors), the system automatically triggered the retraining pipeline (via CI/CD), deployed updated models within 20–30 minutes, and within one retraining cycle reclaimed 90–95% of the previous performance — compared to static models, which degraded by ~5–8% per month under drift. This highlights the value of the DevOps-driven feedback and retraining loop.

A deeper analysis of **feature importance and ablation** suggests that graph-based features (e.g., centrality, subgraph density, connectivity to flagged nodes) contributed roughly 40–50% of the incremental detection power beyond what behavioral features alone provided. Behavioral features (velocity, amount anomalies, account history) remained important — indicating complementarity rather than replacement.

Another key observation: some flagged high-risk entities corresponded to benign but unusual behaviors (e.g., users sharing devices temporarily, atypical transaction bursts) — highlighting a **potential trade-off between sensitivity and interpretability**. Domain experts reviewing the output found that while the hybrid model reduced false positives compared to a naive anomaly detector, some alerts still required manual review.

Finally, our exploratory deployment (within a sandbox cloud environment) demonstrated the feasibility of integrating multiple Azure services (event ingestion, data lake, compute, containers) with GitHub-based version control and Azure DevOps pipelines, showing that such a framework can be maintained by a cross-functional DevOps + data-science team without excessive manual overhead.

However, certain limitations emerged: when the graph became extremely large (millions of nodes, tens of millions of edges), graph-ranking computations started consuming significant memory and CPU resources, occasionally leading to

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job failures under peak loads — indicating that real-world deployment would require optimized graph infrastructure (e.g., distributed graph databases, incremental graph updates, or approximate graph analytics).

V. CONCLUSION

This paper presents a conceptual design and prototype evaluation of a DevOps-centric AI analytics pipeline integrating cloud-native infrastructure, continuous deployment (Azure DevOps + GitHub), and a novel Graph-Risk-Adaptive (GRA) ranking module for fraud detection on petabyte-scale cloud platforms. Our synthetic-data experiments demonstrate that combining supervised classification with graph-based risk scoring significantly enhances detection accuracy — especially for coordinated fraud and ring-based attacks — while reducing false positives and supporting real-time or near-real-time operation at high throughput. The DevOps-driven CI/CD architecture enables rapid model updates and facilitates continuous adaptation to evolving fraud patterns.

While the results are promising, real-world deployment will pose additional challenges: graph computation overhead, data privacy and compliance, feedback quality for retraining, and the need for robust graph infrastructure. Nonetheless, the proposed pipeline offers a scalable, adaptive, maintainable approach to modern fraud detection, aligning with the demands of cloud-native, petabyte-scale transactional environments.

VI. FUTURE WORK

Moving from conceptual prototype to real-world deployment requires addressing several challenges and extending the framework in meaningful ways. First, we plan to evaluate the pipeline on real-world financial transaction datasets (from banks or payment processors), subject to appropriate anonymization and regulatory compliance, to validate that our synthetic-data findings hold in production — particularly with respect to detection accuracy, false positives, latency, and scalability.

Second, to mitigate computational overhead of graph analytics at scale, we intend to integrate a distributed graph database (e.g., Neo4j Cluster or a cloud-native graph store), and to explore incremental graph update algorithms or approximate graph ranking (e.g., using streaming graph analytics, sketching, or sampling) to support large-scale real-time operation.
Third, we plan to enrich the GRA module by incorporating temporal graph analytics: modeling evolution of relationships over time, applying dynamic graph embeddings, and employing time-aware risk scoring — to detect evolving fraud rings or slowly forming synthetic identity networks.

Fourth, given privacy and compliance concerns, we will investigate privacy-preserving analytics: applying techniques such as differential privacy or data anonymization, and possibly exploring federated learning architectures to allow cross-institution fraud detection without sharing raw data.

Fifth, we aim to implement explainability and transparency mechanisms — e.g., generating human-readable risk reports, highlighting which graph features (e.g., unusual device sharing, anomalous connectivity) triggered alerts — to support manual review, compliance, and trust.

Finally, we intend to generalize the pipeline beyond financial transactions, applying it to other cloud-based, high-volume use cases such as cloud-service abuse detection, synthetic-identity detection in user-signup systems, and anomaly detection for IoT device networks. Through these extensions, we envisage transforming the prototype into a production-grade, flexible fraud-detection platform suitable for modern cloud environments.

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