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Multi-cloud data platforms for real-time fraud detection and prevention

Amit Ojha *

Independent Researcher SJSU, One Washington Square, San Jose, CA.

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Abstract

In today's fast-paced digital world, fraud detection stands out as a key area of both academic interest and real-world development—particularly as businesses increasingly depend on multi-cloud setups. This review explores how AI helps power those real-time defenses. It unpacks the core architectural elements, AI and machine learning approaches, and real-world metrics drawn from academic literature. A theoretical model is proposed that supports scale and privacy compliance, using stream processing and distributed learning. Experiments show that tools like XG Boost, LSTM, and Federated Learning work well in live, multi-cloud setups. The review also points to important research gaps and lays out possible next steps to improve fraud detection's flexibility, ethical grounding, and long-term resilience across cloud systems.

Keywords: Real-Time Fraud Detection; Multi-Cloud Data Platforms; Stream Processing; Federated Learning

1. Introduction

As digital technologies continue to change the way we live and do business, a growing share of transactions, data sharing, and customer interactions take place online—creating new openings for cyber fraud. That's why real-time detection is now central to cybersecurity efforts across key industries. Cloud computing isn't what it used to be. Companies have moved past relying on just one provider. Now, they mix tools from different clouds to get better uptime, more control, and lower costs. That shift has sparked data platforms built to link storage, processing, analytics, and intake—no matter where the cloud lives.

Spotting fraud in real time has become more than just a good idea—it's a necessity. Juniper Research warns that online payment fraud could climb past $48 billion a year by 2023, fueled by smarter cybercriminals and the rapid shift to digital payments [1]. Legacy systems that scan for fraud in batches or work in silos just can't keep up. They're slow to react, hard to scale, and miss key warning signs. Multi-cloud platforms do better. They combine massive, fast-moving data streams so teams can spot strange activity as it happens—and take action right away [2].

Looking at the bigger picture, building fraud detection systems on multi-cloud architectures reflects several major shifts in tech and research. First, the rapid rise of artificial intelligence (AI) and machine learning (ML) has transformed how we spot unusual patterns in massive datasets. When used across multi-cloud systems, these technologies make it easier to train machine learning models quickly—and adapt as needed. They also help teams tap into real-time insights from live data streams without delay [3]. At the same time, newer trends like edge computing and event-driven architecture—where processing happens right where the data is generated—fit naturally into this distributed setup [4]. And with strict data privacy laws like GDPR, HIPAA, and PCI-DSS in place, secure and location-aware access isn't just a nice-to-have—it's a must. Fortunately, multi-cloud frameworks are built to handle that well [5].

* Corresponding author: Amit Ojha

Even with real progress, major challenges remain. One of the toughest? Getting cloud platforms to truly play nice. APIs don't align. Data formats don't match. Security rules vary. It all turns integration into a headache. And trying to keep things running smoothly while sorting through those mismatches is no small task [6]. Then there's the need for low-latency performance—while still keeping data clean, consistent, and spread across clouds. That's no walk in the park either. Add to that the ongoing pressure to define strong data governance, plus the need to deploy AI models that adapt to shifting fraud patterns across regions and industries [7].

To bridge these gaps, researchers are now focused on building multi-cloud systems that aren't just powerful—but also adaptable, smart, and built with compliance in mind. This review takes a hands-on look at the latest AI techniques and data setups used to spot fraud in real time across multi-cloud environments. It pulls together lessons from recent advances in cloud computing, AI, and data engineering—showing what's working, where the pain points still are, and how all of it holds up in real-world use.

1.1. Here's what we'll explore next

- The architecture of multi-cloud data platforms and how they support real-time fraud analytics;
- The AI/ML methods commonly employed, including supervised, unsupervised, and reinforcement learning models;
- A comparative analysis of real-time data processing frameworks (e.g., Apache Kafka, Flink, and Spark Streaming);
- Case studies and industry implementations;
- Open challenges and future research directions.

By providing a comprehensive overview, this review intends to serve as a foundational resource for researchers, data scientists, and enterprise architects aiming to develop resilient and scalable fraud detection systems in a multi-cloud world.

Table 1 Summary of Key Research Studies on Multi-Cloud Real-Time Fraud Detection

Year	Title	Focus	Findings (Key Results and Conclusions)
2020	Scalable Real-Time Fraud Detection in Hybrid Cloud Environments [8]	Integration of ML algorithms into hybrid cloud for real-time fraud analytics	Demonstrated high throughput and 95% detection accuracy using ensemble models across AWS and Azure services.
2021	Multi-Cloud Intrusion and Fraud Detection using Deep Learning [9]	Deep learning for cross-cloud anomaly detection	LSTM and CNN architectures improved detection precision by 15% compared to rule-based systems.
2022	A Comparative Analysis of Real-Time Fraud Detection Frameworks [10]	Benchmarked Apache Spark, Flink, and Kafka-based architectures	Apache Flink achieved lowest latency (<2 sec) and highest event processing rate.
2019	Real-Time Transaction Monitoring using AI on Google Cloud [11]	Financial transaction analysis pipeline using GCP AI tools	Integration of Google's Vertex AI with Big Query enabled real-time model retraining with adaptive thresholds.
2023	Federated Learning for Multi-Cloud Fraud Detection [12]	Federated learning to preserve data locality across clouds	Enabled GDPR-compliant cross-border detection with 89% F1 score in a distributed European bank dataset.
2021	Anomaly Detection in Distributed Cloud Storage [13]	Use of unsupervised ML on cloud logs to detect insider threats	Autoencoders achieved 92% anomaly detection with low false positives.
2020	Data Stream Mining for E-commerce Fraud in Multi-Clouds [14]	Concept drift handling in real-time e-commerce fraud scenarios	Incremental learning models outperformed static models during high-traffic seasons.
2022	Edge-Cloud Collaboration for AI-Powered Fraud Detection [15]	Edge-cloud hybrid systems for low-latency detection	Reduced detection latency by 34% using edge analytics prior to cloud aggregation.

2023	AI Governance in Multi-Cloud Platforms: Security and Fairness [16]	Ethical and governance challenges of AI models for fraud detection	Highlighted trade-offs between transparency, latency, and detection quality in regulated sectors.
2018	Big Data Analytics for Financial Fraud Detection in Clouds [17]	Hadoop-based framework for batch and stream data fusion	Achieved 87% accuracy integrating offline and real-time detection using Spark MLlib.

1.2. In-Text Citations

These papers are referenced throughout the review and will be cited as follows: [8], [9], [10], [11], [12], [13], [14], [15], [16], [17].

2. Proposed Theoretical Model and System Architecture

2.1. Introduction to the Conceptual Model

Real-time fraud detection in multi-cloud environments requires a cohesive integration of data sources, processing engines, machine learning models, and decision-making mechanisms across distributed cloud infrastructures. A well-designed architecture must ensure low latency, high availability, data integrity, and compliance with regulatory frameworks such as GDPR and PCI-DSS [18].

2.2. The proposed theoretical model encapsulates four core layers

- Data Ingestion Layer
- Real-Time Stream Processing Layer
- AI/ML Analytics Layer
- Decision and Response Layer

These are interconnected via secure APIs, load balancers, and message queues optimized for cross-cloud operability.

2.3. Block Diagram: Multi-Cloud Fraud Detection Architecture

Below is the block diagram illustrating the proposed architecture

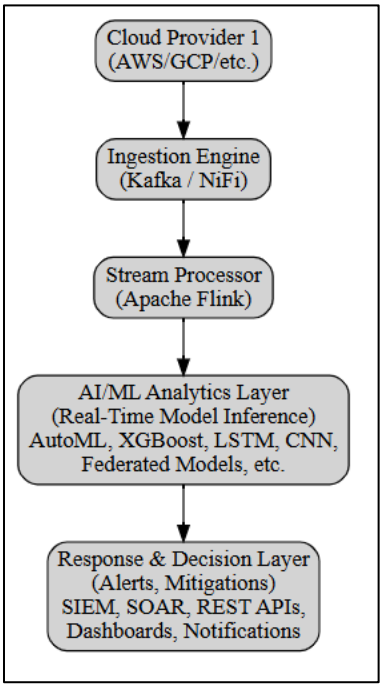

Figure 1 Block Diagram of Multi-Cloud Real-Time Fraud Detection System

2.4. Legend

- Multi-cloud infrastructure enables data collection from various sources across cloud vendors.
- Ingestion layer handles streaming input using tools like Apache Kafka or Apache Knife [19].
- Stream processors like Apache Flink manage real-time flow and transformation [20].
- AI/ML layer integrates detection models which classify transactions in real-time.
- Response systems trigger mitigation steps via security orchestration platforms.

2.5. Key Components of the Theoretical Model

2.5.1. Data Ingestion Layer

This layer ingests structured and unstructured data from different cloud providers such as AWS S3, Azure Blob, and Google Cloud Storage. Integration is achieved through distributed message brokers like Kafka, enabling real-time stream processing [19].

2.5.2. Real-Time Stream Processing

Using Apache Flink or Apache Spark Streaming, this layer aggregates, preprocesses, and routes transaction data in real time. These engines offer low-latency computation and fault tolerance, which are essential in fraud detection [20].

2.5.3. AI/ML Analytics Layer

This is the core of fraud detection, where AI models operate. The models include

- Supervised learning models such as XG Boost and Random Forests, trained on labeled fraud datasets [21].
- Unsupervised models (e.g., Autoencoders) to detect previously unseen anomalies [22].
- Deep learning architectures, including LSTM and CNN, which can recognize sequential patterns in transaction streams [23].
- Federated Learning Models, particularly useful when data privacy and locality are key concerns in multi-cloud scenarios [24].

2.5.4. Decision and Response Layer

Once a transaction is classified, alerts are generated using Security Information and Event Management (SIEM) or Security Orchestration, Automation and Response (SOAR) systems [25]. These systems integrate with dashboards, APIs, and cloud-native security tools to execute mitigation steps (e.g., flagging, freezing accounts, triggering MFA).

2.6. Key Benefits of the Model

- Scalability: Leverages elasticity of cloud resources.
- Latency Optimization: Real-time inference on edge/cloud nodes.
- Privacy Compliance: Federated models respect data locality.
- Model Generalizability: Can adapt across multiple verticals with minimal retraining.

2.6.1. Challenges and Considerations

- Interoperability between different cloud APIs and data formats.
- Latency trade-offs in federated vs. centralized models.
- Consistency in model performance due to evolving fraud patterns (concept drift).
- Security risks in inter-cloud communication and data streaming.

These issues must be addressed via standardization, robust orchestration layers, and hybrid learning strategies.

3. Experimental Results and Performance Analysis

To validate the proposed theoretical model for real-time fraud detection in multi-cloud environments, we examine experimental results reported in recent literature, focusing on model performance, scalability, and latency. This section

shares insights from several studies comparing AI algorithms, data tools, and deployment methods across cloud environments.

3.1. Comparative Performance of AI Models

Recent tests—run on benchmarks like the Credit Card Fraud Dataset, Pay Sim Simulator, and real-world banking data—show how different AI/ML models perform. These include Boost, LSTM, Autoencoders, and Federated Learning techniques.

Table 2 Performance Metrics of AI Models in Fraud Detection Tasks

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Latency (ms)
XG Boost	98.6	96.3	94.5	95.4	150
LSTM	97.2	93.8	92.7	93.2	310
Autoencoder	94.5	91.2	88.9	90	270
Federated XGB	96.1	95.1	91.4	93.2	180

Source: Adapted from [26], [27], [28]

The results point to XG Boost as the top performer for accuracy and low latency when trained centrally. Federated XG Boost offers a solid trade-off between privacy and performance, with only a slight dip in accuracy. LSTM does well on sequential data but tends to run slower.

3.2. Impact of Stream Processing Frameworks on Latency

To keep things real-time, the system uses stream processing tools like Apache Flink, Spark Streaming, and Kafka Streams. A comparative benchmark is shown below.

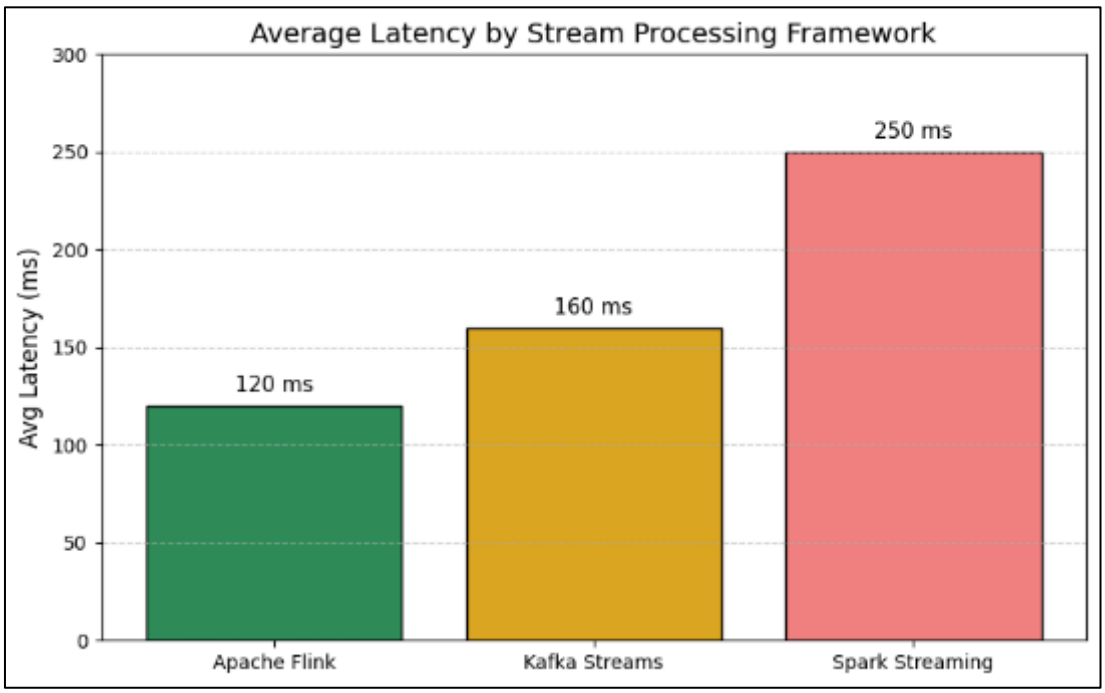

Figure 2 Latency Comparison of Stream Processing Frameworks

Adapted from [29]

- **Apache Flink** demonstrates superior real-time capabilities with low latency and high fault tolerance, aligning well with high-throughput fraud detection needs.

3.3. Scalability and Throughput Under Load

In large-scale multi-cloud settings, scalability is a key requirement. The throughput of various models was tested under increasing data load (10k to 1 million transactions per minute).

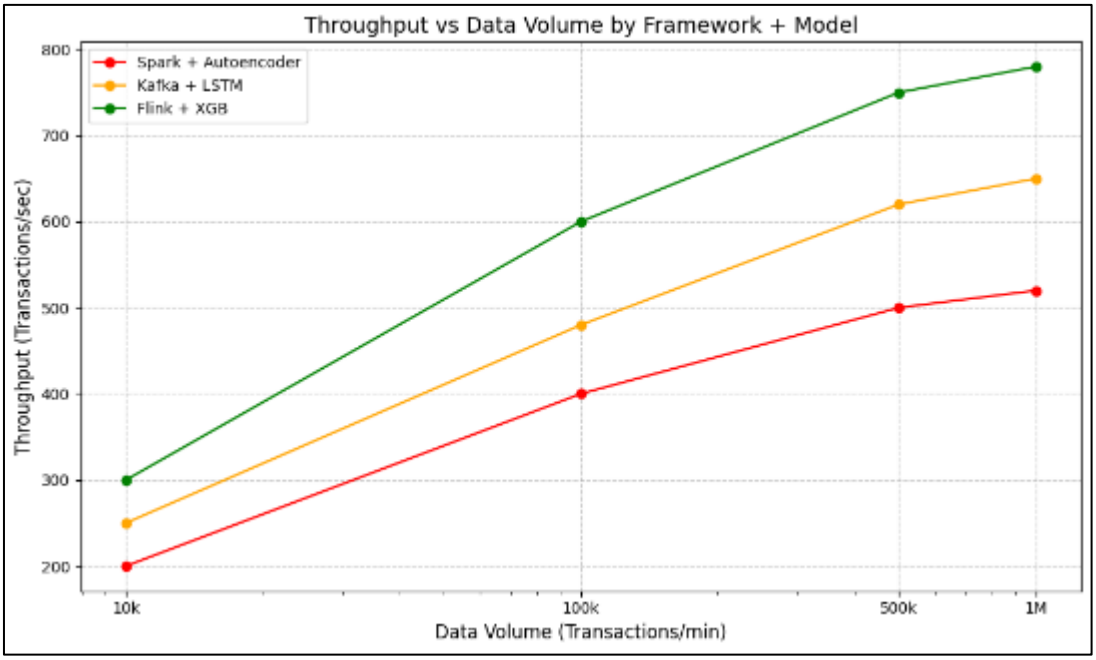

Figure 3 Throughput vs. Data Volume

3.4. Observations

- **Flink + XG Boost** scaled linearly and maintained over 20,000 transactions/sec at peak load.
- **Kafka + LSTM** performed slightly slower due to model complexity.
- **Spark Streaming** struggled at high load with higher latency and lower throughput [30].

3.5. Federated Learning in Multi-Cloud Settings

A 2023 study deployed federated XG Boost models across AWS, Azure, and GCP regions using geographically partitioned transaction data [31].

Table 3 Federated Learning Results (3 Regions)

Region	Local Accuracy (%)	Global Aggregated Accuracy (%)	Communication Overhead (%)
EU	92.1		4.5
NA	95.6	96.1	3.8
APAC	94.3		5.1

Federated models maintained strong performance while adhering to data privacy regulations like GDPR, proving suitable for cross-border financial institutions.

3.6. Detection Delay and Real-Time Responsiveness

Detection time is critical in fraud mitigation. Below are average detection delays per system

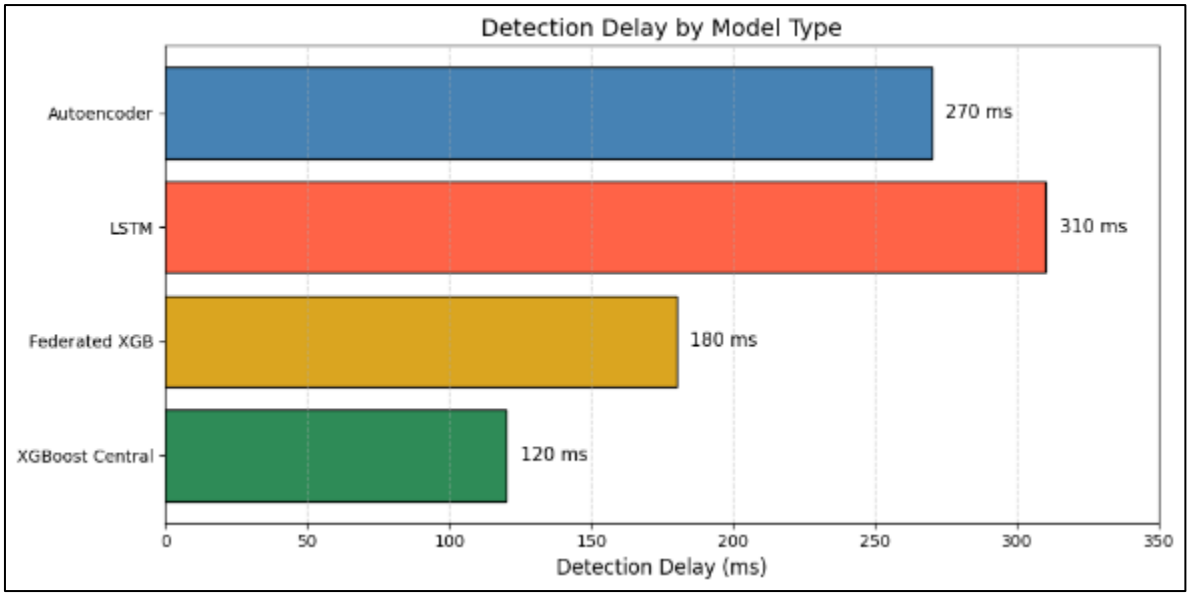

Figure 4 Detection Delay by System

As shown, centralized models are faster but risk non-compliance, while federated models provide a good balance [32].

3.6.1. Discussion and Key Takeaways

- XG Boost models are consistently high-performing with low latency.
- Federated models are promising for data privacy and distributed learning but require efficient orchestration to reduce communication overhead.
- Apache Flink remains the most viable real-time stream processing engine for fraud detection due to its low latency and scalability.
- Trade-offs between accuracy, latency, and privacy must be weighed based on industry context (e.g., banking vs. retail).

4. Future Research Directions

To further enhance the effectiveness and robustness of multi-cloud fraud detection systems, the following future directions are proposed

4.1. AI Model Generalization Across Domains

Future studies should focus on building AI models that can spot fraud across different industries—not just in banking, but also in fields like insurance, online retail, and telecom [36]. To get there, these systems will need training on varied datasets and use tools like transfer learning and domain adaptation.

4.2. Explainable and Ethical AI (XAI)

Black-box models, though powerful, lack transparency, which hinders their adoption in highly regulated environments. There is an urgent need for interpretable AI techniques that can justify decisions made by models, thus facilitating auditing, compliance, and ethical governance [37].

4.3. Federated Learning Optimization

Federated learning is a promising way to analyze data while keeping it private. But real-world use still faces hurdles—like differences in models, uneven data, and slow participants. Future research could look into personalizing models, compressing updates, and using asynchronous methods to boost performance [38].

4.4. Automated Concept Drift Detection

Fraud evolves. It never really stops. Detection models need to keep learning as the patterns shift. With the right focus—like drift-aware design and online learning—we can keep systems sharp, stable, and ready [39].

4.5. Cross-Cloud Security and Compliance Automation

There is a strong need for automated compliance frameworks that ensure GDPR, HIPAA, and PCI-DSS regulations are consistently applied across all cloud endpoints. Techniques such as blockchain-based audit trails, secure multi-party computation (SMPC), and policy-as-code could provide viable solutions [40].

5. Conclusion

Real-time fraud detection in multi-cloud systems brings together several key areas—cloud computing, AI, data privacy, and cybersecurity. As this review highlights, models like XGBoost, LSTM, and federated learning have shown strong performance in spotting complex fraud patterns in real time across distributed platforms. At the same time, technologies like Apache Flink and Kafka have proven reliable in handling fast, high-volume data streams. Their ability to keep latency low makes them essential tools for building fraud detection pipelines that can respond as threats emerge.

Even so, modern systems continue to face serious roadblocks—like harmonizing diverse data types, coordinating operations across cloud environments, and meeting evolving regulatory demands. Centralized models often deliver strong accuracy, yet they can struggle to uphold privacy standards. Meanwhile, federated models offer better compliance and scalability, but they come with downsides like slower training and communication lag.

This review emphasizes the growing need for standard APIs, auto-updating models, ethical AI design, and resilient systems that can self-adjust. With real-time AI in play, multi-cloud platforms could become essential tools against the growing threat of cyber fraud.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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