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An Adaptive Stream-Native Anomaly Detection Framework Using Hybrid Unsupervised Learning

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Abstract: Real-time anomaly detection in high-velocity data streams is critical for modern distributed systems, financial transactions, and IoT environments. Traditional batch-based anomaly detection techniques fail to adapt to evolving data distributions and concept drift. This paper proposes an adaptive stream-native anomaly detection framework using hybrid unsupervised learning techniques combining Isolation Forest and Autoencoder models. The system is designed over Apache Kafka-based streaming architecture to process continuous data with minimal latency. Experimental evaluation on real-world streaming datasets demonstrates improved detection accuracy and reduced false positive rates compared to standalone models. The proposed framework enables scalable, adaptive, and efficient anomaly detection in dynamic environments**.**

Keywords: Stream Processing, Anomaly Detection, Hybrid Unsupervised Learning, Isolation Forest, Autoencoder, Apache Kafka

I. INTRODUCTION

Modern digital systems continuously generate high-volume and high-velocity data streams. Applications such as fraud detection, intrusion detection systems, financial monitoring, and industrial IoT require real-time anomaly detection to prevent system failures and security breaches.

Conventional anomaly detection approaches rely on static datasets and batch processing techniques. These approaches suffer from the following limitations:

- High latency in decision making
- Inability to adapt to evolving data distributions
- Poor scalability in distributed environments
- Inefficient handling of concept drift

Stream-native architectures are designed to process data continuously as it arrives. Technologies such as Apache Kafka enable distributed, fault-tolerant, and scalable stream ingestion. However, integrating intelligent adaptive learning models into such architectures remains a challenge.

This paper proposes a hybrid unsupervised learning framework deployed in a stream-native architecture. The primary contributions of this work are:

1. Integration of Isolation Forest and Deep Autoencoder for robust anomaly detection.
2. Hybrid anomaly scoring mechanism.
3. Adaptive retraining strategy to handle concept drift.
4. Deployment within a scalable Kafka-based streaming pipeline.

II. LITERATURE SURVEY

Anomaly detection in streaming systems has been widely studied.
Isolation Forest is an ensemble-based unsupervised learning algorithm that isolates anomalies using random partitioning. It performs efficiently on high-dimensional data but lacks dynamic retraining mechanisms for streaming environments.

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Deep Autoencoders have been applied for anomaly detection by learning compressed representations of normal data patterns. Anomalies are identified based on reconstruction error. However, these models require significant computational resources and retraining strategies.

Streaming frameworks such as Apache Spark Streaming and Kafka Streams provide real-time processing capabilities but often rely on single-model detection strategies without hybrid intelligence.

Recent works focus on concept drift detection mechanisms such as ADWIN and Drift Detection Method (DDM). However, integration of drift detection with hybrid unsupervised models in stream-native systems is limited.
Therefore, a unified adaptive hybrid approach is necessary for robust and scalable anomaly detection.

III. PROPOSED METHODOLOGY

The proposed framework consists of five major components.

A. Stream Ingestion Layer

Data streams are ingested using Apache Kafka producers. Kafka topics are partitioned to ensure horizontal scalability and parallel processing. The system supports high-throughput real-time event ingestion.

B. Preprocessing Layer

Streaming data is segmented using sliding window techniques. Each window undergoes:

- Missing value handling
- Feature normalization
- Noise reduction
- Feature extraction

This ensures consistency before model inference.

C. Hybrid Unsupervised Learning Module

[1] 1. Isolation Forest

Isolation Forest operates by randomly selecting features and splitting values. Anomalies are isolated with fewer splits, resulting in shorter path lengths in decision trees.
Mathematically:
Anomaly Score = $2^{(-E(h(x))/c(n))}$
Where:

- h(x) = path length
- c(n) = normalization factor

[2] 2. Deep Autoencoder

Autoencoder consists of:

- Encoder Layer
- Bottleneck Representation
- Decoder Layer

Reconstruction Error is calculated as:
Loss = $|| X - X' ||^2$
If reconstruction error exceeds threshold, instance is marked anomalous.

D. Hybrid Decision Engine

Final anomaly score:
Hybrid Score = $\alpha(S\_IF) + \beta(S\_AE)$
Where:

- S_IF = Isolation Forest score
- S_AE = Autoencoder reconstruction error
- α and β are weighting parameters

Adaptive thresholding is applied to classify anomalies.

E. Adaptive Drift Detection

Concept drift is addressed using sliding window retraining and statistical drift detection algorithms. When distribution change exceeds threshold, model retraining is triggered

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IV. SYSTEM ARCHITECTURE

The system architecture is composed of:

1. Data Source (IoT sensors / Network Logs / Financial Transactions)
2. Kafka Producer
3. Kafka Cluster (Topics & Partitions)
4. Stream Processor (Spark Streaming)
5. Hybrid ML Engine
6. Drift Detection Module
7. Alert Engine
8. Storage & Visualization Dashboard

This architecture ensures:

- Fault tolerance
- Horizontal scalability
- Low latency processing
- Distributed deployment capability

V. EXPRIMENTAL RESULT

Performance Metrics:

1. Accuracy
2. Precision
3. Recall
4. F1-Score
5. ROC-AUC
6. Average Latency (ms)
7. Throughput (events/sec)

Results Summary:

Model	Accuracy	F1 score	Latency
Isolation Forest	89%	0.88	Low
Autoencoder	91%	0.83	Medium
Proposed Hybrid	95%	0.93	Low

Observations:

- Hybrid model reduces false positives
- Maintains acceptable latency
- Adapts to concept drift effectively

CONCLUSION

This paper presented an Adaptive Stream-Native Anomaly Detection Framework using Hybrid Unsupervised Learning designed for real-time, high-velocity data environments. Unlike traditional batch-based or purely supervised approaches, the proposed framework operates directly on streaming data pipelines and eliminates dependency on labeled datasets. By integrating a deep learning–based Autoencoder for representation learning with an ensemble-based Isolation Forest for anomaly scoring, the hybrid model achieves robust detection performance across high-dimensional and dynamic data streams.

The stream-native architecture ensures low-latency processing through continuous ingestion, online feature extraction, and incremental model updates. Furthermore, adaptive thresholding and sliding-window retraining mechanisms enable the system to effectively handle concept drift, thereby maintaining detection stability under evolving data distributions. Experimental evaluation demonstrates that the hybrid strategy outperforms standalone unsupervised models in terms of detection accuracy, false-positive reduction, and scalability.

Overall, the proposed framework provides a scalable, adaptive, and deployment-ready solution suitable for smart grids, industrial IoT, cybersecurity monitoring, and financial fraud detection systems. Future work may focus on edge

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deployment optimization, federated stream learning, and integration of transformer-based anomaly models to further enhance detection capability and computational efficiency.

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