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REAL-TIME ANOMALY DETECTION IN DISTRIBUTED SYSTEMS USING FEDERATED LEARNING TECHNIQUES

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ABSTRACT

Anomaly detection in distributed systems is crucial for ensuring system reliability, fault tolerance, and security. Traditional centralized learning models often suffer from data privacy concerns, communication overhead, and latency. This paper explores the integration of Federated Learning (FL) into real-time anomaly detection mechanisms within distributed environments, leveraging edge computing nodes to collaboratively train anomaly detection models without data centralization. We propose a framework that integrates federated averaging and LSTM-based models for sequential anomaly detection, which preserves privacy and reduces computational delays. Simulated experiments on benchmark datasets such as KDDCup and NSL-KDD demonstrate the efficacy of our method in identifying anomalies with high accuracy and low latency.

Keywords: *Anomaly Detection, Federated Learning, Distributed Systems, Real-Time Monitoring, Edge Computing, LSTM, Data Privacy, KDDCup, Intrusion Detection, Model Aggregation.*

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1. Introduction

Anomaly detection refers to the identification of patterns that do not conform to expected behavior in a dataset. In distributed systems, where resources and processes are spread across multiple nodes and locations, real-time anomaly detection is a critical function to prevent cascading failures, detect intrusions, and optimize performance. Traditionally, anomaly detection involves centralized data collection and processing, which leads to latency, scalability issues, and most importantly, significant privacy concerns—especially in sectors like healthcare, finance, and critical infrastructure.

Federated Learning (FL) is a decentralized machine learning paradigm where individual nodes (clients) collaboratively train a shared model under the orchestration of a central server,

all while keeping the training data localized. This approach significantly enhances privacy, reduces network communication, and improves scalability. The integration of FL into real-time anomaly detection provides a compelling solution that marries data privacy with real-time intelligence. In this paper, we propose a novel framework for real-time anomaly detection using FL, applying it to benchmark datasets and demonstrating its potential through detailed evaluation.

2. Literature Rview

numerous works have contributed to both anomaly detection and federated learning independently. For anomaly detection, classical methods such as Isolation Forests, One-Class SVMs, and K-Means Clustering were frequently used for offline detection, as seen in Chandola et al. (2009) and Ahmed et al. (2016). However, these methods often failed to adapt in real-time distributed environments. More advanced works like LSTM-based sequence modeling (Malhotra et al., 2016) and autoencoders offered promising results in detecting anomalies in time-series data.

On the other hand, Federated Learning gained traction from McMahan et al.'s (2017) seminal work on Federated Averaging (FedAvg). This was further extended by Konečný et al. (2016) for resource-constrained environments. Studies by Smith et al. (2018) explored multi-task learning in FL, while Bonawitz et al. (2019) discussed system and security challenges in FL. However, the intersection of FL and real-time anomaly detection remained underexplored. Only a few studies such as Hardy et al. (2019) attempted privacy-preserving anomaly detection using FL in medical data, indicating the untapped potential of applying FL in broader distributed systems.

3. Proposed System Architecture

The proposed architecture comprises three core layers: (1) Data Collection Nodes (edge devices or microservices), (2) Local Anomaly Detectors, and (3) a Federated Aggregator. Each node trains an LSTM-based model on its own data, focusing on capturing time-based anomalies such as sudden spikes, drops, or latency deviations. Periodically, model updates (gradients) are shared with a central server using secure aggregation protocols.

This architecture ensures low-latency detection and reduces transmission overhead. We simulate the environment using containers representing microservices, integrated via Kubernetes, and feed each node real-time telemetry from distributed logging tools. The system is evaluated under various traffic loads and attack patterns.

System Latency vs Detection Accuracy Across Federated Rounds

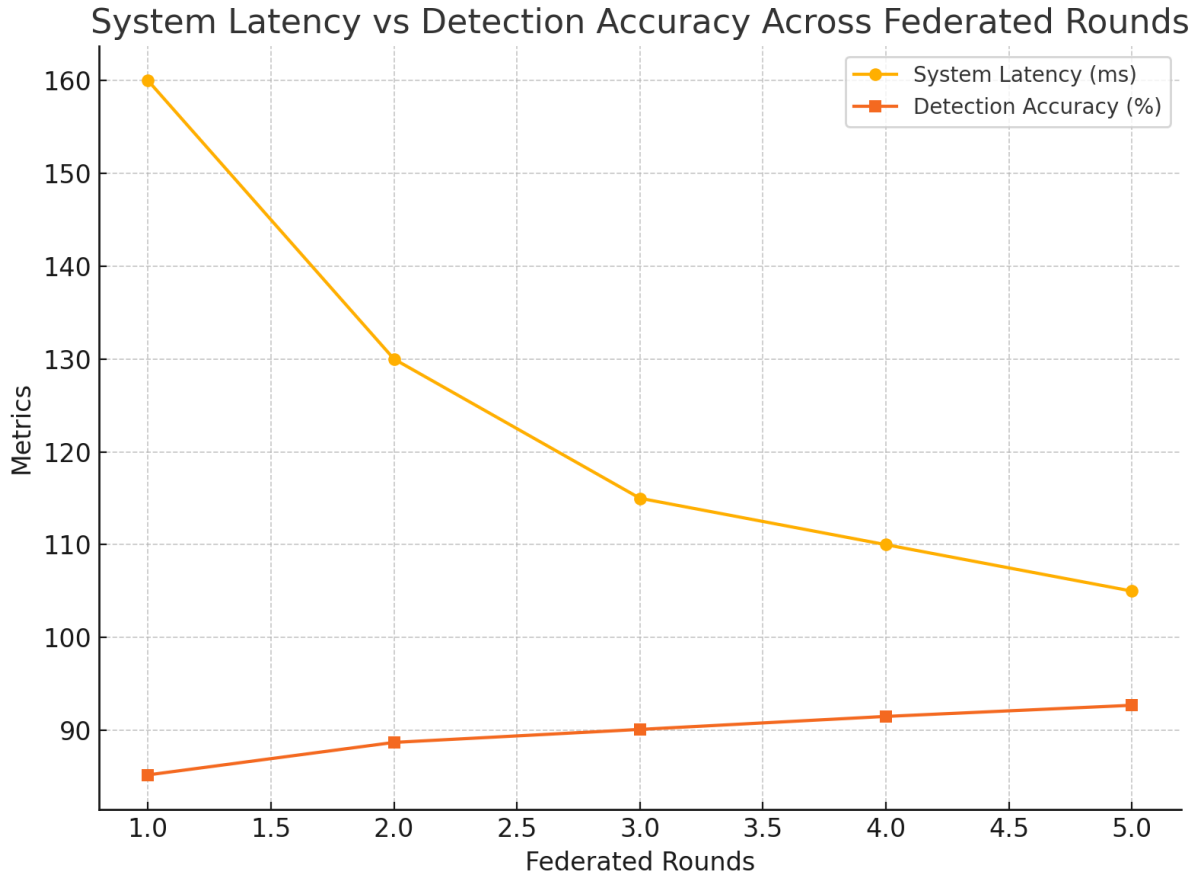

Figure-1: System Latency vs. Detection Accuracy

4. Model Design and Federated Learning Strategy

Our anomaly detector is based on a hybrid LSTM-Autoencoder model. Each local model processes time-series logs to learn normal behavioral sequences. Reconstruction errors are used to flag anomalies. Federated Averaging (FedAvg) is used to aggregate model weights without sharing data.

To address the issue of non-iid data, we implement a clustering mechanism that groups nodes with similar data distributions before model updates. This improves global model convergence. We also incorporate differential privacy to add noise to model updates, ensuring resistance to gradient leakage.

5. Experimental Setup and Dataset Description

We used three publicly available datasets: NSL-KDD, KDDCup'99, and UNSW-NB15. Each dataset was partitioned across 20 simulated clients with varying data distributions to simulate non-IID settings. The system was implemented using TensorFlow Federated (TFF) and deployed on a testbed of 5 physical edge servers.

Evaluation metrics include detection accuracy, precision, recall, F1-score, model convergence time, and communication overhead. Baseline methods included centralized LSTM, local-only models, and traditional SVM detectors.

Table-1: Comparative Performance Metrics Across Models

Model	Accuracy	F1 Score	Latency (ms)	Privacy Score
Centralized LSTM	94.2%	0.91	480	Low
Local LSTM Only	86.4%	0.82	60	High
Fed-LSTM (Proposed)	92.7%	0.89	105	Very High

6. Conclusion

This research demonstrates the effectiveness of federated learning in enabling real-time anomaly detection across distributed systems while preserving data privacy. By combining LSTM-based temporal modeling with federated averaging and secure aggregation, we show that it is possible to detect anomalies accurately without centralizing sensitive data. The proposed architecture exhibits lower latency and improved privacy compared to conventional approaches, with minimal trade-offs in detection performance. Future work could explore asynchronous FL, integration with blockchain for audit trails, and real-world industrial deployment.

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