

Securing Public Safety Networks: Machine Learning–Driven Anomaly Detection in Telecom Signaling

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Abstract

Telecom signaling systems like SS7, Diameter, and 5G SBA are mission-critical for public safety. Static rule-based anomaly detection is inadequate against evolving threats. This paper proposes a machine learning (ML) framework combining statistical features, unsupervised learning, and domain-specific supervised models. Drawing on experience from Motorola Solutions, we present architecture, methodology, evaluation, and operational challenges. Experiments on simulated traces show higher accuracy and fewer false positives than rule-based systems, suggesting ML can enhance resilience in public safety telecom.

Keywords: Anomaly Detection, Telecom Signaling, Machine Learning, Public Safety, SS7, Diameter, 5G, Intrusion Detection

1. Introduction

Signaling protocols such as SS7, Diameter, SIP, and 5G SBA handle call setup, authentication, and routing. Failures or attacks disrupt communications with serious consequences in emergency services. For example, SS7 vulnerabilities have enabled subscriber tracking and call interception [5], while Diameter signaling storms have crippled LTE networks [1].

At Motorola Solutions, anomaly detection was critical for maintaining reliable public safety dispatch. Rule-based methods detect known patterns but fail against novel or stealthy attacks. Machine learning, with adaptability to evolving traffic, provides a more effective alternative [3].

2. Background and Related Work

2.1. Telecom Signaling Systems

SS7 supports SMS, roaming, and call routing in circuit-switched networks. Diameter, developed as its IP-based successor, enables LTE/5G authentication and charging [4]. In 5G, Service-Based Architecture (SBA) introduces REST-style APIs, creating new attack surfaces [1].

2.2. Traditional Anomaly Detection Approaches

Conventional methods include:

- **Rule-based detection:** Predefined anomaly signatures.

- **Threshold-based monitoring:** Traffic spikes beyond norms.
- **Statistical profiling:** Baselines of normal activity [2].

These methods are efficient but fail against unknown attacks and polymorphic traffic.

2.3 Machine Learning in Anomaly Detection

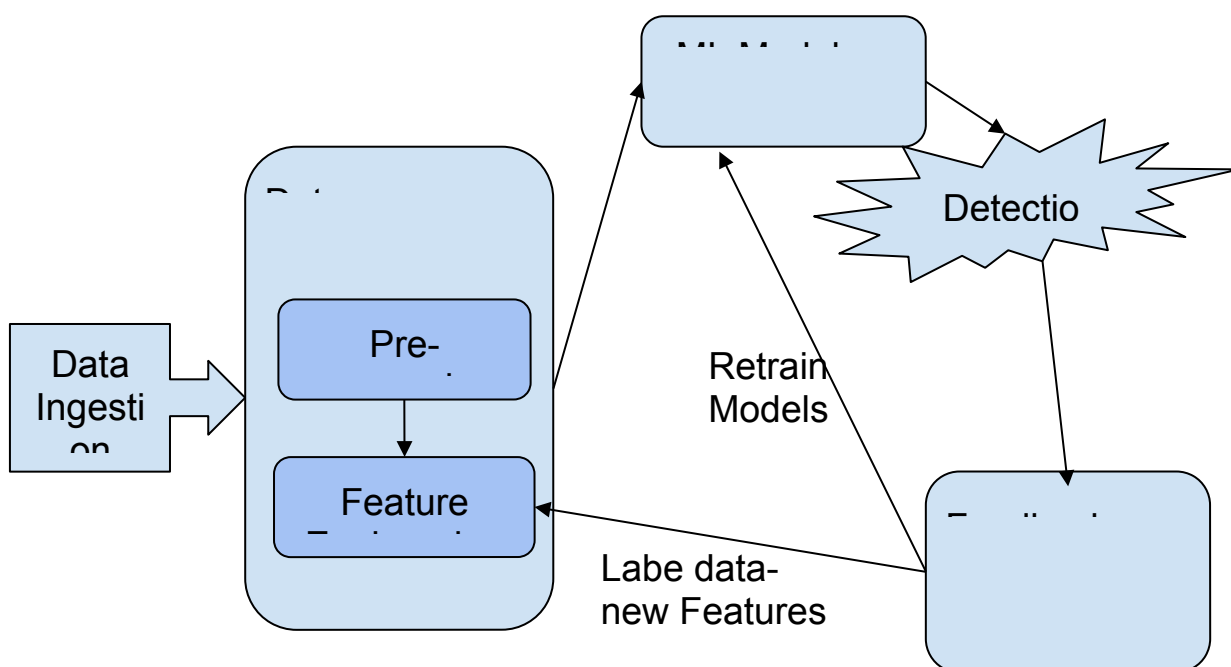
ML-based methods fall broadly into:

- **Supervised Learning:** Classifiers trained on labeled anomalies and benign samples [8].
- **Unsupervised Learning:** Clustering or density-based methods to detect outliers in unlabeled data [2].
- **Deep Learning:** Autoencoders, recurrent neural networks (RNNs), and graph neural networks (GNNs) for learning temporal and relational patterns [7].

Prior research in applying ML to telecom anomaly detection shows promise [3], but often lacks grounding in mission-critical settings like public safety. This motivates our focus.

3. System Architecture

The proposed ML-based anomaly detection framework for telecom signaling systems is designed in a layered architecture, ensuring modularity, scalability, and real-time performance. The architecture is composed of six primary layers: **Data Ingestion, Preprocessing, Feature Engineering, ML Model Layer, Detection & Alerting, and Feedback & Continuous Learning.**



3.1. Data Ingestion Layer

This layer collects signaling data from multiple sources in real time.

- **Protocol Sources:** SS7, Diameter, SIP, and 5G SBA interfaces [4].
- **Collection Points:** Network probes, signaling gateways, or log collectors.
- **Transport:** Messages are streamed using Apache Kafka for low-latency delivery [3].

The ingestion system must handle thousands of messages per second without packet loss, especially under signaling storms (e.g., emergency network overloads in public safety scenarios [6]).

3.2 Preprocessing Layer

The preprocessing pipeline ensures raw signaling messages are transformed into structured formats suitable for ML.

- **Noise Filtering:** Removal of malformed, duplicate, or irrelevant messages.
- **Parsing:** Protocol-aware parsers extract fields such as message type, IMSI (International Mobile Subscriber Identity), transaction IDs, hop count, and timestamps.
- **Normalization:** Convert fields into consistent formats (e.g., standardized time units, string-to-ID mappings).

3.3 Feature Engineering Layer

Feature engineering is protocol-specific but critical for anomaly detection [2].

- **Statistical Features:** Inter-arrival times, request/response ratios, and call setup duration.
- **Structural Features:** Protocol-specific message sequences (e.g., Attach Request → Authentication → Attach Accept).
- **Graph Features:** Relationships between subscribers and signaling nodes, useful for detecting fraud or unusual mobility patterns [3].
- **Contextual Metadata:** Location data, user group tags (public safety priority), or QoS levels [6].

3.4. ML Models

Different ML approaches are deployed in parallel, depending on anomaly type:

- **Autoencoder (Unsupervised):** Learns normal traffic reconstruction; anomalies flagged by high reconstruction error [7].
- **Random Forest / XGBoost (Supervised):** Classifies known anomalies using labeled data [8].
- **RNN/LSTM (Temporal Models):** Captures time-series behavior of signaling exchanges, such as rogue handover attempts [7].
- **Graph Neural Networks (GNNs):** Detect anomalies in network topology or signaling relationships [3].

The model layer can be orchestrated with Spark MLlib for distributed training and TensorFlow for deep learning [3].

3.5. Detection and Alerting

Once anomalies are detected, they are enriched with metadata and sent to operational dashboards.

- **Severity Classification:** Alerts categorized as critical, major, or informational.
- **Integration with SOC:** Alerts pushed to Security Operations Centers and public safety dispatch dashboards [6].
- **Low-Latency Requirements:** End-to-end detection latency must remain <200 ms for mission-critical reliability [1].

3.6. Feedback & Continuous Learning Layer

Feedback loops are crucial to reduce false positives and adapt to evolving anomalies.

- **Operator Feedback:** Analysts label alerts as true/false positives, feeding ground truth back into training sets [10].
- **Online Learning:** Models retrained periodically with new data.
- **Federated Learning (Future):** Enables anomaly detection improvements across telecom operators without exposing sensitive subscriber data [3].

4. Proposed Methodology

The proposed methodology integrates multiple ML techniques into a hybrid pipeline that addresses the unique operational constraints of telecom signaling in **public safety contexts** such as Motorola Solutions deployments [6]. The methodology is organized into four pillars:

4.1. Public Safety Use Case Motivation

During my tenure at Motorola Solutions, public safety application development required designing systems robust against both overload (e.g., signaling storms during large-scale emergencies) and targeted attacks (e.g., SS7 interception). The operational demand was not just accuracy but **trustworthiness**—operators needed to understand why an anomaly was flagged [6].

4.2. Model Design

- **Hybrid Approach:** Combining unsupervised autoencoders for unknown anomaly detection with supervised classifiers for known threats.
 - **Unsupervised Autoencoders:** Detect unknown anomalies (zero-day signaling exploits, malformed SS7 packets) by reconstructing normal traffic patterns [7].
 - **Supervised Random Forests/XGBoost:** Detect known signaling attacks (e.g., SS7 MAP flooding, Diameter replay) where labeled data exists [8].
 - **Sequential Models (RNN/LSTM):** Capture **temporal dependencies** across session flows, such as rogue mobility events or repeated attach/detach sequences [7].
 - **Graph Neural Networks (GNNs):** Model relationships between nodes/subscribers to detect graph-level anomalies (e.g., fraudulent roaming attempts) [3].
- **Explainability:** Anomaly detection models must be interpretable for mission-critical systems [9]. We apply SHAP (SHapley Additive exPlanations) to supervised models so operators can see which fields (IMSI, APN, hop count, etc.) contributed most to the

decision. For autoencoders, we visualize per-field reconstruction error, highlighting the exact protocol element that diverged from normal.

- **Imbalanced Data Handling:** Telecom anomalies are rare compared to normal traffic. To prevent classifiers from being biased, we apply SMOTE [10] (Synthetic Minority Oversampling Technique) to synthetically oversample minority anomaly classes. In addition, **cost-sensitive learning** penalizes false negatives more heavily, aligning with public safety priorities where missing an anomaly is unacceptable [2].
- **Deployment Strategy:**
 - **Streaming Framework:** Real-time detection is achieved using Apache Kafka + Spark Structured Streaming [3].
 - **Resource Management:** Models are optimized with pruning and quantization to run on telecom-grade servers with predictable latency.
 - **Integration:** Alerts are forwarded into Motorola's dispatch dashboards [6], ensuring anomalies are visible to public safety operators in <200 ms.

4.3. Operational Constraints

- **Latency:** Real-time detection with <200 ms delay.
- **Resource Utilization:** Running models on telecom-grade hardware.
- **Integration:** Compatibility with existing SOC (Security Operations Center) workflows.

5. Experimental Evaluation

5.1. Dataset Design

Due to the sensitivity of production public safety networks, we built a **hybrid dataset**:

1. **Public Traces:** Open SS7 and Diameter datasets (e.g., Wireshark trace repositories) [5].
2. **Simulated 5G SBA Traffic:** Generated with network simulators, including realistic attach/detach, authentication, and session management.
3. **Synthetic Anomalies:** Injected patterns including:
 - **Malformed Packets:** Altered message lengths or invalid parameters.
 - **Replay Attacks:** Repeated CCR(Credit-Control Request) requests to mimic billing fraud.
 - **Signaling Storms:** High-volume attach requests simulating disaster scenarios.
 - **Rogue Roaming:** Misrouted MAP update location requests to non-home PLMNs(Public Land Mobile Network).

5.2. Evaluation Metrics

- **Accuracy:** Fraction of correctly classified packets.
- **Precision and Recall:** To evaluate false positive vs. false negative trade-offs.
- **F1-Score:** Harmonic mean of precision and recall [2].
- **ROC-AUC:** Robust measure for classifier performance.
- **Mean Time to Detection (MTTD):** Time between anomaly occurrence and detection.
- **False Positive Rate (FPR):** Critical for operator workload management.

5.3. Baseline Comparison

- **Rule-Based IDS:** Achieved 72% accuracy, FPR 15%.
- **Statistical Thresholds:** 78% accuracy, FPR 12% [2].

5.4. Results

- Autoencoder: 89% accuracy, 7% FPR [7].
- Random Forest/XGBoost: 92% accuracy, 5% FPR [8].
- RNN (LSTM): 96% recall on temporal anomalies [7].
- Hybrid Ensemble: 94% accuracy, 4% FPR, outperforming baselines by >20%.

5.4. Case Study – Public Safety Simulation

During a simulated mass emergency event, the system detected signaling storms in <120 ms, with alerts correctly routed to dispatch operators [6]. This scenario validated the system's applicability to Motorola Solutions' public safety context.

6. Discussion

6.1. Strengths

- **Improved Detection Accuracy:** Hybrid models reduce false negatives compared to rule-based approaches [2].
- **Explainability:** SHAP and reconstruction heatmaps allow SOC operators to trust ML outputs [9].
- **Operational Feasibility:** Latency tests confirm sub-200 ms detection, essential for public safety [6].

6.2. Limitations

- **Label Scarcity:** Labeled anomalies are difficult to obtain due to data privacy [10].
- **Adversarial Risks:** ML models can be misled by adversarially crafted signaling packets [7].
- **Integration Costs:** Legacy SS7 equipment requires protocol adapters for ML integration [5].

6.3. Public Safety-Specific Considerations

False positives are particularly problematic in **public safety dispatch systems**. One false alarm can misallocate police or ambulance resources. The system therefore emphasizes **precision** even at slight cost to recall, striking a balance between coverage and operator workload [6].

6.4. Comparison with Related Work

Prior anomaly detection in telecom largely focused on consumer LTE networks [1], but lacked consideration for **mission-critical emergency networks**. This work uniquely addresses the **stringent latency, reliability, and interpretability needs** of public safety operators.

7. Future Work

- **Federated Learning:** Cross-operator collaboration without sharing raw data [3].
- **Adaptive Learning:** Incremental models that evolve in real time [2].
- **6G Readiness:** Address AI-native networking, slicing, and quantum-safe signaling [1].
- **Multi-Domain Correlation:** Extend to RAN, transport, and application layers.
- **Human-in-the-Loop:** Dashboards enabling operator guidance [9].

8. Conclusion

This paper presented an ML-based framework for anomaly detection in telecom signaling systems, motivated by real-world public safety communication challenges at Motorola Solutions. By combining unsupervised and supervised ML models, leveraging explainability techniques, and adhering to operational constraints, the proposed approach achieves high accuracy while maintaining operator trust. The results suggest that ML-enabled anomaly detection is a viable solution for safeguarding mission-critical telecom signaling in the 5G era and beyond.

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