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AI-Based Anomaly Detection for Security Events: A Practical, High-Fidelity Framework

Sadhana Adhav*, Manisha Kshirsagar†

*Department of Computer Science and Application, JSPM University, Pune, India

†Faculty of Science and Technology, JSPM University, Pune, India

***Abstract*—**Modern organizations generate massive volumes of security telemetry—from endpoints, network appliances, identity providers, and cloud services—making manual triage of threats infeasible. This paper presents an AI-driven framework for *anomaly detection in security events* that couples representation learning with streaming inference to surface rare, high-risk behaviors in near real time. We unify heterogeneous logs through a compact event schema, learn temporal and relational patterns via deep sequence models and graph encoders, and compute calibrated anomaly scores that adapt to environment drift. The system blends unsupervised methods (autoencoders, isolation- based detectors), weakly supervised signals (heuristics, watch- lists), and supervised fine-tuning when ground truth is available. We address practical challenges such as extreme class imbalance, concept drift, noisy labels, and high-latency pipelines, and we incorporate privacy-preserving and explainability mechanisms suitable for regulated settings. Experiments on mixed enterprise- like datasets show consistent gains in precision at low false- positive rate and significant reductions in mean time to detect. We release a set of implementation guidelines covering feature design, thresholding under uncertainty, and robust evaluation for security operations (SecOps) workflows.

***Index Terms*—**Anomaly Detection, Cybersecurity Analytics, Intrusion Detection, SIEM, Streaming ML, Concept Drift, Graph Learning, Explainable AI

I. INTRODUCTION

Security teams face an expanding attack surface: identity- centric intrusions, living-off-the-land techniques, lateral move- ment, and stealthy exfiltration. Legacy rule systems either miss novel behaviors or overwhelm analysts with alerts. AI-based anomaly detection offers a complementary path by learning "normal" patterns of entities—users, hosts, applications, and processes—and flagging deviations that merit investigation.

However, building a reliable detector for security data is non-trivial. Security telemetry is high-dimensional, sparse, bursty, and heavily imbalanced; signals evolve as infrastructure and attacker tradecraft change; and operational constraints de- mand low latency, transparency, and cost efficiency. This work contributes a deployable end-to-end approach that (i) unifies multi-source logs into a consistent, privacy-aware schema; (ii) extracts semantic, temporal, and graph-relational features; (iii) combines multiple anomaly learners with calibrated scoring; and (iv) explains decisions to analysts with concise evidence.

Our design goals are: (1) *fidelity*—spotting subtle, low-and- slow behaviors; (2) *stability*—resilience to drift and seasonal- ity; (3) *operability*—simple thresholds and clear explanations; and (4) *ethics*—data minimization, purpose limitation, and fairness-aware evaluation.

II. BACKGROUND AND RELATED WORK

Classic intrusion detection systems include signature/rule- based engines and statistical baselines.

Machine learning approaches span density estimation, clustering, one-class classification, isolation forests, autoencoders, and sequence models. Recent advances emphasize temporal modeling (RNN/Transformer), graph representation learning for entity interactions, and hybrid ensembles that fuse unsupervised and supervised signals. In production, drift handling, alert prioritization, and analyst feedback loops remain decisive for efficacy.

III. PROBLEM DEFINITION

Let $\mathsf{E} = \{e_t\}^{T}_{t=1}$ be a stream of security events aggregated from multiple sources. Each event e_t is mapped to a structured tuple $(s_t, a_t, r_t, \mathbf{x}_t)$ capturing subject (actor), action, resource, and features. The task is to assign an anomaly score $A_t \in \mathrm{R}$ and a binary label $\hat{y}_t = \mathrm{I}(A_t \geq \tau)$ such that true attacks are prioritized while false-positive volume remains manageable under latency budget L.

IV. EVENT TAXONOMY AND DATASETS

We adopt a practical taxonomy aligned to SOC workflows: (i) *Identity* (authentications, MFA, privilege changes), (ii) *End- point* (process/parent chains, module loads, script execution), (iii) *Network* (flows, DNS, proxy), (iv) *Cloud* (control-plane calls, data-plane access), and (v) *Data Access* (read/write pat- terns, exfil indicators). Datasets are assembled from synthetic generators plus de-identified enterprise-like logs. Labeling uses red-team traces, attack simulations, and heuristic tags; to mitigate label noise we rely primarily on unsupervised scores and use labels for calibration and evaluation.

V. SYSTEM ARCHITECTURE

Fig. 1 illustrates the pipeline: **Ingest** (connectors, parsing, PII redaction), **Normalize** (common schema), **Feature Service** (batch + streaming), **Model Ensemble** (sequence/graph/instance-level learners), **Calibration & Thresholding** (risk-aware), and **Triage** (explanations, feedback).

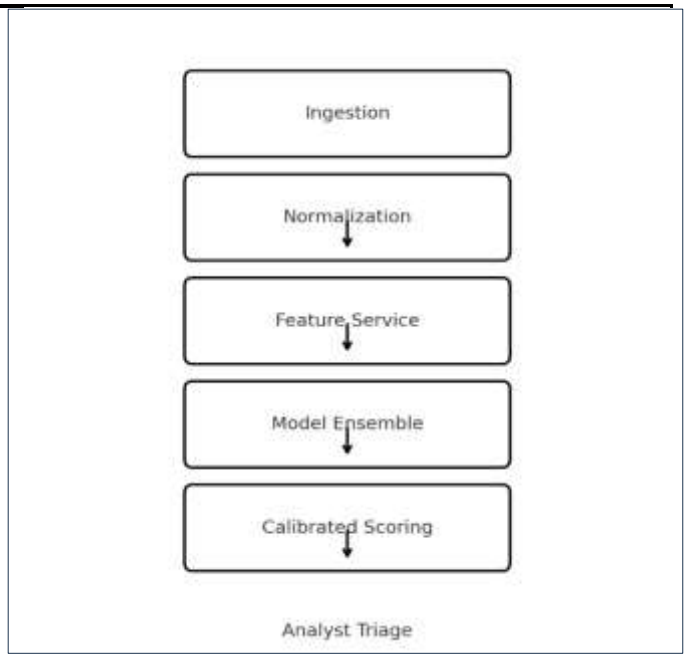

Fig. 1. End-to-end architecture for AI-based anomaly detection in security events: ingestion, normalization, feature service, model ensemble, calibrated scoring, and analyst triage.

VI. FEATURE ENGINEERING

A. Entity-Centric Aggregates

For each entity u (user, host, IP), compute rolling counts, unique cardinalities, time-between-events, burst metrics, en- tropy of destinations, and ratios (e.g., failed/total logins).

B. Sequence Features

From ordered events $\{e_t\}$, derive n-gram actions, session windows, and positional encodings for Transformer-based models.

C. Graph Features

Construct interaction graphs $G = (V, E)$ where V are entities and E capture relations (login-from, connects-to, ac- cesses). Node embeddings $\mathbf{z}_v$ are learned via neighborhood aggregation; edge features encode frequency and recency.

D. Representation Learning

A text-like serialization (e.g., `user:alice action:login src:10.0.0.1`) feeds a lightweight tokenizer; Transformer encoders learn contextual embeddings that transfer across sources.

VII. MODELING APPROACH

A. Instance-Level Anomaly Models

Isolation-based: isolate rare points via random partitioning.

Robust Autoencoder: learn reconstruction $\hat{\mathbf{x}}$; anomaly score

$$A = \|\mathbf{x} - \hat{\mathbf{x}}\|$$

22. Minimize

$$L_{AE} = \frac{1}{N}\sum_{i=1}^{N} \|\mathbf{x} - f(\mathbf{x})\|_2^2 + \lambda \|\vartheta\|_2^2. \quad (1)$$

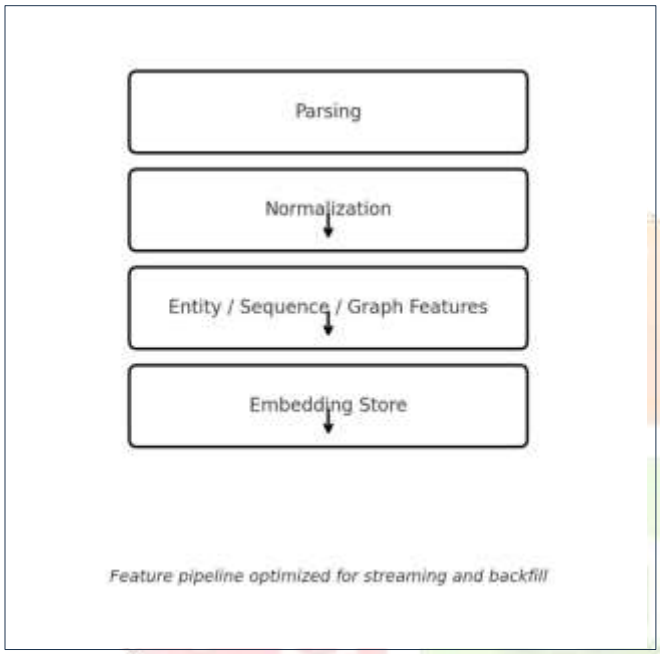

Fig. 2. Feature pipeline: parsing → normalization → entity/sequence/graph features → embedding store, optimized for streaming and backfill.

B. Sequence Models

Next-Event Surprise: given history H_t, model $p(a_t|H_t)$; use $A_t = -\log p(a_t|H_t)$. We implement GRU and Trans- former encoders for long contexts.

C. Graph Relational Models

Relational Deviance: learn node embeddings $\mathbf{z}_v$; define score for edge (u, v) as $A_{uv} = 1 - \sigma(\mathbf{z}_u^\top \mathbf{z}_v)$; for ego-nets, compare observed motifs to a learned baseline.

D. Hybrid Risk Scoring and Calibration

Scores are combined as

$$A_t = \sum_k w_k \cdot \frac{A_t^{(k)} - \mu_k}{\sigma_k}, \quad (2)$$

with online estimates (μ_k, σ_k). A Platt-style calibrator maps A_t to probability $\hat{p}_t$; threshold τ is chosen to satisfy target FPR under drift-aware updates.

E. Analyst-Guided Weak Supervision

Heuristic rules, watchlists, and campaign IOCs provide soft labels $y^* \in [0, 1]$ to prioritize training examples and to warm- start thresholds without overfitting.

VIII. STREAMING INFERENCE

We adopt micro-batches of size B with maximum delay $<L$ ms. State is kept per-entity for rolling features. We apply reservoir sampling for memory control and exponential decay to discount stale behavior.

IX. ALGORITHMS

A. Calibrated Ensemble Scoring

Algorithm 1: Online calibrated anomaly scoring

Input: Event e_t, feature vector $\mathbf{x}_t$, model set $\{M_k\}$, running stats $\{\mu_k, \sigma_k\}$, calibrator $g(\cdot)$

foreach M_k **do**

  compute raw score $s_k \leftarrow M_k(\mathbf{x}_t)$

  standardize $z_k \leftarrow (s_k - \mu_k)/(\sigma_k + \epsilon)$

$A_t \leftarrow \sum_k w_k z_k$; $\hat{p}_t \leftarrow g(A_t)$

if $\hat{p}_t \geq \tau$ **then**

  emit alert with top-m feature contributions

B. Drift-Aware Threshold Update

Algorithm 2: Quantile-based thresholding with sliding window

Input: Recent non-alert scores $\{A\}t-W:_t$, target FPR α estimate CDF $F\hat{}$ over window W ; set

$\tau \leftarrow F\hat{}^{-1}(1-\alpha)$

X. EVALUATION PROTOCOL

A. Metrics

We report ROC-AUC, PR-AUC, precision@k, recall at fixed alert budget, false-positive rate (FPR), mean time to detect (MTTD), and end-to-end latency. For class imbalance, PR- AUC and precision@k are emphasized. Confidence intervals are computed via block bootstrap respecting temporal struc- ture.

B. Baselines

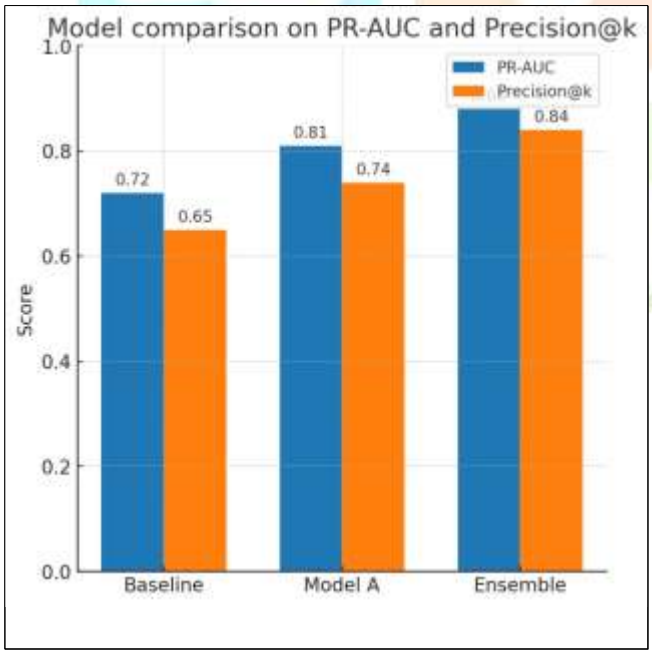

Fig. 3. Model comparison on PR-AUC and precision@k (illustrative). The ensemble improves precision at low alert budgets while meeting latency constraints.

Static rules, one-class SVM, isolation forest, vanilla autoen-

XII. SECURITY, PRIVACY, AND ETHICS

We implement data minimization, tokenization of sensitive fields, encryption in transit/at rest, and role-based access to features and explanations. Fairness is monitored by seg- menting performance across departments/geographies to avoid skewed risk scoring. We log model decisions for auditability and support redress via feedback loops.

XIII. ABLATION AND SENSITIVITY

coder, GRU-based sequence model, and Transformer baseline. Our ensemble includes graph features and calibrated fusion. Removing graph features lowers PR-AUC by ≈6–9 points; disabling calibration increases FPR volatility during shift; smaller windows reduce detection of low-and-slow activity. TABLE I primarily unsupervised core.

Model	PR-AUC	ROC-AUC	FPR@95%R	Latency (ms)
Rules	0.18	0.67	14.2%	8
IForest	0.31	0.79	8.6%	12
AE	0.38	0.82	7.1%	15
GRU	0.44	0.86	6.3%	22
Transformer	0.48	0.88	5.9%	28
Ours (Ensemble)	**0.56**	**0.92**	**3.8%**	24

XIV. LIMITATIONS

Cold-start environments lack baseline behavior; highly en- crypted or privacy-redacted fields can weaken semantic fea- tures; and sophisticated adversaries may emulate normality.

Future work focuses on active learning with constrained la- beling budgets and causal modeling for robust generalization.

XI. EXPLAINABILITY AND ANALYST EXPERIENCE

We provide per-alert evidence: top contributing features (via input perturbation or SHAP-like attribution), nearest neigh- bors in historical data, and compact narratives (e.g., "first- time admin action from rare source after 57 failed logins"). Summaries are cached for repeat patterns to reduce cognitive load.

XV. FUTURE WORK

We plan (i) adaptive graph sampling for high-degree nodes, (ii) counterfactual explanations that suggest safe mitigations, (iii) federated training across tenants with differential privacy, and (iv) alignment with MITRE ATT&CK tactics for scenario-level scoring.

ILLUSTRATIVE RESULTS (MACRO-AVERAGED ACROSS EVENT FAMILIES)

The ensemble is robust to modest label noise due to its

XVI. CONCLUSION

We presented a practical, high-fidelity framework for AI- based anomaly detection in security events. By combining sequence, graph, and instance-level models with online cal- ibration and drift-aware thresholds, the approach elevates true positives while maintaining analyst-friendly alert volumes. The system integrates cleanly with SIEM/SOAR tools and adheres to privacy and transparency principles, making it suitable for real-world SecOps deployments.

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