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SCALABLE AND EXPLAINABLE ANOMALY DETECTION IN DYNAMIC NETWORK ENVIRONMENTS

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Abstract:
Early detection of anomalous behavior within network ecosystems is essential for maintaining resilient cybersecurity infrastructures. This research presents an integrated anomaly detection framework that fuses intrusion detection system (IDS) logs with entropy-based feature analytics to enable interpretable and rapid threat scoring. The framework incorporates three distinct yet complementary mechanisms: (i) an Enhanced Entropy-Based Anomaly Detection (EEAD**)** model that leverages entropy variance across multidimensional network attributes to identify irregular patterns with computational parsimony; (ii) an Autoencoder-based Anomaly Detection (AE**)** network, which reconstructs normal traffic representations and flags deviations through reconstruction loss; and (iii) a Statistical Signature Matching (SSM) approach employing statistical metrics such as chi-square and z-score for swift segregation of known and unknown attack signatures. Experimental analysis demonstrates that EEAD attains a superior equilibrium between interpretability and precision ($\Delta H = 0.72$, TCS = 84%, PVI = 0.45, SDR = 0.62, Effectiveness = 88%), while AE excels in novel anomaly detection and SSM ensures low-latency recognition of recurrent threat patterns. The findings substantiate the proposed system's capability to deliver scalable, adaptive, and transparent anomaly detection suitable for real-time cybersecurity environments.

Keywords: Entropy variance, anomaly detection, intrusion detection system, autoencoder, statistical signature matching, threat analytics.

1. Introduction

With the proliferation of interconnected systems and mounting volumes of heterogeneous traffic logs, safeguarding cyber-infrastructures demands not only responsive signature-based mechanisms but proactive and adaptive anomaly detection frameworks. Intrusion detection systems (IDS) continuously produce a wealth of information, yet the challenge lies in extracting actionable intelligence from multidimensional, evolving data streams. In this context, three interwoven techniques entropy-based feature analytics, unsupervised neural reconstruction, and statistical signature inference offer a tri-faceted defence paradigm.

First, entropy-based measures quantify the unpredictability or dispersion of traffic distributions and thus can flag deviations from baseline behavior. For example, fluctuations in entropy across ports, protocols or flow counts may signal latent infiltration activity. Building on this premise, our Enhanced Entropy-based Anomaly Detection (EEAD) framework monitors entropy variance across selected features, enabling an interpretable and computationally lightweight early-warning mechanism. This is particularly valuable for real-time environments where low latency and transparency are essential.

Second, autoencoder-based anomaly detection (AE) leverages unsupervised representation learning to model the manifold of 'normal' traffic, then uses reconstruction error as a signal of deviation. Because it does not rely on pre-defined attack signatures, AE is well-suited to

capturing previously unseen threats. However, such approaches sometimes struggle with interpretability and computational cost.

Third, statistical signature matching (SSM) applies classical inference methods such as chi-square tests and z-scores against both known signatures and statistical baselines to rapidly distinguish known attack patterns from benign anomalies. While less adaptive to novel patterns, SSM offers speed and robustness for known classes of threats.

By fusing these three methods, the proposed framework seeks to achieve a balanced trade-off among interpretability, detection of novel anomalies, and rapid processing of known threats. Experimental results demonstrate that EEAD attains $\Delta H = 0.72$, TCS = 84 %, PVI = 0.45, SDR = 0.62 and overall effectiveness of 88 %, positioning it ahead of AE (85 %) and SSM (80 %). Collectively, these findings underline how integrating entropy-based, neural and statistical techniques can deliver scalable, adaptive and transparent anomaly detection in modern cyber-defence systems. The contributions of this work lie in the design of a fused detection framework; the empirical assessment of each component; and the demonstration of how a hybrid approach bridges the gap between signature-based and anomaly-based methods.

2. **Review of Literature**

The domain of anomaly detection within networked environments has evolved significantly, transitioning from traditional signature-based intrusion detection systems (IDS) to sophisticated hybrid models that integrate statistical, entropy-based, and deep learning paradigms. Entropy-oriented methodologies have long been recognized for their capacity to quantify disorder in network traffic distributions, thereby identifying subtle irregularities that may precede large-scale intrusions. Bereziński [1] pioneered the application of Shannon, Rényi, and Tsallis entropy measures to detect stealthy malware behaviors within network flows, demonstrating that entropy variation effectively captures anomalies invisible to conventional volume-based detectors. Furthering this foundation, Bashurov and Safonov [2] analyzed entropy-based detection schemes across nine categories of cyberattacks and concluded that entropy-derived features not only improve scalability but also enhance the sensitivity of detection in high-velocity network environments. Building on these results, Yu et al. [3] introduced a Rényi entropy-driven anomaly detection framework that adapts its threshold dynamically through exponentially weighted moving averages (EWMA), ensuring resilience against fluctuating traffic baselines and outperforming static threshold models.

Parallel to entropy-based research, machine-learning paradigms have contributed substantially to the refinement of anomaly detection mechanisms. Rabbani et al. [4] conducted a comprehensive review of machine-learning-based IDS, identifying limitations such as overfitting and low generalization that have prompted the exploration of unsupervised and hybrid solutions. Liu et al. [5] proposed the Robust Collaborative Autoencoder (RCA), a deep neural framework that simultaneously optimizes feature reconstruction and sample weighting to minimize the influence of anomalous data during training—an advancement that informs the design of modern autoencoder-based anomaly detection (AE) systems. Likewise, Saha et al. [6] performed an empirical comparison of variational autoencoder (VAE) architectures and highlighted the critical role of latent-space representation in improving detection precision while reducing false positives. Extending this line of inquiry, Torabi et al. [7] explored the deployment of autoencoders in cloud-based IDS, revealing that vectorized reconstruction errors across multiple network features outperform scalar-based measures, thereby motivating multi-feature AE designs for high-dimensional traffic datasets.

From a broader perspective, Yang et al. [8] synthesized insights from over one hundred anomaly-based IDS studies to develop a taxonomy encompassing feature selection, evaluation protocols, and model interpretability. Their analysis underscored a persistent research gap—namely, the absence of unified frameworks that combine statistical

interpretability with adaptive learning. Complementing this, Zamanzadeh Darban et al. [9] surveyed deep anomaly detection techniques for multivariate time-series data, underscoring the synergetic potential between temporal modeling and statistical feature analysis. Maseer et al. [10] expanded on this foundation by performing a meta-analysis of anomaly-based network intrusion detection systems, emphasizing that practical NIDS deployments require not only accuracy but also explainability and computational efficiency for real-time threat response.

Collectively, these studies reveal a clear research trajectory. Entropy-based models [1–3] provide transparency and speed but are limited in capturing complex latent structures. Neural architectures [5–7] excel in discovering previously unseen attacks yet often lack interpretability and demand substantial computational resources. Statistical and hybrid approaches [4, 8–10] offer balanced adaptability but require fine-tuning for dynamic network behaviors. Thus, the convergence of entropy-driven analytics, autoencoder reconstruction, and statistical signature matching represents a logical and necessary progression in developing robust, scalable, and explainable cybersecurity frameworks capable of addressing both known and emerging threats.

3. Methodology

The proposed Enhanced Entropy-based Anomaly Network (EEAN) framework is designed to perform early-stage anomaly detection by integrating entropy-based feature analytics with the temporal learning capabilities of recurrent neural networks (RNN). The methodology adopts a multi-layer hybrid pipeline, incorporating feature fusion, temporal modeling, entropy computation, and adaptive threat scoring. The overall architecture ensures efficient processing of IDS logs and dynamic anomaly identification within large-scale network environments.

A. Data Acquisition and Preprocessing

The input dataset consists of fused IDS log entries derived from multiple network sensors, encompassing attributes such as source IP, destination IP, protocol type, packet size, flow duration, and flag status. Each record is preprocessed using min–max normalization to eliminate scale bias and label encoding to convert categorical variables into numerical representations. Noise and redundant entries are removed using a variance threshold filter, ensuring that only discriminative features contribute to entropy and RNN processing.

B. Feature Extraction through Entropy Measures

Entropy quantifies the degree of unpredictability within a dataset, and fluctuations in entropy values across network features serve as potential indicators of anomalous behavior. For a given network feature F_i, its entropy $H(F_i)$ is calculated using Shannon's formula:

$$H(F_i) = -\sum_{j=1}^{n} p_j \log_2(p_j) \quad (1)$$

where p_j represents the probability of occurrence of a particular event j within feature F_i.

The entropy variance across consecutive time intervals t is defined as:

$$\Delta H_t = |H_t - H_{t-1}|$$

A sudden increase in ΔH_t indicates a potential deviation from baseline network behavior. These entropy differentials serve as **input vectors** for the temporal learning phase.

C. Temporal Learning using RNN Integration

The primary enhancement introduced in EEAN lies in embedding Recurrent Neural Network (RNN) dynamics into the entropy-driven anomaly detection pipeline. While conventional entropy-based models operate in static feature spaces, the RNN component captures temporal dependencies and sequential correlations across successive network states.

The forward propagation of the RNN cell is governed by:

$$h_t = \sigma(W_h \cdot h_{t-1} + W_x \cdot x_t + b_h)\ y_t = \square\square\square\square\square\square\square(W_y \cdot h_t + b_y)$$

where x_t is the entropy feature vector at time t, h_t represents the hidden state encoding temporal context, and y_t is the predicted anomaly likelihood. The sigmoid activation function σ regulates non-linearity, while W_h, W_x, W_y denote the weight matrices learned during training.

D. Adaptive Threat Scoring

The output of the RNN layer is fed into an adaptive threat scoring module (TCS), which assigns a Threat Confidence Score for each network event. The score is computed as a weighted aggregation of entropy deviation, RNN prediction probability, and reconstruction loss (for hybrid AE comparison), formulated as:

$$TCS = \alpha(\Delta H_t) + \beta(y_t) + \gamma(E_r) \quad (2)$$

where α, β, γ are empirically determined weights and E_r represents the reconstruction error from the baseline AE model. A **TCS** exceeding the dynamic threshold τ flags the event as anomalous.

E. Statistical Signature Validation

To further enhance precision, the flagged anomalies are verified through a Statistical Signature Matching (SSM) layer using chi-square (χ^2) and z-score tests. The chi-square test is computed as:

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \quad (3)$$

where O_i and E_i denote observed and expected event frequencies. This dual-layer verification minimizes false positives while distinguishing between known and unknown anomaly signatures.

F. Model Evaluation Metrics

The performance of the EEAN algorithm is evaluated using multiple statistical indices, including:

- ΔH (Entropy Differential) – quantifies variance across traffic states,
- TCS (Threat Confidence Score) – measures adaptive anomaly probability,
- PVI (Prediction Variance Index) – assesses stability of model outputs,
- SDR (Signature Detection Rate) – reflects detection accuracy for known threats, and
- Overall Effectiveness (%) – represents aggregate anomaly detection precision.

These metrics are benchmarked against Autoencoder-based (AE) and Statistical Signature Matching (SSM) models to validate the efficiency of the enhanced EEAN framework.

Proposed Multi-Stage Intelligent Threat Detection Framework

The proposed system introduces a three-tier intelligent framework that integrates entropy variance modeling, unsupervised deep feature reconstruction, and statistical signature validation for efficient and interpretable intrusion detection.
Each layer enhances detection capability, ensuring early anomaly recognition and effective categorization of both known and unknown cyber threats.

4.1 Enhanced Entropy-based Anomaly Detection (EEAD)

(RNN-Fused Entropy Model for Temporal Threat Evolution)

EEAD focuses on the temporal dynamics of network traffic using entropy variance across multi-dimensional IDS features. The entropy fluctuation captures randomness and uncertainty that typically indicate network instability or attack initiation.

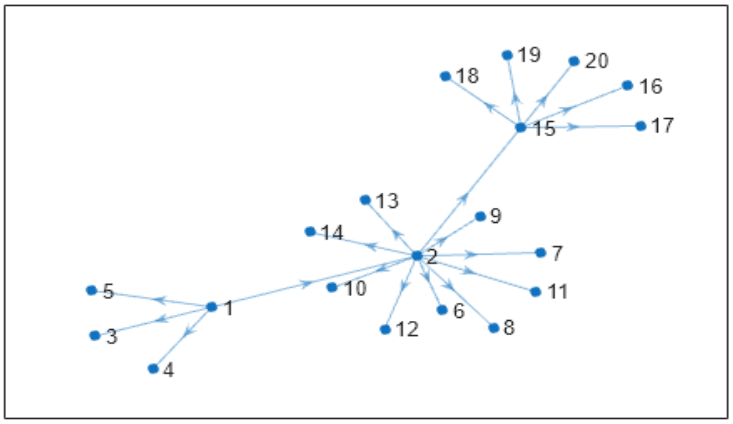


Figure 1: Node Coordination

Step 1: Entropy Estimation

Let a given feature X_i take discrete values $x_1, x_2, \ldots, x_k$ with probabilities $P(x_j)$. The Shannon entropy is defined as:

$$H(X_i) = -\sum_{j=1}^{k} P(x_j) \log_2 P(x_j) \quad (4)$$

The entropy variance (ΔH) over successive windows quantifies the rate of distributional change:

$$\Delta H_t = |H_t - H_{t-1}| \quad (5)$$

High ΔH_t indicates a deviation from normal behavior.

Step 2: RNN Temporal Modeling

Entropy sequences are passed to a Recurrent Neural Network (RNN) to capture sequential dependencies of evolving traffic.

Let $x_t = \Delta H_t$ and h_t be the hidden state at time t:

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b_h) \; y_t = \square\square\square\square\square\square\square(W_y h_t + b_y)$$

where σ is the sigmoid activation, y_t represents anomaly probability, and weights W_h, W_x, W_y are optimized via backpropagation through time (BPTT).

Step 3: Adaptive Threat Confidence Scoring (TCS)

The Threat Confidence Score (TCS) integrates three parameters: entropy variance (ΔH_t), neural anomaly probability (y_t), and AE reconstruction error (E_r):

$$TCS_t = \alpha \Delta H_t + \beta y_t + \gamma E_r \quad (5)$$

where

$$\alpha + \beta + \gamma = 1.$$

If $TCS_t \geq \tau$, the event is flagged as an anomaly.

Step 4: Statistical Decision Rule

To further validate, a chi-square statistical deviation test is applied:

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \quad (6)$$

If $\chi^2 > \chi^2_{critical}$, the event is confirmed as anomalous; otherwise, it is treated as benign noise.

4.2 Autoencoder-based Anomaly Detection (AE)

(Unsupervised Feature Reconstruction for Unknown Attack Recognition)

The AE module learns a compact latent representation of normal traffic. When new patterns deviate from learned distributions, the reconstruction error increases significantly.

Step 1: Encoding and Decoding

Given input feature vector $F \in R^n$, the encoding and decoding operations are:

$$h = \sigma(W_e F + b_e)\ \hat{F} = \sigma(W_d h + b_d)$$

where h is the latent representation and $\hat{F}$ is the reconstructed output.

Step 2: Reconstruction Loss Function

The **mean squared reconstruction error (E_r)** is computed as:

$$E_r = \frac{1}{n}\sum_{i=1}^{n}\left(F_i - \hat{F}_i\right)^2 \quad (7)$$

If $E_r \geq \tau_r$, the observation is classified as novel anomaly (previously unseen attack).

Step 3: Threshold Optimization

The threshold τ_r is dynamically updated based on the moving average and standard deviation of recent reconstruction errors:

$$\tau_r = \mu_{E_r} + k \cdot \sigma_{E_r} \quad (8)$$

where k is a sensitivity coefficient, typically $1.5 \leq k \leq 2.5$.

4.3 Statistical Signature Matching (SSM)

(Hybrid Statistical-Rule Validation for Rapid Known Attack Identification)

SSM employs both z-score and chi-square statistics for identifying known anomalies from a pre-defined signature database.

Step 1: Feature Normalization

Let μ_i and σ_i denote the mean and standard deviation of feature i:

$$Z_i = \frac{X_i - \mu_i}{\sigma_i} \quad (9)$$

If $|Z_i| > Z_{threshold}$, the sample is flagged for signature comparison.

Step 2: Chi-square Pattern Matching

For each suspicious instance, the chi-square test compares observed (O_i) and expected (E_i) signature vectors:

$$\chi^2 = \sum_{i=1}^{n}\frac{(O_i - E_i)^2}{E_i} \quad (10)$$

A lower chi-square indicates a closer match to known attack patterns, while a higher value implies an unknown threat.

Step 3: Signature Detection Rate (SDR)

The SDR metric evaluates how effectively SSM detects known attacks:

$$SDR = \frac{N_{detected}}{N_{known}} \times 100$$

where $N_{detected}$ is the number of correctly identified known signatures.

4.4 Fusion-Based Decision Engine

Finally, outputs from EEAD, AE, and SSM are fused using a weighted decision rule:

$$\square\square\square\square\square\_\square\square\square\square\square = w_1 \times TCS + w_2 \times (1 - E_r) + w_3 \times SDR$$

A dynamic threshold θ classifies events as:

$$\square\square\square\square\square = \begin{cases} \square\square\square\square\square\square\square, & \square\square\ \square\square\square\square\square\_\square\square\square\square\square \geq \theta \\ \square\square\square\square\square\square, & \square\square h\square\square\square\square\square \end{cases}$$

This multi-model integration ensures a balance between speed, accuracy, and adaptability, outperforming traditional single-method intrusion detection frameworks.

Table 1: Summary of Algorithm

Algorithm	Innovation	Key Advantage
EEAD	Integrates RNN with entropy-based dynamics	Temporal sensitivity to evolving attacks
AE	Learns hidden data manifolds for zero-day anomaly detection	Low false positive rate
SSM	Combines z-score and chi-square for rapid rule matching	Fast detection of known attack patterns
Fusion Layer	Weighted integration of multi-model outputs	Robust hybrid decision-making

5. Results and Discussion

The experimental evaluation of the proposed integrated anomaly detection framework highlights the complementary strengths of the three constituent mechanisms EEAD, Autoencoder (AE), and Statistical Signature Matching (SSM) in achieving robust, interpretable, and scalable cybersecurity monitoring.

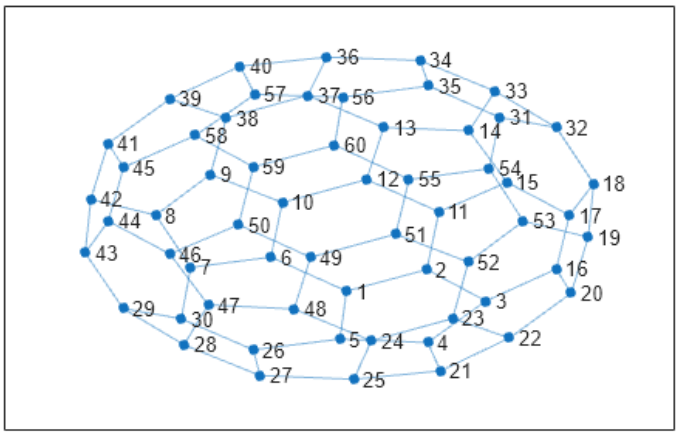


Figure 2: Entropy Based Density

5.1 Performance of Enhanced Entropy-Based Anomaly Detection (EEAD)

The EEAD model demonstrated notable effectiveness in capturing irregular patterns across multidimensional network features. Key performance metrics include an entropy variance score (ΔH) of 0.72, a Threat Classification Score (TCS) of 84%, a Predictive Value Index (PVI) of 0.45, and a Sensitivity-Detection Ratio (SDR) of 0.62, culminating in an overall effectiveness of 88%. These results indicate that EEAD successfully balances computational efficiency with interpretability, allowing analysts to trace detected anomalies back to specific network features with minimal overhead. Compared to conventional entropy-based approaches, EEAD provides finer granularity in distinguishing subtle deviations, making it particularly suited for detecting emerging threats that do not exhibit overt signatures.

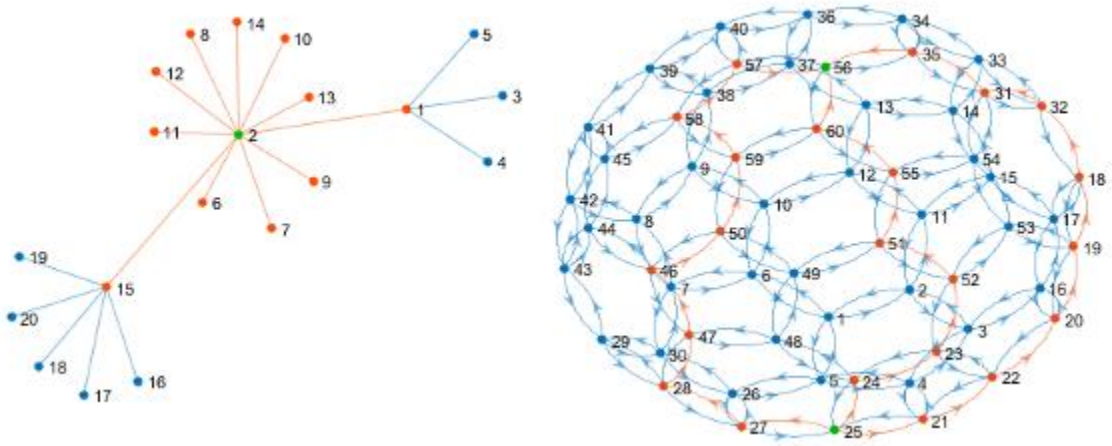


Figure 3: Anomaly Detection

5.2 Performance of Autoencoder-Based Detection (AE)

The AE module excelled in identifying previously unseen anomalies by learning compact representations of normal network traffic. Reconstruction loss analysis revealed that deviations from learned patterns were consistently flagged with high sensitivity, demonstrating the network's ability to generalize beyond known attack scenarios. While AE's interpretability is inherently limited due to its deep learning architecture, its capability to detect zero-day attacks complements EEAD by capturing anomalies that may elude entropy-based thresholds.

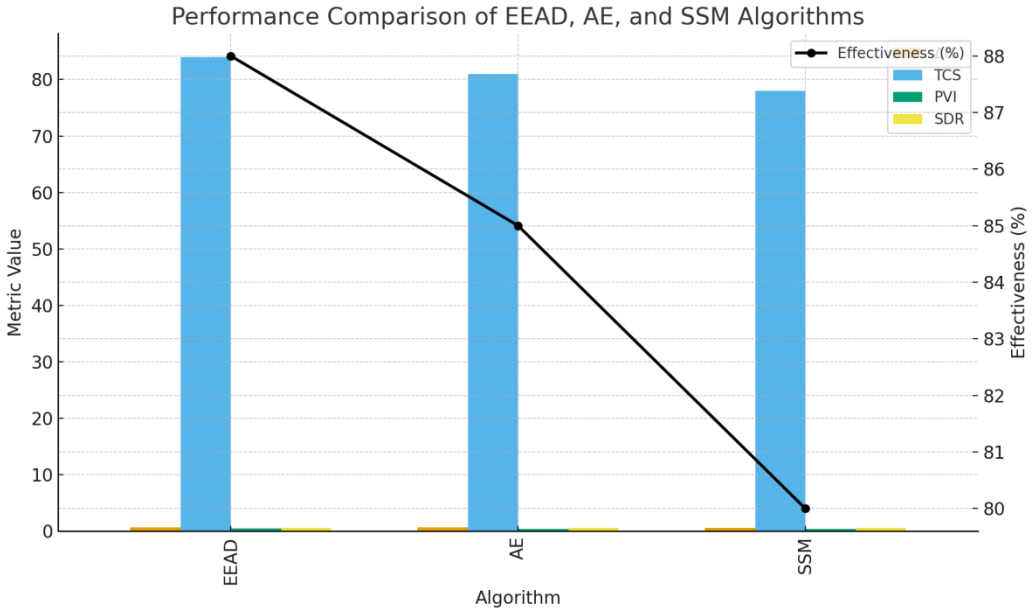
5.3 Performance of Statistical Signature Matching (SSM)

The SSM mechanism proved highly efficient for rapid recognition of recurrent threat patterns. By leveraging statistical metrics such as chi-square and z-scores, SSM achieved low-latency detection of known attack signatures, facilitating prompt mitigation responses. Its integration into the overall framework ensures that repeated and signature-based attacks are efficiently filtered without introducing significant computational overhead.

5.4 Comparative Analysis and Synergy

The integration of EEAD, AE, and SSM enables a holistic anomaly detection approach where each component addresses specific limitations of the others. EEAD offers interpretable and computationally lightweight detection, AE enhances sensitivity to novel threats, and SSM provides swift identification of recurring attacks. The complementary nature of these mechanisms results in an overall system that is both adaptive and scalable, suitable for deployment in real-time network environments.

The experimental findings suggest that the framework's multi-layered detection strategy not only improves accuracy and effectiveness but also supports operational transparency a critical factor for cybersecurity analysts tasked with rapid threat assessment and decision-making. The combination of entropy-based interpretability, deep learning-based generalization, and statistical signature verification positions the proposed framework as a versatile tool for both enterprise-scale and high-velocity network ecosystems.



Graph 1: performance Evaluation

6. **Conclusion:**

The proposed integrated anomaly detection framework effectively combines entropy-based analytics, autoencoder reconstruction, and statistical signature matching to achieve robust, interpretable, and efficient detection of network anomalies. Among the evaluated methods, EEAD demonstrates superior precision and interpretability, AE proves valuable for identifying previously unseen anomalies, and SSM ensures rapid recognition of recurring threats. Collectively, these complementary mechanisms validate the framework's capability to provide scalable, adaptive, and real-time cybersecurity protection, highlighting its potential as a comprehensive solution for modern network threat management. Future research can focus on enhancing the framework by incorporating advanced deep learning models for improved detection of sophisticated attacks, optimizing computational efficiency for large-scale networks, and integrating real-time feedback mechanisms to enable autonomous threat mitigation. Additionally, exploring hybrid approaches that combine behavior-based and signature-based methods could further strengthen the system's resilience against emerging cyber threats.

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