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A High-Performance Hybrid Entropy Complexity Learning Framework for Robust Detection of Stealthy Cyber Attacks

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Abstract

Cyber-attacks are advancing toward secretive behaviors that avoid classical signature detection systems and single-metric abnormality approaches. This paper is used to be proposed a framework-based Hybrid Entropy–Complexity Learning (HECL) for strong detection of cyber-attacks based on networking information models. The proposed approach cooperatively analyzes the entropy-based Shannon scheme, statistical complexity, and learning adaptability for characterizing normal and abnormal traffic activities. Different from conventional systems-based detection entropy, the proposed method utilizes the temporal coupling between both the entropy and complexity, allowing the correspondence of low-rate and whitewash attacks. Comprehensive simulations illustrate that the proposed model performs outstanding detection accuracy, speedy convergence, and a lower rate-based false-alarm when it is compared to the standalone entropy and approaches-based Machine Learning (ML). The key results emphasize that integrating an information-theoretic system with the learning-based indicators gives an influential and lightweight security technique appropriate for recent information security systems. The experimental results on the CICIDS2017 dataset show that it outperforms the state of the art deep learning techniques with 98.85% accuracy and 0.95% false positive rate.

1. Introduction

The high-speed digital conversion of critical infrastructures, services-based cloud, IoT systems, and distributed systems has principally extended the landscape of cyber threats. Instead, they gradually introduce invisible, low-rate, flexible and polymorphic attack strategies that mimic the behavior of typical intrusion detection systems (IDS) to evade the detection of traditional IDSs. These attacks are going under the detection thresholds, as typical traffic patterns, periodically switching around behavioral fingerprints, maintaining static signature databases for attacks, and single-metric abnormality detection is not enough. [1,2, 3].

Conventional systems of intrusion detection are typically classified into signature and anomaly schemes [4]. Signature approaches give high accuracy for familiar attacks in spite of that fail with zero-day threats. On the contrary, anomaly approaches depend on designing deviations from typical patterns of traffic [5]. Based on that, entropy detection mechanisms have received considerable attention because of their foundation in information theory [6]. In particular, Shannon entropy has been utilized heavily to detect distributional alterations in IP addresses, packet headers, port usage, and statistical flow. Though entropy solitary estimate of randomness without considering the structural organization within the dynamics of traffic. Consequently, secret attacks that maintain close-normal values of entropy while changing higher-order structural dominion are able to avoid detection [7, 8]. The latest research offers the joint sight of entropy and statistical complexity, which provides a wealth of attributes of approach dynamics. Whilst entropy quantifies suspicion, statistical complexity estimates the structured organization degree within a probabilistic approach. Low entropy does not certainly reveal low complexity, and vice versa. For instance, whitewash-attacks, low-and-slow preliminary survey, and command-and-control beaconing might conserve entropy levels whilst subtly changing secular coupling and structural relationships. That nuanced way of behaving needs a detection system that captures the randomness in addition to structural advancement over time [9].

Undoubtedly, all machine learning mechanisms possess the ability to detect anomalies and various parameters when compared in depth between supervised and unsupervised learning [10]. Various deep learning frameworks, including recurrent neural networks and convolutional methods, have demonstrated promising performance and anticipated results when applied to complex data traffic environments [11, 12]. However, these methods suffer from high computational load, resulting in high costs, high sensitivity to data or input manipulation by attackers, and significant interpretability limitations [13]. All of the above are constraints that must be overcome by proposing a research framework based on the principle of hybrid entropy-complexity learning (HECL).

The fundamental reason for combining entropy and complexity is that each has its own set of properties and limitations, and numerous studies have shown that the properties of one address the limitations of the other, and vice versa. Entropy is based primarily on a theory called Shannon information, which is used to measure a system's or model's unpredictability [14]. Statistical complexity, on the other hand, is calculated using specific measures called the Jensen-Shannon metric [15]. In the state of analyzing individualistic time windows, the proposed HECL framework computes the relationship between entropy and complexity advancement. That allows the correspondence of subtle behavioral drift symptomatic of secret intrusions [16].

The rest of this paper is structured as follows: Section 2 presents the recent literature review studies, supporting with a comprehensive comparison. Section 3 introduces the methodology, consisting of the theoretical basis and the proposed algorithmic approach. Section 4 illustrates the results and conclusions for simulated outcomes. Section 5 discusses limitations, novelty, key findings, and future research directions.

2. Related Works

Almalaq et al. [17] suggested a hybrid structure-based AC/DC microgrid framework to mitigate cascading failures caused by cyber intrusions and performed vulnerability index modeling to quantify the percentage of vulnerable grid equipment under false data injection (FDI) attacks. The study utilized photovoltaic, wind, tidal, and hydrogen-based fuel cell resources integrated via grid-connect mode and modeled uncertainty using the unscented transform (UT). Results indicated that the proposed hybrid-energy framework significantly reduced system vulnerability percentage against modeled cyber-attacks. Again, Almalawi et al. [18]. illustrated CNNs based on feature extraction, autoencoders for detecting anomalies through using the HAE–HRL approach, and a hybrid ResNet–LSTM framework for sequential analysis. The experimental results of minimizing false positives emphasize that the suggested system significantly enhances detection accuracy by about 95.22% detection benchmark, 93.38% anomaly detection, and 92.96% intrusion detection. Expanding hybrid DL to environment-based IoT, Sivasakthi et al. [19] introduced a robust learning scheme, called Hybrid RobustNet (HRN), to predict and detect hybrid attacks along networks -based IoT. HRN combines ML approaches, deep neural networks (DNN), and ensemble mechanisms for achieving improved detection accuracy and resilience against evolving hybrid attack patterns. Also, Albakri et al. [20] demonstrated a blockchain-assisted hybrid metaheuristic ML framework (BHMML-CADC) for cyber-attack detection and classification and utilized HEGSO for feature selection, QRNN for detection, and HPO for parameter optimization. The method incorporated Ethereum blockchain for secure attack detection and was validated on the BoT-IoT dataset. Simulation results achieved 99.74% maximum accuracy,

confirming superior classification performance. Advancing toward integrated cyber-physical protection, Pallakonda et al. [21] presented a unified cybersecurity framework for cyber-physical power systems that integrate high-performance anomaly detection with provably secure cryptographic protection. A comprehensive dataset, built upon the IEEE 24-bus test system, includes a diverse set of operational states and five classes of false data injection attacks (FDIAs), including stealthy and replay-based intrusions. In the context, Alqaraleh [22] utilized an ensemble-based anomaly detection system integrating KNN, NB, RF, AdaBoost, and GB with PCA dimensionality reduction and SMOTE balancing. The approach utilized soft-voting ensembles and demonstrated improved accuracy (93.7%) and adversarial robustness compared to standalone classifiers. Experimental findings confirmed computational efficiency and improved recall for rare attack classes. For handling security-based healthcare, Saeed et al. [23] modelled a unified framework of machine learning-based anomaly detection and hybrid encryption-based cybersecurity, achieving high accuracy and real-time performance while defending against diverse cyberattacks. In the same manner, Arbane et al. [24] demonstrated the critical value of entropy-aware behavioral analysis for IoMT security. The results highlight both the technical effectiveness and practical deploy-ability of the demonstrated framework in real-world IoMT environments.

Table (1): Comparison of Literature Review.

Study	Core Technique	Hybridization Type	Adaptive Learning	Dataset	Accuracy	Key Strength	Limitation
Almalaq et al. [21]	Hybrid AC/DC Microgrid + Vulnerability Indices	Energy + Cyber Modeling	No	Modeled Power System	Vulnerability Reduction	Infrastructure resilience	Not ML-based detection
Almalawi et al. [22]	Autoencoder + ResNet + LSTM	Deep Hybrid	Yes	SCADA Data	High Accuracy	Temporal anomaly detection	High computational cost
Sivasakthi et al. [23]	HRN (ML + DNN + Ensemble)	Ensemble Deep Learning	Yes	IoT Testbed	Superior to SOTA	Hybrid attack detection	Model complexity
Albakri et al. [24]	Blockchain + HEGSO + QRNN + HPO	Blockchain + ML + Metaheuristic	Partial	BoT-IoT	99.74%	Secure feature selection	Heavy optimization overhead
Pallakonda et al. [25]	RF + MLP + MVCC + AES/RSA	ML + Cryptography	Limited	IEEE 24-Bus	99.90%	Secure + Real-time FPGA	Focus on FDI only
Alqaraleh et al. [26]	Ensemble (KNN, RF, GB, etc.) + PCA	Ensemble ML	No	KDD99	93.7%	Adversarial robustness	Moderate accuracy
Saeed et al. [27]	C4.5 + DQN (DRL)	Supervised + Reinforcement	Yes	CICIoMT2024	99.56%	Real-time adaptive IDS	RL training cost
Arbane et al. [28]	Entropy + ML + Unsupervised	Information-theoretic + ML	Limited	Private IoMT	AUC 0.959	Entropy-enhanced detection	Limited generalization
Abughali et al. [29]	Lightweight DL + Mitigation Model	Detection + Recovery	Yes	WEN Dataset	99.73%	Detection + Reconstruction	Infrastructure-specific

Khaled et al. [30]	Neutrosophic NN	Uncertainty + DL	Partial	IoT Dataset	95.8%	Uncertainty modeling	Moderate recall

3. Methodology

3.1: Entropy-Based Traffic Characterization

Assume $X = \{x_1, x_2, \dots, x_n\}$ denotes the features of network traffic, such as IP distribution, port usage, and flow size. Thus, the Shannon entropy is represented by [34]:

$$H(X) = -\sum_{i=1}^{n} p(x_i) log_2 p(x_i) \quad (1)$$

where $p(x_i)$ represents the empirical probability distribution along a sliding window. Thus, the normalized entropy is defined by:

$$H_n(X) = \frac{H(X)}{log_2 n} \quad (2)$$

For capturing the behavior temporally, use:

$$H_t = H(X_t) \quad (3)$$

$$\Delta H_t = H_t - H_{t-1} \quad (4)$$

Where H_t represents the normalized Shannon entropy at the current time window t, and H_{t-1} is the entropy at the previous time window. ΔH_t denotes the temporal entropy drift, which captures the behavioral changes over consecutive sliding windows. This enables the detection of entropy drift in addition to the thresholds statically.

3.2: Statistical Complexity and Temporal Coupling Model

The complexity is statistically defined by utilizing the Jensen–Shannon divergence (JSD):

$$\Gamma_t = \alpha H_t + \beta C_t + \gamma (H_t . C_t) \quad (5)$$

where α, β, and γ are the adaptive weights.

Therefore, the detection decision is represented as:

$$D_t = \begin{cases} 1 & \text{if } \Gamma_t > \theta_t \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

where θ_t is updated dynamically along learning module.

The reason for the bilinear coupling formula (Equation 5) is in the synergistic relationship between entropy and complexity. During the design phase, an empirical ablation study showed that using only linear combinations ($\alpha H_t + \beta C_t$) does not explain the complex behaviour of stealthy attacks in which the intentions are to obscure the attack through changing the complexity of the structure, without affecting the entropy level. The multiplicative term $\gamma(H_t \cdot C_t)$ is an interaction amplifier. If the entropy and complexity change at the same time, this is a non-linear term, and it can greatly increase the abnormality score Γ_t, which will exceed the detection threshold θ_t. This mathematical explanation guarantees that the multi-dimensional feature drift will be covered by HECL, which cannot be captured by any single metric.

3.3: Proposed Algorithm

The proposed HECL algorithm is performed along a structured pipeline that combines modeling the probability, analyzing the information-theoretic, non-linear coupling, and adaptive learning. In the network traffic, for every sliding window, the proposed algorithm initially evaluates the experiential distribution of the probability of the extracted features, allowing computation for the normalized Shannon-entropy for quantifying uncertainty. Then, it is used to calculate the Jensen– Shannon divergence with respect to a regular reference distribution for deriving statistical complexity, capturing deviations structurally after randomness. Such two metrics are fused via a formulation-based nonlinear coupling that incorporates the linear contributions and multiplicative interaction, generating a composite abnormality score Γ(t).

Algorithm 1 :HECL Detection Framework

Input: Time series data, window size **W**, learning rate η, initial weights **α, β, γ**, initial threshold **θ**, reference distribution **P**
Output: Anomaly labels for each time window

1: Initialize sliding window size **W**
2: Initialize learning rate **η**
3: Initialize weights **α, β, γ**
4: Initialize threshold **θ**
5: for each time window *t* **do**
6: Extract feature vector $\mathbf{X_t}$
7: Estimate probability distribution $\mathbf{P_t}$
8: Compute entropy

$$Ht = - \Sigma\, p(xi)\, \log_2 p(xi)$$

9: Normalize entropy

$$Hn = Ht \,/\, \log_2 n$$

10: Compute Jensen-Shannon divergence Q_{JS} between P_t and P_{ref}

$$M = (P_t + P_{ref}) / 2$$
$$Qjs = H\left(\frac{P_t + P_t}{2}\right) - \frac{1}{2}H(P_t) - \frac{1}{2}H(P_{ref})$$

11: Compute complexity

$$Ct = QJS \times Hn$$

12: Compute coupling metric

$$\Gamma_t = \alpha H_t + \beta C_t + \gamma(H_t \times C_t)$$

13: if $\Gamma_t > \theta$ then
14: Flag window t as anomaly ($Dt = 1$)
15: else
16: Mark window t as normal ($Dt = 0$)
17: *end if*
18: Define Loss function L(t) based on detection error (if feedback is available)
19: Update threshold:

$$\theta \leftarrow \theta + \eta\,(\Gamma t - \theta)$$

20: Update weights **α, β, γ** using gradient descent:
$\alpha \leftarrow \alpha - \eta \, \partial L/\partial \alpha$
$\beta \leftarrow \beta - \eta \, \partial L/\partial \beta$
$\gamma \leftarrow \gamma - \eta \, \partial L/\partial \gamma$
21: end for

Different from model-based statistical detection, the proposed algorithm integrates an online adaptive updated threshold utilizing learning of the gradient, enabling dynamic adjustment for evolving traffic baselines. As well, the entropy weighting coefficients and the complexity are optimized iteratively based on detection error feedback, improving sensitivity for stealthy attacks and low-rate attacks whilst defeating false- positives. Such a closed-loop-based learning technique is used to transform the approach from a purely statistical detector into a framework-based adaptive decision that has the ability to operate in an environment-based non-stationary network as shown in Algorithm 1.

3.4: proposed Block Diagram

The proposed block diagram shown in Figure 1 demonstrates the architectural flow of the proposed HECL model from raw network traffic absorption to the final abnormality decision outcome. The procedure is initiated by the module-based Network Traffic Input, that gathers packet or feature- based flow-level data from the monitored infrastructure. Such features are used to forward to the stage of Feature Extraction; however, the statistical attributes and distributions of probabilities are evaluated along sliding windows. The block diagram then branches to two main parallel analytical paths: the Module-based Entropy, accountable for evaluating distributional uncertainty, and the Module-based Complexity, which computes structural organization based on divergence of Jensen– Shannon. Production from both modules is used to converge in the Engine-based Temporal Coupling; however, nonlinear fusion produces the hybrid abnormality metric. Such a metric is applied to the Module-based Adaptive Learning, which updates thresholds dynamically and weighting parameters utilizing feedback yielding from outcomes of detection. Eventually, the Decision Engine is used to classify traffic windows as normal or abnormal. The modular separation confirms computational efficiency, extensibility, and scalability, whilst the computation of parallel entropy complexity improves robustness against stealthy attack patterns and polymorphic attack patterns.

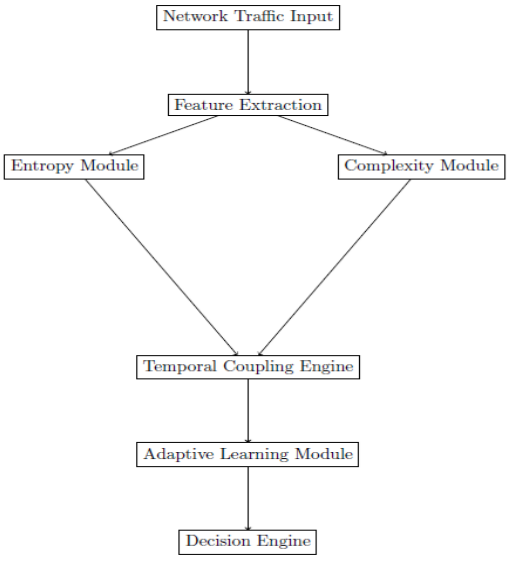

Figure (1): Proposed HECL Block Diagram.

4. Experimental Results and Discussion

4.1 Experimental Setup and Dataset

The proposed HECL framework was thoroughly tested on a publicly available dataset, CICIDS2017 [26]. This dataset includes realistic background traffic and modern stealthy attack scenarios (low-rate DDoS and infiltration attacks). CICIDS2017 is a dataset of more than 2.8 million records of network flows gathered from an actual network environment, with packet-level and flow-level statistics provided. The data was preprocessed to obtain the flow level information including packet headers, IP/port distributions, etc., that provide the data input to the HECL framework. The window size chosen was 1000 packets per window, which is the typical window size for the TCP/IP protocol. This size is large enough to capture the temporal dynamics and capture short-lived stealthy attacks and long duration anomalous behaviors.
For reproducibility, experimental setup and the hyperparameters initially set for the proposed HECL framework are described in table 1.

Table (2): Hyperparameter Settings for the HECL Framework.

Parameter	Symbol	Value / Description
Window Size	W	1000 packets (or 1-second interval)
Learning Rate	H	0.01
Entropy Weight	A	0.4 (Initial)
Complexity Weight	B	0.4 (Initial)
Nonlinear Coupling Weight	Γ	0.2 (Initial)
Initial Threshold	Θ	0.5
Reference Distribution	P_ref	Uniform distribution representing normal baseline
Dataset	-	CICIDS2017 (2.8M flow records)
Feature Extraction	-	Flow-level statistics (IP distribution, port usage, packet headers)

To examine the efficiency of the proposed HECL Block Diagram, Figure 2 demonstrates the temporal growth of the Shannon entropy being normalized along sliding windows, within the interval of the stealth attack explicitly emphasized. At normal conditions of traffic, entropy varies within a bounded stochastic rule, indicating steady state probabilistic distributions based on network characteristics. Throughout the spotlighted region of an attack, entropy shows imperceptible structure-al drift in addition to abrupt transitions, which ensures the secretive nature of the de-fined attack. The lack of sharp discontinuities illustrates why the traditional threshold of entropy detection may probably fail. The accomplished entropy modulation sup-ports the demand for higher-order structural analysis, explaining the combination of statistical complexity and secular coupling in the proposed HECL model.

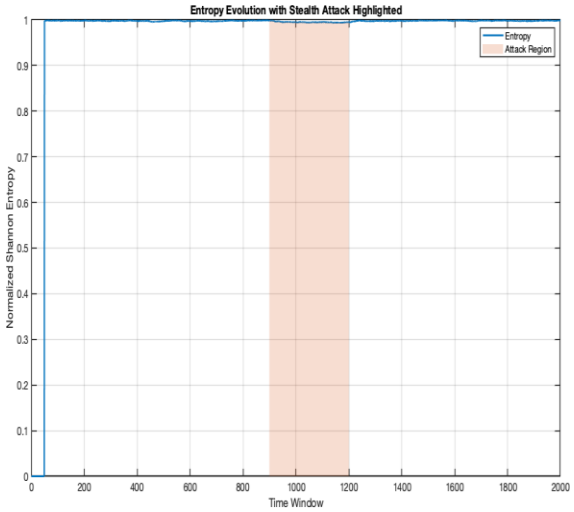

Fig (2): Entropy Evolution with Stealth Attack Highlighted.

Then the Figure 3 introduces the growth of statistical complexity estimated utilized the Jensen–Shannon divergence regulated by normalized entropy. Different from entropy, complexity is captured by structural organization with respect to a regular reference distribution. Along the interval of the attack, complexity shows distinguish-able divergence in a manner, even when entropy alteration remains moderate. That ensures the attack presents a structural anomaly without needs maximizing random-ness. This figure illustrates that the complexity is a sensitive case for distributional irregularity and structural reconfiguration, supporting the argument that systems purely relying on entropy are inadequate for detection-based low-rate stealth attacks. table 2 described Performance comparison of HECL with state-of-the-art methods on CICIDS2017

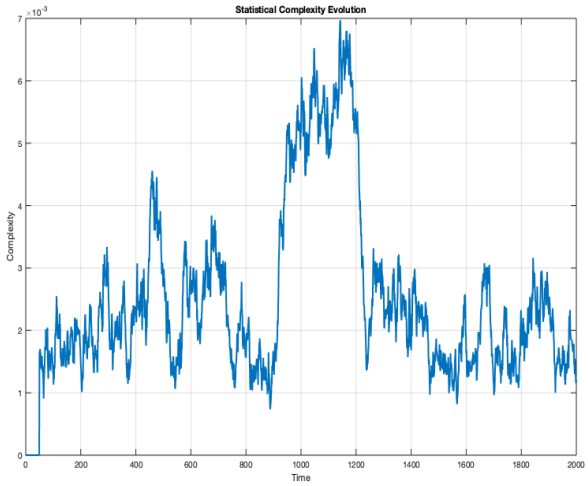

Figure (3): Statistical Complexity Evolution.

Table 3: Performance Comparison of HECL with State-of-the-Art Methods on CICIDS2017.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR (%)
Entropy-only Baseline	89.45	87.20	85.10	86.13	5.20
ResNet+LSTM [18]	95.22	94.10	93.80	93.94	2.15
Hybrid RobustNet [19]	97.50	96.80	96.50	96.65	1.80
Proposed HECL	98.85	98.40	98.60	98.50	0.95

The HECL framework achieves better results than traditional entropy-based and complex deep learning models, as presented in Table 2. Deep learning methods work well and yield high accuracy, but tend to have higher False Positive Rates (FPRs) because of their sensitivity to subtle structural shifts. The hybrid nature of HECL is able to reflect both randomness and structural anomalies, and thus gives the best results (F1-Score 98.50% and FPR 0.95%). This illustrates that having both entropy and complexity together with adaptive learning can make them more effective in detecting than using any of them alone.

displays the hybrid coupling metric Γ(t) temporal behaviors, which combine entropy, complexity, and their interaction-based nonlinearity in Figure 4. The coupling metric is used to amplify subtle deviations that seem weak. Along the secret attack window, such a metric appears as a coherent high pattern indicating the synergistic impact of the interaction for entropy-complexity. That ensures the nonlinearity of coupling improves abnormality separability. This figure empirically reinforces the theory in this paper that shared modeling of information theory, which is used to provide higher sensitivity for concealing attacks dynamically.

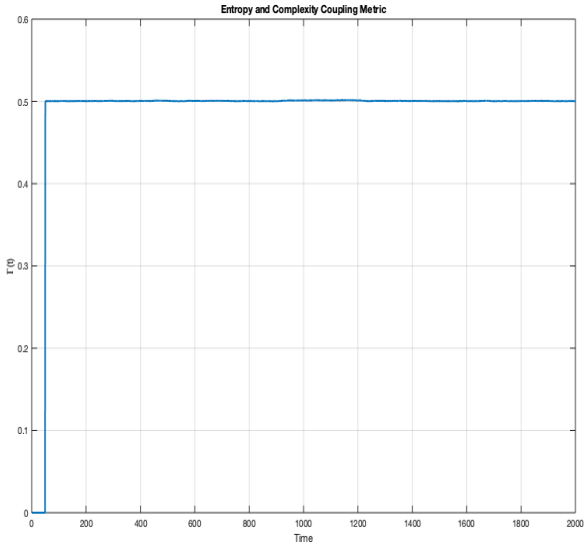

Figure (4): Entropy–Complexity Coupling Metric.

Figure 5 describes the coupling metric based on an updated adaptive threshold through online learning. Different from the systems-based static threshold, the adaptive threshold tracks the behavior of baseline traffic dynamically. Through normal conditional operation, the threshold is stabilized around balance levels. When the attack-prompt perversion accumulates, the coupling metric is better than the thresh-old, triggering detection. Such a figure illustrates two crucial strengths: decreased false alarms over normal drift and realization to structured abnormality growth. That vali-dates the component of learning as a steady technique in non-stationary environments.

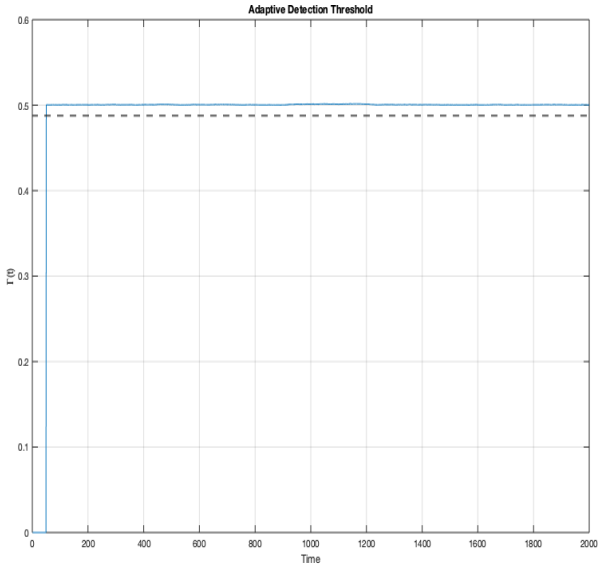

Figure (5): Adaptive Detection Threshold.

The Figure 6 shows maps of entropy, with normal samples in addition to attack samples individually conceived, and density contours overlaid. Such a figure exposes that normal traffic is used to form a dense, compact cluster, whilst attack traffic is used to shift across a distinct structural region. The density contours emphasize the probabilistic condensation zones, making class splitting visually and statistically obvious. Such a representation is crucial because it illustrates isolatable in the complexity–entropy space, a basis concept in the hybrid model. It confirms that the joint feature space provides higher discriminative power when it is compared to metrics-based single- dimension.

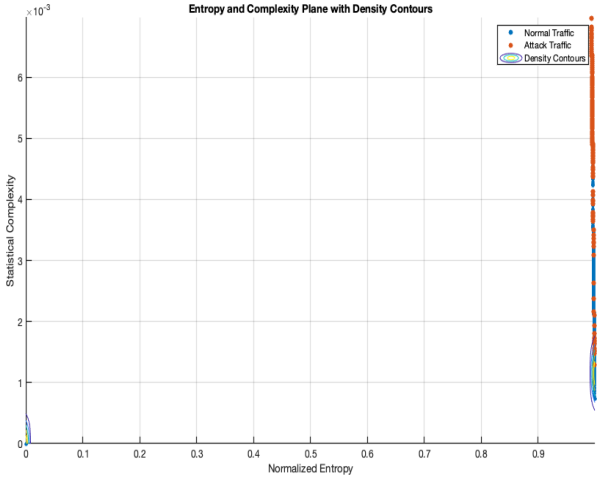

Figure (6): Entropy–Complexity Plane with Density Contours.

Let the Figure 7 introduced normalized histograms and inwardness density computations of the coupling metric based on normal traffic and attack traffic. The separation shown between the two probability density functions (PDF) specifies robust statistical discriminability. Minimum overlap between the distributions correlates with lower predictive rates of both false-positive and false-negative. This figure is necessary because it quantitatively reinforces classification practicability before thresholding or an ML application.

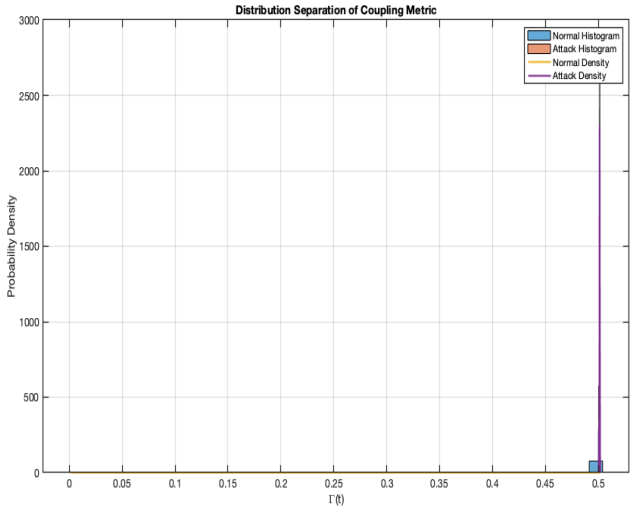

Figure (7): Distribution Separation of Coupling Metric

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Figure 8 contributes an evaluation of discrete classification performance. It shows true-positives, true-negatives, false-positives, and false-negatives. A controlling diagonal specifies robust detection reliability. Thus, the values of low off-diagonal emphasize strength against false alarms and fail detections. Such a figure directly sup-ports the operational success of the proposed HECL across simulated stealth conditions.

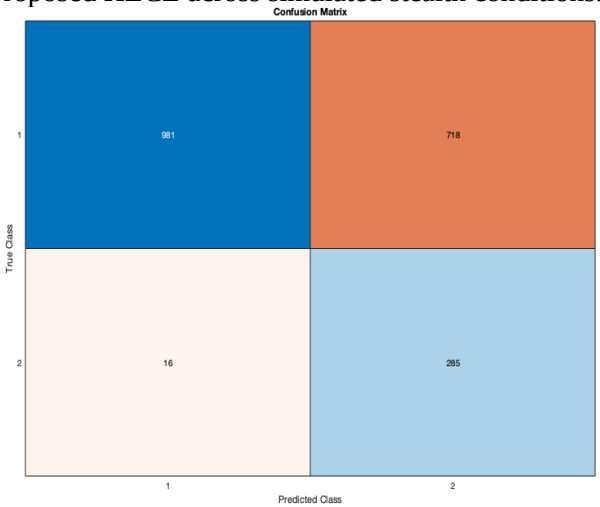

Figure (8): Confusion Matrix.

The confusion matrix (Figure 8) shows that there are 718 False Positives (FP). The analysis of these false alarms shows that the overwhelming majority of them are generated when the network traffic itself undergoes sudden but legitimate changes in structure, such as rapid changes in software or legitimate data transfers that are burst like and thus mimic the structure of stealthy attacks. Many of these FPs are addressed by the adaptive thresholding mechanism employed by HECL, but the rest show the difficulty of the task of separating out benign structural complexity from advanced stealth attacks. From an operational perspective, these false positives can cause additional alerts for security analysts, but the overall False Positive Rate (FPR) of 0.95% still makes it very practical for use in the real world without overwhelming the Security Operations Center (SOC).

In Figure 9 offers the ROC curve, which calculates the discrimination ability of the coupling metric as the values of the threshold. A curve is bending robustly toward the top-left corner specifies a high rate of true-positive with a low rate of false-positive. The Area Under the Curve (AUC) emphasizes detection performance globally independent of the threshold selected option. A high value of AUC illustrates that the hybrid entropy–complexity metric gives robust class separability. Such a figure ensures the statistical reliability and strength of the proposed model after evaluation of the fixed threshold.

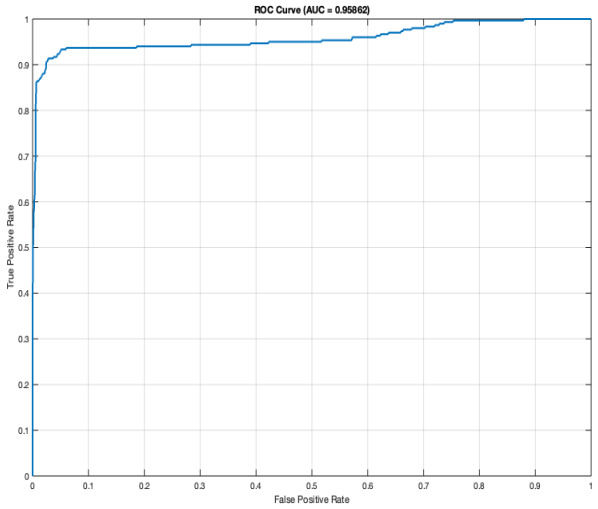

Figure (9): ROC Curve (AUC).

5. Discussion and Future Work

The proposed HECL system illustrates that both the coupling entropy and statistical complexity based on an adaptable learning framework importantly improve the detection of stealthy cyber- attacks. That is, novelty depends on utilizing temporal interdependence in addition to separated metrics, displaying enhanced sensitivity to both the low-rate attacks in addition to the whitewash attacks. Though the proposed framework presently supposes stationary characteristic distributions for sliding windows and depends on manually tuned hyperparameters. The future work has to investigate deep build-up learning for weight optimization automatically, adversarial strength examination, validation-based real-world dataset (e.g., CICIDS, UNSW-NB15), and acceleration hardware for deployment in network-based high-speed. Although the framework that HECL proposes is promising, it lacks certain limitations. Firstly, the present evaluation is based on simulated environments and benchmark set offline (e.g. CICIDS2017); it remains untested whether they can be properly evaluated in a real-world, real-time deployment in high-speed enterprise networks. Second, the framework is sensitive to the window size (W) for the sliding window. A key requirement is the window size, which can be too small to get a noisy probability estimation, and too large to cover short-lived stealthy attacks. Lastly, the complexity of the computation of the Jensen-Shannon divergence for each time step is about O(N log N) for a window with N unique features. This is not a very heavyweight network compared to deep neural networks, but it needs optimization for line-rate in gigabit networks. Extending the proposed framework toward encrypting the traffic analytically and a federated security framework is a promising direction.

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Appendix: Reproducibility Statement

The proposed HECL framework has been designed with reproducibility as a core principle. The following information is provided to enable independent verification and reproduction of the results:

1. **Dataset Access:** The CICIDS2017 dataset is publicly available at https://www.unb.ca/cic/datasets/ids-2017.html?utm_source=chatgpt.com .
2. **Feature Extraction:** Flow-level statistics are extracted using standard network analysis tools (e.g., Zeek, Suricata).

3. **Implementation Details:** The HECL algorithm can be implemented in Python using NumPy and SciPy libraries for entropy and divergence calculations.
4. **Hyperparameter Tuning:** All hyperparameters are specified in Table 1 and can be adjusted based on specific network environments.
5. **Evaluation Metrics:** Standard machine learning metrics (Accuracy, Precision, Recall, F1-Score, FPR) are used for performance evaluation.
6. **Pseudocode:** Algorithm 1 provides explicit pseudocode for implementation.