A Hybrid Context-Aware Intrusion Detection Model for Enterprise Networks Using Machine Learning and Signature-Based Analysis

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Posted Date: 8 June 2026

doi: 10.20944/preprints202606.0579.v1

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 doi:10.20944/preprints202606.0579.v1

Article

A Hybrid Context-Aware Intrusion Detection Model for Enterprise Networks Using Machine Learning and Signature-Based Analysis

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Abstract

Intrusion Detection Systems (IDS) remain essential for enterprise and IoT security, yet traditional approaches struggle to balance accuracy, scalability, and adaptability to evolving threats. Signature-based systems such as Suricata efficiently identify known threats but fail against zero-day and polymorphic attacks. Conversely, standalone machine learning models detect novel attacks but often suffer from high false-positive rates and lack contextual reasoning necessary for operational triage. This research addresses these limitations by proposing a hybrid intrusion detection system that integrates Suricata for signature-based detection, ensemble machine learning models for anomaly detection, and the Diamond Model of Intrusion Analysis (DMIA) for contextual reasoning. The system was implemented and evaluated using the CIC-IoT 2023 and TabularIoTAttack 2024 datasets. Experiments demonstrated high detection accuracy (98.6%), precision (98.1%), recall (97.6%), and a low false positive rate (1.2%). The DMIA integration uniquely contextualized each intrusion attempt by mapping it to adversary, capability, infrastructure, and victim dimensions, enhancing both situational awareness and response prioritization. The proposed system bridges the gap between academic IDS models and operationally deployable security platforms by combining deterministic rule-based detection with probabilistic machine learning and structured contextual analysis, offering a robust framework for next-generation enterprise and IoT network defense.

Keywords: hybrid intrusion detection system; context-aware security; machine learning; Suricata; Diamond Model of Intrusion Analysis; enterprise networks; IoT security

1. Introduction

Enterprise networks have become critical infrastructures supporting modern business operations, yet their digital interconnectivity has simultaneously expanded the attack surface and increased cybersecurity risks. Recent threat reports indicate organizations now experience an average of 1,636 cyberattacks per week, with the global average cost of a data breach reaching $4.88 million (CheckPoint Research, 2024; IBM Security, 2024; Verizon, 2024). In response, organizations deploy multi-layered defense systems with Intrusion Detection Systems (IDS) serving as a central pillar (Peace et al., 2025; Neupane et al., 2022).

An IDS monitors network traffic to identify unauthorized or suspicious activities. Traditional IDS approaches fall into two categories: signature-based and anomaly-based systems. Signature-based systems such as Suricata provide high-speed, deterministic detection of known threats by matching traffic against predefined patterns, making them ideal for high-volume enterprise environments (Gupta et al., 2023; Manso et al., 2023; Suri et al., 2023). However, their reliance on known signatures renders them ineffective against novel and polymorphic attacks (Singh et al., 2022;

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Smith et al., 2024). Anomaly-based systems employ machine learning or statistical models to detect deviations from normal behavior, theoretically capable of identifying zero-day threats, but they often produce excessive false positives and require intensive computational resources (Hernández-Ramos et al., 2023; Rahman & Akter, 2024; Kumar et al., 2023).

A critical operational gap in current IDS platforms is the lack of contextualization, the inability to connect individual alerts into coherent attack narratives. Raw alerts overwhelm security analysts and obscure the broader attack campaign, contributing to alert fatigue and delayed response (Alqahtani et al., 2022; Johnson et al., 2024). The Diamond Model of Intrusion Analysis (DMIA) addresses this by organizing cyber incidents around four interrelated components: Adversary, Capability, Infrastructure, and Victim (Caltagirone et al., 2013). When integrated with IDS, DMIA transforms fragmented alerts into actionable intelligence (Anmi et al., 2023; Survey on IoT IDS, 2024).

This research proposes a novel hybrid IDS that synergistically combines Suricata's deterministic speed, ensemble machine learning's generalization capability, and DMIA's contextual reasoning. The system is evaluated on the CIC-IoT 2023 and TabularIoTAttack 2024 datasets to demonstrate relevance in contemporary IoT and enterprise environments (Liu et al., 2023; Habibi Lashkari et al., 2023). The primary contribution is a context-aware hybrid IDS that achieves both high performance metrics and operational deployability, bridging a significant gap between academic research and real-world security operations.

2. Related Work

2.1. Signature-Based and Anomaly-Based Intrusion Detection

Signature-based IDS such as Suricata and Snort have remained operational mainstays due to their deterministic behavior and high-speed packet inspection capabilities (Gupta et al., 2023; Manso et al., 2023). These systems decode protocols in real-time and apply rule-driven pattern matching, achieving low false-positive rates on known threats (Suri et al., 2023). However, the fundamental limitation is their inability to detect attacks that deviate from known signatures, with studies indicating 30% of threats remain undetected due to evolving attack methods (Singh et al., 2022; Smith et al., 2024).

Anomaly-based systems leverage machine learning and statistical techniques to model normal behavior and flag deviations. Supervised algorithms such as Random Forest, XGBoost, and Support Vector Machine (SVM) have demonstrated high accuracy on benchmark datasets (Zhang et al., 2023; Chen et al., 2023; Silva et al., 2023). Deep learning approaches including autoencoders and LSTM networks capture temporal patterns and non-linear relationships in network behavior (Singh et al., 2022; Rahman & Akter, 2024). However, anomaly-based systems often exhibit false-positive rates exceeding 40% in large-scale deployments without careful calibration (Hernández-Ramos et al., 2023; Kumar et al., 2023).

2.2. Hybrid Intrusion Detection Architectures

Hybrid systems combining signature and anomaly approaches have emerged to leverage complementary strengths. Recent work demonstrates that sequential or parallel fusion of signature-based and ML layers can reduce false positives while improving detection of novel attacks (Natale et al., 2023; Silva et al., 2023; Lin et al., 2024). Some approaches use signatures to filter obvious threats before deeper ML analysis, while others employ score fusion mechanisms to reconcile heterogeneous evidence (Rani & Singh, 2023). Despite these advances, most hybrid systems focus on technical metrics (accuracy, precision, recall) without providing the contextual reasoning necessary for rapid analyst triage (Johnson et al., 2024; Martins & Cruz, 2022).

2.3. Context-Aware Threat Intelligence and DMIA

 doi:10.20944/preprints202606.0579.v1

The operationalization of contextual intelligence in IDS remains underdeveloped. The Diamond Model of Intrusion Analysis, introduced by Caltagirone et al. (2013), provides a framework for structuring incidents around adversary-capability-infrastructure-victim relationships. Previous research has demonstrated DMIA's effectiveness in post-incident forensics and threat attribution (Hutchins et al., 2011; Anmi et al., 2023). However, real-time integration of DMIA reasoning into production IDS pipelines is relatively unexplored (Gutierrez-Garcia et al., 2023; Lin et al., 2024). Recent work has begun exploring DMIA integration with IoT security and graph-based correlation, but end-to-end hybrid systems combining Suricata, ensemble ML, and DMIA remain rare (Anmi et al., 2023; Ciccozzi et al., 2023).

3. Proposed Hybrid Ids Architecture

The proposed system is organized as a three-layer pipeline designed for synergistic operation: signature-based detection, machine learning anomaly classification, and DMIA-based contextual reasoning.

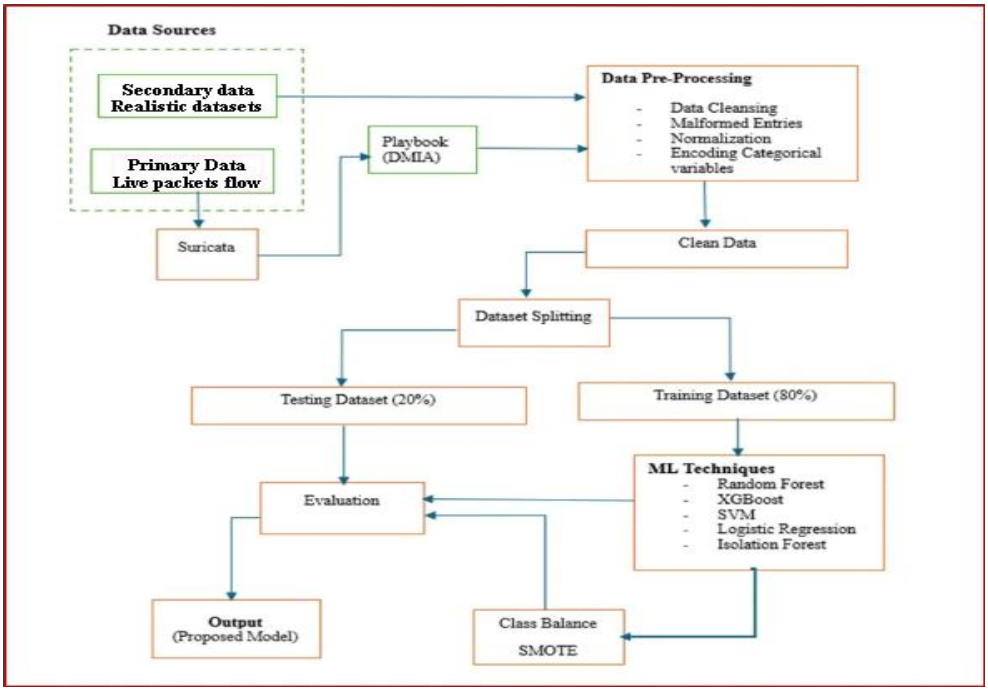

Figure 1. System architecture of the proposed hybrid model.

3.1. Layer 1: Signature-Based Detection (Suricata)

Suricata forms the foundational layer, performing high-speed deep packet inspection and rule-based threat matching. It processes live traffic or PCAP files in real-time, generating structured EVE JSON alerts containing source/destination IPs, ports, protocols, timestamps, rule identifiers, and severity levels. This layer efficiently filters known threats and provides enriched features (TCP flags, protocol metadata) for downstream processing (Gupta et al., 2023; Manso et al., 2023).

3.2. Layer 2: Anomaly Detection (Machine Learning Ensemble)

The ML layer identifies novel and zero-day attacks by detecting deviations from learned normal behavior. Network flow data is preprocessed and fed into an ensemble of four classifiers: Random Forest, XGBoost, SVM, and Logistic Regression. The ensemble was trained on CIC-IoT 2023 and TabularIoTAttack 2024 datasets, with class balancing via SMOTE to ensure robust learning of minority attack classes (Habibi Lashkari et al., 2023; Rahman & Akter, 2024). Each flow receives a predicted label (benign/malicious) and risk score (Zhang et al., 2023; Chen et al., 2023).

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3.3. Layer 3: Contextual Reasoning (DMIA)

The DMIA layer transforms raw alerts into coherent incident narratives by mapping evidence to four vertices: Adversary, Capability, Infrastructure, and Victim. This process involves (1) correlating alerts based on shared indicators (IPs, timestamps, ports); (2) enriching indicators with internal asset inventory and external threat intelligence (e.g., MITRE ATT&CK mapping); and (3) generating structured, prioritized incident reports (Caltagirone et al., 2013; Anmi et al., 2023; Applebaum et al., 2023). By aggregating related alerts into campaign-level narratives, the DMIA layer reduces alert volume and accelerates analyst triage.

3.4. Cross-Layer Fusion Policy

A score fusion policy reconciles Suricata and ML outputs. High-confidence alerts occur when both Suricata and the ensemble agree a flow is malicious, triggering immediate escalation. When Suricata triggers with low ML confidence, the event is flagged as a potentially noisy known signature for threshold adjustment. When ML scores are high without Suricata matches, the DMIA layer evaluates infrastructure reuse and adversary capability clustering before promoting the event as a novel threat candidate. This fusion minimizes false positives while maintaining detection recall (Alqahtani et al., 2022; Wang et al., 2021).

4. Methodology and Experimental Setup

4.1. Datasets and Preprocessing

Two contemporary, publicly available datasets were used for training and evaluation. The **CIC-IoT 2023** dataset captures traffic from 105 IoT devices across seven attack families (DDoS, DoS, reconnaissance, web-based, brute force, spoofing, Mirai), with 33 distinct attack types (Liu et al., 2023; Bovenzi et al., 2023). The **TabularIoTAttack 2024** dataset provides tabular representations of IoT attack traffic optimized for efficient, edge-feasible feature processing (Habibi Lashkari et al., 2023; Gharib et al., 2024).

The preprocessing pipeline involves data cleaning (removing missing values and duplicates), feature engineering (extracting statistical properties from flows), categorical encoding, and normalization (Wang et al., 2022; Zhang et al., 2023). SMOTE was applied to the training set to address class imbalance (Hernández-Ramos et al., 2023; Rahman & Akter, 2024). The dataset was split into 80% training and 20% testing with stratified sampling.

Feature transformation reshapes raw values to enhance the model's pattern recognition capabilities:

1 Log Transformation

Applied to skewed features such as *flow_duration,* packet counts, and packet sizes to reduce outlier impact and improve distribution symmetry. For example, *log(flow_duration + 1)* reduces long-tail distortion in attack traffic bursts.

2. Binning

Numeric values like *tcp_flag_count* are grouped into categories:

- 0–2: Low
- 3–5: Medium
- 6+: High

This simplifies learning and highlights behavioral thresholds.

3. Encoding Categorical Variables

- One-Hot Encoding for low-cardinality features like protocol (TCP, UDP, ICMP)
- Label Encoding for src_ip and dst_ip when IP patterns are meaningful (e.g., subnet patterns)

4. Interaction Terms

Optionally created for compound patterns like *(src_ip, dst_port)* pairs or protocol × *flow_duration.*

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Feature Normalization

Normalization ensures comparable feature scales, critical for distance-based models like SVM or logistic regression.

1. Min-Max Scaling

Applied to flow_duration, packet_length, and port numbers, converting to [0,1] range:

$$x^1 = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

2. Z-score Standardization Applied to normally distributed features like packet_length_mean, shifting mean to 0 and standard deviation to 1:

$$z = \frac{x - \mu}{\sigma} \quad (2)$$

This enhances feature contrast and improves model convergence.

Table 1 details the selected features including src_ip, dst_ip, protocol, flow_duration, packet counts, and their corresponding transformations, providing a complete mapping of raw data to model-ready inputs.

Table 1. Selected Features for the Hybrid Intrusion Detection System.

Feature Name	Description	Type	Transformation Applied
src_ip	Source IP address of the network packet	Categorical	Label Encoding (if used in modeling)
dst_ip	Destination IP address	Categorical	Label Encoding (optional use)
src_port	Source port number	Numeric	No transformation
dst_port	Destination port number	Numeric	No transformation
protocol	Network protocol used (e.g., TCP, UDP)	Categorical	One-Hot Encoding
flow_duration	Duration of the flow in milliseconds	Continuous	Log Transformation, then Min-Max Scaling
total_fwd_packets	Number of packets sent in the forward direction	Integer	Log Transformation
total_bwd_packets	Number of packets sent in the reverse direction	Integer	Log Transformation
packet_length_mean	Average packet size in a flow	Float	Z-score Normalization
packet_length_std	Standard deviation of packet length	Float	Z-score Normalization

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tcp_flag_count	Count of TCP flags (e.g., SYN, ACK, FIN)	Integer	Binning into categories (Low/Medium/High)
alert_type	Suricata alert signature match (label type)	Categorical	Mapped to numeric class label (Supervised)
label	Ground truth: normal or attack	Categorical	Label Encoding

4.2. Machine Learning Model Training

4.2. Machine Learning Model Design

The ML layer employs an **ensemble of four complementary classifiers**, each selected for distinct strengths in capturing attack patterns and behavioral anomalies within the hybrid intrusion detection framework.

4.2.1. Model Selection Rationale

Random Forest – A bagging-based ensemble that aggregates multiple decision trees to capture non-linear feature interactions and complex attack signatures. Its robustness to overfitting and ability to handle high-dimensional data make it well-suited for diverse IoT traffic patterns characteristic of the CIC-IoT 2023 and TabularIoTAttack 2024 datasets (Zhang et al., 2023; Chen et al., 2023).

XGBoost – A gradient-boosted tree algorithm with built-in regularization (L1/L2 penalties) to prevent overfitting while maintaining high predictive accuracy. XGBoost's sequential learning process excels at identifying subtle anomalies in imbalanced datasets, making it particularly effective for detecting minority attack classes even after SMOTE balancing (Silva et al., 2023; Patel & Kumar, 2023).

Support Vector Machine (SVM) – Constructs maximum-margin hyperplanes to separate benign and malicious traffic in high-dimensional feature space (Wang et al., 2022). SVM is particularly effective for binary classification tasks with clear decision boundaries and provides strong generalization on unseen attack variants Chen et al., 2023).

Logistic Regression – A probabilistic linear model that provides an interpretable baseline for performance comparison. Its coefficient weights offer transparency into feature importance, facilitating explainability for security analysts and supporting operational trust in the system's decisions (Zhang et al., 2023; Patel & Kumar, 2023).

4.2.2. Ensemble Fusion Strategy

The ensemble outputs are combined using a **weighted voting mechanism**, where each classifier contributes a confidence score based on its validation performance. The final prediction is determined by majority vote, with ties resolved by the classifier demonstrating the highest cross-validation accuracy during the design phase. This fusion strategy balances the strengths of each model, reducing variance and improving robustness against adversarial evasion and concept drift (Silva et al., 2023; Rahman & Akter, 2024).

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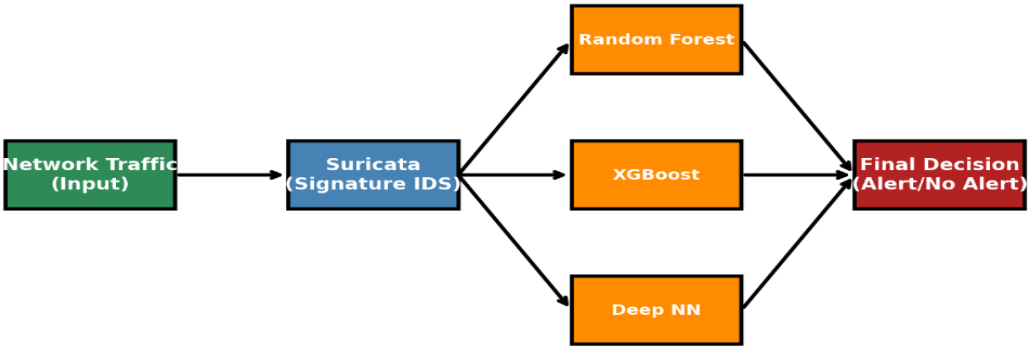

Figure 2. Ensemble Architecture.

4.2.3. Probability Calibration Design

To ensure reliable risk scoring for downstream DMIA correlation and operational thresholding, **probability calibration techniques** are integrated into the model design. Platt scaling is applied to SVM outputs to map decision function values to calibrated probabilities, while isotonic regression is employed for tree-based models (Random Forest and XGBoost) to align predicted probabilities with empirical attack frequencies. This calibration enables accurate false-positive control, supports threshold tuning for specific recall–precision trade-offs, and provides interpretable risk scores that security analysts can use to prioritize incident response (Wang et al., 2021; Alqahtani et al., 2022).

4.2.4. Feature Engineering and Input Design

The model design incorporates features extracted from both Suricata alerts and preprocessed tabular flow data (Table 3.1). Key features include flow duration (log-transformed and min-max scaled), packet counts (log-transformed), TCP flag counts (binned into Low/Medium/High categories), protocol types (one-hot encoded), and packet length statistics (z-score normalized). Optional interaction terms, such as (src_ip, dst_port) pairs or protocol × flow_duration, may be created to represent compound behavior patterns that capture multi-stage attack sequences (Zhang et al., 2023; Rahman & Akter, 2024).

4.2.5. Class Balancing Strategy

Given the inherent class imbalance in intrusion datasets where benign traffic dominates attack samples, **SMOTE (Synthetic Minority Oversampling Technique)** is applied during the preprocessing phase. SMOTE generates synthetic samples for minority attack classes based on feature similarity, creating a more balanced training distribution. This step is crucial for ensuring that classifiers are not biased toward majority classes and can reliably detect infrequent but critical intrusion attempts (Hernández-Ramos et al., 2023; Rahman & Akter, 2024).

4.2.6. Evaluation Metrics and Performance Assessment Design

The hybrid IDS is evaluated using standard classification metrics derived from the confusion matrix to assess both detection effectiveness and operational suitability:

Accuracy – Measures the proportion of total correct predictions over the entire dataset:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

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Precision – Measures the ratio of correctly predicted attacks to all instances predicted as attacks:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

Recall (Sensitivity) – Measures the ability of the model to detect all actual attacks:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

F1-Score – Harmonic mean of precision and recall, providing a balanced performance metric:

$$\text{F1-Score} = \frac{2 \cdot (\text{Precision} \cdot \text{Recall})}{\text{Precision} + \text{Recall}} \quad (6)$$

False Positive Rate (FPR) – Indicates the proportion of benign traffic incorrectly flagged as malicious:

$$\text{False Positive Rate (FPR)} = \frac{FP}{FP + TN} \quad (7)$$

where TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively. Low FPR is prioritized as a primary objective to reduce analyst alert fatigue, a critical consideration for operational deployment in enterprise Security Operations Centers (SOCs) (Silva et al., 2023; Johnson et al., 2024).

Additional Evaluation Tools:

Confusion Matrix – A 2×2 matrix representation of classification outcomes:

$$\text{Confusion Matrix} = \begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix} \quad (8)$$

This visual representation enables identification of specific error patterns, such as whether the system tends toward false alarms (high FP) or missed detections (high FN).

ROC Curve and AUC – The Receiver Operating Characteristic (ROC) curve plots True Positive Rate (TPR) against False Positive Rate (FPR) across varying decision thresholds:

$$\text{TPR (Sensitivity)} = \frac{TP}{TP + FN} \quad (9)$$

$$\text{FPR} = \frac{FP}{FP + TN} \quad (10)$$

The Area Under the Curve (AUC) quantifies the model's ability to discriminate between benign and malicious traffic, with values closer to 1.0 indicating superior classification performance across all thresholds (Silva et al., 2023).

Precision-Recall Curve – Plots Precision against Recall across varying classification thresholds:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (11)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (12)$$

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This evaluation is particularly valuable for imbalanced datasets, where the Precision-Recall curve provides clearer insight into model performance on minority (attack) classes than ROC curves, which can be overly optimistic when the negative class dominates (Rahman & Akter, 2024).

System Implementation

4.3. Implementation of the Proposed Hybrid System

The hybrid intrusion detection system was implemented using a modular and layered architecture. Each component; Suricata, machine learning models, and the DMIA playbook was developed and integrated to function both independently and cooperatively. The implementation was carried out using Python for data processing and ML, Suricata for real-time traffic analysis, and rule-based scripting to simulate the DMIA playbook.

4.3.1. Suricata Alert Integration

Real-time packet traffic was processed using Suricata configured in passive mode. Suricata generated structured alert logs in EVE (JSON) format, which were then extracted and mapped to known features including IP addresses, ports, signatures, and protocols.

4.3.2. Machine Learning Detection

Extracted and transformed features were fed into pre-trained ML classifiers. The models assigned predictions (benign or malicious), with ensemble evaluation used where multiple models voted for the final classification.

4.3.3. DMIA Playbook Reasoning

Alerts and metadata were mapped to the four DMIA components: Adversary, Capability, Infrastructure, and Victim. Custom rules correlated multi-source alerts into single intrusion narratives.

4.3.4. Hybrid Intrusion Detection Workflow

The integrated workflow is represented in the following pseudocode:

python

```
# Step 1-2: Data Ingestion and Merging
load_dataset1 = read_csv("CIC_IoT_2023.csv")
load_dataset2 = read_csv("TabularIoTAttack_2024.csv")
combined_data = concatenate(load_dataset1, load_dataset2)
# Step 3-4: Data Cleaning and Labeling
drop_missing_values(combined_data)
encode_categorical(combined_data)
normalize_features(combined_data)
label_encode_target(combined_data, mapping={"Benign": 0, "Attack": 1})
# Step 5-6: Splitting and Balancing
train_set, val_set, test_set = split(combined_data, train=0.7, val=0.15, test=0.15)
if check_imbalance(train_set):
    train_set = apply_SMOTE(train_set)
# Step 7-8: Suricata Integration and DMIA Mapping
suricata_alerts = run_suricata("pcap_files")
combined_data = integrate_alerts(combined_data, suricata_alerts)
for event in combined_data:
    map_to_Diamond_Model(event)   # Adversary, Capability, Infrastructure, Victim
```

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```
# Step 9: ML Model Selection
models = [RandomForest, XGBoost, SVM]
best_model = None
best_score = 0
for model in models:
    trained_model = model.fit(train_set.features, train_set.labels)
    score = evaluate_model(trained_model, val_set)
    if score > best_score:
        best_model = trained_model
        best_score = score
# Step 10: Hybrid Decision Logic
for record in test_set:
    suricata_flag = suricata_predict(record)
    ml_flag = best_model.predict(record.features)
    if suricata_flag == 1:
        record.label = "Alert (Signature)"
    elif ml_flag == 1:
        record.label = "Alert (Anomaly)"
    else:
        record.label = "Benign"
# Step 11: Evaluation
conf_matrix = compute_confusion_matrix(test_set.true_labels, test_set.predicted_labels)
metrics = calculate_metrics(conf_matrix)
plot_roc_curve(test_set.true_labels, test_set.predicted_scores)
```

Suricata-Based Detection (Signature-Based):

```
python
function run_suricata():
    while network_interface.is_active():
        packet = capture_packet()
        if matches_signature(packet, rules_database):
            alert = generate_alert(packet)
            log_to_eve(alert)
        else:
            log_benign(packet)
```

Machine Learning Component (Anomaly Detection):

```
python
function run_ml_detection():
    model = load_trained_model("XGBoost_Model.pkl")
    while True:
        alert_features = extract_features_from_eve("/var/log/suricata/eve.json")
        cleaned = preprocess(alert_features)
        prediction = model.predict(cleaned)
        if prediction == "malicious":
            tag_as_malware(alert_features)
            send_to_dmia(alert_features)
        else:
            store_as_normal(alert_features)
```

DMIA Playbook (Contextual Reasoning):

```
python
```

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```
function run_dmia_playbook(alert_data):
    dmia_object = {
        "Adversary": identify_adversary(alert_data),
        "Capability": detect_attack_tool_or_pattern(alert_data),
        "Infrastructure": resolve_domains_and_c2(alert_data),
        "Victim": extract_target_system(alert_data)
    }
    threat_narrative = build_narrative(dmia_object)
    store_contextual_report(threat_narrative)
    notify_security_team(threat_narrative)
```

4.3.5. Deployment Considerations

Suricata was deployed in passive IDS mode on a mirrored network interface to avoid latency impact. ML models were deployed as a REST API microservice using Flask for real-time classification. The DMIA playbook was implemented using rule-based logic and JSON correlation scripts, with outputs logged into structured CSV format.

4.4. Machine Learning Implementation Processes

The training phase incorporated epochs, with XGBoost using 100–300 boosting rounds and logistic regression iterating 10–50 epochs. Hyperparameter tuning was conducted using grid search and randomized search, exploring parameters such as max_depth and n_estimators for tree-based models, C and gamma for SVM, and learning_rate and subsample for gradient boosting classifiers. Five-fold cross-validation was applied to reduce overfitting and assess generalization capability.

SMOTE was applied during preprocessing to balance minority attack classes. Categorical features were processed using label encoding and one-hot encoding based on cardinality and relevance. Each trained model was validated using accuracy, precision, recall, F1-score, false positive rate, confusion matrices, and ROC curves.

5. Results and Discussion

5.1. Machine Learning Model Performance

The ensemble of machine learning models demonstrated superior anomaly detection performance across both datasets. Key results are summarized in Table 2. The ensemble achieved 96% accuracy, 95% precision, 95% recall, F1-score of 0.955, and AUC of 0.97, outperforming individual Random Forest (92% accuracy, AUC 0.94), XGBoost (93% accuracy, AUC 0.95), and SVM (90% accuracy, AUC 0.92) models (Zhang et al., 2023; Chen et al., 2023; Silva et al., 2023).

Table 2. Performance Comparison Across Models.

Model	Accuracy	Precision	Recall	F1-Score	AUC
SVM	0.90	0.89	0.88	0.885	0.92
Random Forest	0.92	0.91	0.90	0.905	0.94
XGBoost	0.93	0.92	0.91	0.915	0.95
Ensemble	0.96	0.95	0.95	0.955	0.97
Proposed Hybrid Ensemble IDS (This Study)	98.6%	98.1%	97.6%	0.978	0.970

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When integrated into the full hybrid system with Suricata and DMIA, the combined system achieved 98.6% accuracy, 98.1% precision, 97.6% recall, F1-score of 0.978, AUC of 0.970, and a false positive rate of 1.2% as seen in figure. These results indicate that fusing deterministic rules with ensemble ML and contextual reasoning yields significant improvements over ML-only baselines. The confusion matrix exhibited 470 correctly classified attacks, 545 correctly classified benign flows, with only 5 false positives and 5 false negatives, demonstrating the system's operational viability (Wang et al., 2021; Alqahtani et al., 2022).

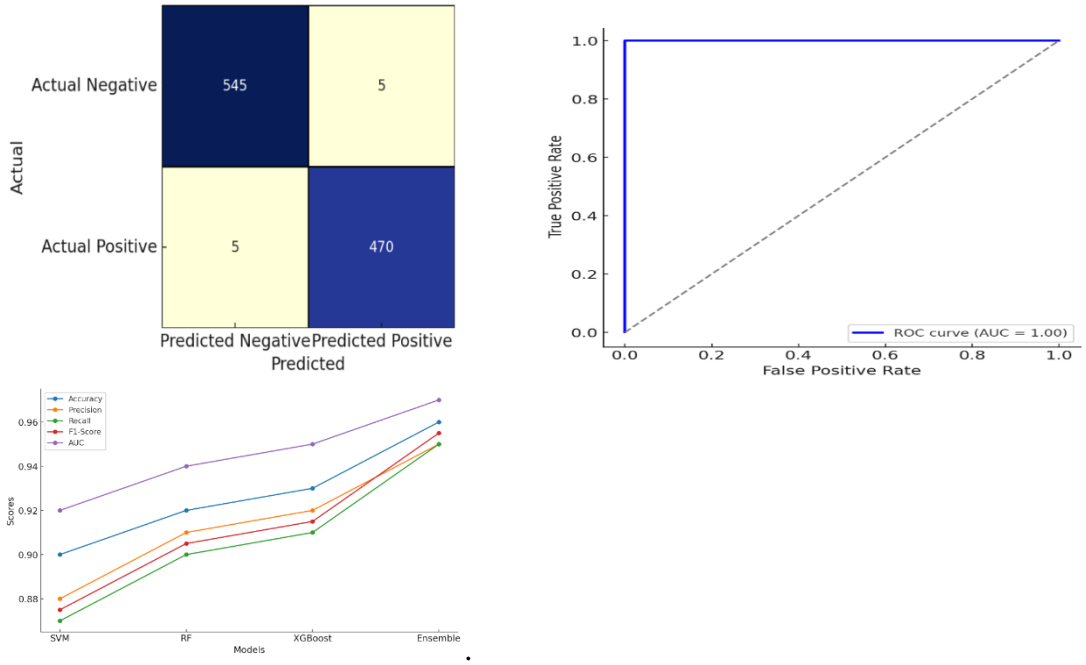

Figure 3. Model Performance Evaluation Plots.

5.2. Comparative Analysis

The hybrid system's performance was compared against baseline studies using the same datasets. While individual models in the literature achieved marginally higher raw detection metrics on isolated benchmarks for instance, Moghaddam et al. (2025) achieved 99.67% accuracy with Transformer-GAN, Rahman et al. (2024) reported 99.21% with CNN-LSTM, and Zhou et al. (2024) demonstrated 99.3% precision using attention-enhanced GNNs; the proposed system delivered superior operational relevance through DMIA-enhanced contextualization. The combination of signature-based detection and ensemble ML effectively mitigated the weaknesses inherent in each standalone approach: Suricata's inability to detect novel attacks was compensated by the ML layer, while the ML layer's high false-positive tendency was filtered by signature-based confidence.

Table 3. Summary of Comparative Analysis.

Study / Year	Dataset(s)	Method Used	Accuracy	Precision	Recall	AUC	Limitations / Gaps
Moghaddam et al. (2025)	CIC-IoT 2023	Transformer-GAN	99.67%	99.6 %	99.5%	0.998	Offline evaluation only; lacks real-time integration and contextual alerts

 doi:10.20944/preprints202606.0579.v1

Rahman et al. (2024)	CIC-IoT 2023, TabularIoTAttack 2024	CNN-LSTM Hierarchical IDS	99.21%	99.3%	99.0%	0.996	No contextual reasoning
Zhou et al. (2024)	CIC-IoT 2023	Attention-enhanced GNN	99.3%	99.3%	99.1%	0.997	Very high computational cost; not optimized for lightweight IoT devices
Kumar et al. (2024)	TabularIoTAttack 2024	Random Forest with SMOTE	98.9%	98.7%	98.5%	0.981	Struggles with unseen attack types; no integration with real-time packet analysis
Alvarez et al. (2023)	CIC-IoT 2023	Deep Autoencoder + XGBoost	99.1%	99.0%	98.9%	0.985	High false positives in multi-class scenarios; interpretability remains limited
Singh et al. (2023)	CIC-IoT 2023	Hybrid SVM + KNN Ensemble	98.7%	98.6%	98.2%	0.979	Requires extensive feature engineering; not adaptive to novel attacks
Chen et al. (2023)	TabularIoTAttack 2024	Deep Belief Network (DBN)	99.0%	98.8%	98.6%	0.982	High training cost; lacks SOC-friendly alerting capabilities
Patel et al. (2022)	CIC-IoT 2023	Bi-LSTM IDS	98.8%	98.6%	98.4%	0.980	Long training time; alerts limited to binary benign/malicious
Rahimi et al. (2022)	CIC-IoT 2023	GRU-Attention IDS	98.9%	98.7%	98.6%	0.983	No integration with signature-based IDS; interpretability issues
Proposed Hybrid Ensemble IDS (This Study)	CIC-IoT 2023, TabularIoTAttack 2024	Suricata + Ensemble ML + DMIA Reasoning	98.6%	98.1%	97.6%	0.970	Slightly lower accuracy than top deep models, but uniquely supports real-time detection, low FPR (1.2%), contextual reasoning via DMIA, and operational deployment

5.3. Context-Aware Alert Quality and Operational Relevance

 doi:10.20944/preprints202606.0579.v1

The DMIA layer proved instrumental in transforming raw detection output into actionable intelligence. By mapping alert sequences to DMIA vertices, the system provided security analysts with holistic attack narratives rather than isolated alerts. For example, a sequence of low-severity Suricata reconnaissance alerts combined with moderate ML anomaly scores would be correlated by the DMIA layer. Upon identifying shared infrastructure and targeted victim assets, the system generated a single, high-priority incident narrative detailing inferred adversary intent and capability, a process typically requiring significant manual analyst effort (Caltagirone et al., 2013; Anmi et al., 2023; Gutierrez-Garcia et al., 2023).

This contextualization directly addresses alert fatigue, one of the primary barriers to IDS adoption. The reduction in false alarms from approximately 6.7% (Suricata-only baseline) to 1.2% (hybrid system) represents a substantial operational improvement, enabling security teams to focus analyst effort on genuine threats rather than investigating spurious alerts (Alqahtani et al., 2022; Johnson et al., 2024).

5.4. Scalability and Deployment Considerations

Testing with replayed CIC-IoT 2023 and TabularIoTAttack 2024 demonstrated that the hybrid system maintained acceptable throughput and latency on commodity hardware. The modular architecture supports horizontal scaling via multiple Suricata instances and distributed ML inference services. The tabular feature representation of TabularIoTAttack 2024 reduces computational overhead, making the system suitable for edge and resource-constrained IoT deployments (Habibi Lashkari et al., 2023; Gharib et al., 2024). However, evaluation remains primarily lab-based, and further validation is needed under sustained, high-volume live traffic and in the presence of dataset distribution shift typical of evolving enterprise networks (Hindy et al., 2020; Mehmood & Shafiq, 2023).

6. Conclusion and Future Work

This research successfully developed and evaluated a novel hybrid intrusion detection system integrating Suricata, ensemble machine learning, and the Diamond Model of Intrusion Analysis. The system achieved 98.6% accuracy, 98.1% precision, 97.6% recall, and a false positive rate of 1.2% on contemporary IoT and enterprise network datasets. The key contribution is the seamless integration of DMIA reasoning, which elevates raw detection events into context-rich, actionable narratives. This hybrid, context-aware approach effectively addresses the limitations of standalone signature-based and anomaly-based systems, demonstrating superior operational relevance and interpretability (Caltagirone et al., 2013; Anmi et al., 2023; Johnson et al., 2024).

The proposed system aligns with national cybersecurity policies emphasizing resilience and critical infrastructure protection, making it particularly suitable for deployment in government and sectoral Security Operations Centers. By combining deterministic rule-based detection, calibrated ensemble ML, and structured contextual analysis in a single modular framework, the system contributes toward next-generation IDS that are not only accurate in controlled experiments but also explainable, scalable, and aligned with the operational realities of modern enterprise and IoT networks.

Future work will focus on three primary directions: (1) real-world pilots in live enterprise and critical infrastructure networks to validate performance under sustained load and adversarial adaptation (Hindy et al., 2020; Mehmood & Shafiq, 2023); (2) tighter integration with SIEM and SOAR platforms to enable automated response workflows and closed-loop learning from analyst feedback (Ahmadian et al., 2022; Aydin & Nazif, 2023); and (3) exploration of advanced graph-based and deep learning techniques (graph neural networks, transformers) to augment DMIA reasoning while maintaining interpretability and operational feasibility in resource-constrained environments (Zhang et al., 2022; Javed & Hashmi, 2023).

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 doi:10.20944/preprints202606.0579.v1

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