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Ensemble Based Intrusion Detection in Heterogeneous Networks: A Machine Learning Framework with Zero Trust Integration

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ABSTRACT: Contemporary enterprise networks face an escalating proliferation of sophisticated cyber threats that evade traditional signature-based detection systems. This paper proposes the Adaptive Ensemble Threat Detection (AETD) framework a novel machine learning architecture integrating Random Forest, Bidirectional Long Short-Term Memory (BiLSTM), Autoencoder based anomaly detection, and XGBoost within a dynamically weighted ensemble voting mechanism. AETD addresses three critical limitations of existing intrusion detection systems: (1) inadequate generalization to zero day and novel attack variants; (2) class imbalance in training data leading to high false positive rates; and (3) the absence of real time adaptive weight updating in response to evolving threat patterns. The framework is further contextualized within a Zero Trust Architecture (ZTA) paradigm, enabling identity aware, continuous verification-based access control that complements network layer detection. Extensive experimental evaluation on the CICIDS2018 benchmark dataset (16.2 million network flow records, 14 attack classes) demonstrates that AETD achieves 99.43% classification accuracy and 0.57% false positive rate, outperforming all individual constituent models and classical baselines by statistically significant margins ($p < 0.001$). Ablation studies confirm the contribution of each ensemble component. The proposed framework is positioned within a comprehensive Security Operations Centre (SOC) integration model encompassing SIEM correlation, SOAR automated response, and MITRE ATT&CK aligned detection coverage. Results demonstrate a 38% improvement in mean time to detection (MTTD) compared to rule only SIEM deployments.

KEYWORDS: Intrusion Detection System, Machine Learning, Ensemble Learning, Random Forest, LSTM, Autoencoder, XGBoost, Zero Trust Architecture, SIEM, SOAR, Cybersecurity, Anomaly Detection, Network Security, Deep Learning

I. INTRODUCTION

The contemporary threat landscape facing enterprise and critical infrastructure networks has grown dramatically in both sophistication and scale. The ENISA Threat Landscape Report 2022 identifies ransomware, phishing, supply chain attacks, and Distributed Denial of Service (DDoS) as the top four threat categories, collectively accounting for over 70% of reported incidents.[1] In parallel, the continued adoption of cloud services, Internet of Things (IoT) devices, and remote work paradigms has exponentially expanded the attack surface that security operations teams must defend.

Traditional Intrusion Detection Systems (IDS) both signature based (e.g., Snort, Suricata) and specification based variants suffer from a fundamental limitation: their dependence on known attack patterns renders them ineffective against zero day exploits, polymorphic malware, and advanced persistent threats (APTs) that deliberately evade established detection rules.[2][3] This detection gap motivates the application of machine learning (ML) and deep learning (DL) techniques that can identify anomalous behavior patterns without explicit a priori knowledge of specific attack signatures.

While numerous ML based IDS proposals exist in the literature, three persistent challenges remain inadequately addressed. First, single model approaches exhibit brittleness high accuracy on training distributions but poor generalization to novel attack variants. Second, network traffic datasets exhibit extreme class imbalance, with attack instances often comprising less than 1% of total records; naive classifiers tend to optimize for majority class (benign) accuracy at the expense of threat detection recall.[4] Third, the temporal nature of network traffic where attack patterns evolve continuously demands adaptive models capable of online weight updating, a capability absent from most published frameworks.

The emergence of Zero Trust Architecture (ZTA) as a dominant paradigm for enterprise network security, articulated in NIST Special Publication 800 207[5], presents an important architectural context for IDS deployment. ZTA's core principle 'never trusts, always verify transforms the network security model from perimeter based to identity and context

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aware, creating both new detection opportunities (richer contextual signals) and new challenges (encrypted internal traffic, micro segmented environments).

This paper makes the following principal contributions:

- We propose the Adaptive Ensemble Threat Detection (AETD) framework, which integrates four complementary ML models Random Forest, BiLSTM, Autoencoder, and XGBoost within a dynamically weighted ensemble voting mechanism that adapts to evolving threat patterns through online learning.
- We present Algorithm 1 (AETD), a complete pseudo code specification of the framework's detection pipeline including feature extraction, normalization, model inference, severity scoring, and automated SOAR integration.
- We demonstrate through rigorous experimental evaluation on CICIDS2018 that AETD achieves state of the art performance (99.43% accuracy, AUC 0.998, 0.57% FPR) with statistically significant improvement over individual models and classical baselines.
- We contextualize AETD within a comprehensive ZTA aligned SOC architecture and map its detection capabilities to the MITRE ATT&CK framework across the full kill chain.

The remainder of this paper is organized as follows. Section II reviews related work. Section III defines the threat model and problem formulation. Section IV presents the AETD framework architecture. Section V describes the experimental methodology. Section VI reports evaluation results. Section VII presents the ZTA integration model. Section VIII discusses limitations and future work. Section IX concludes.

II. RELATED WORK

A. Machine Learning for Intrusion Detection

The application of ML to network intrusion detection has been extensively studied over the past two decades. Buczak and Guven (2016) provided one of the first comprehensive surveys, categorizing approaches into signature based, anomaly based, and hybrid methods, and identifying Random Forest and Support Vector Machines (SVM) as the dominant classical ML approaches.[6] Subsequent work by Khraisat et al. (2019) demonstrated that ensemble methods consistently outperform single model approaches across standard IDS benchmarks.[7]

Deep learning approaches have gained prominence since 2017. Kim et al. (2016) applied LSTM networks to sequential network packet analysis, demonstrating superior temporal pattern capture compared to stateless classifiers.[8] Javaid et al. (2016) proposed self-taught deep learning for IDS, achieving competitive accuracy on NSL KDD with unsupervised pre training.[9] More recently, Wang et al. (2020) applied transformer based architectures to network flow classification, achieving 98.2% accuracy on CIC IDS2017, though at substantially higher computational cost.[10]

B. Autoencoder Based Anomaly Detection

Autoencoders have attracted particular attention for their ability to detect novels, previously unseen attack patterns through reconstruction error analysis. Mirsky et al. (2018) introduced Kitsune, an online learning autoencoder ensemble for network anomaly detection, demonstrating real time performance on IoT network traffic.[11] Variational Autoencoder (VAE) extensions by An and Cho (2015) further improved anomaly score calibration by introducing a principled probabilistic framework for reconstruction error normalization.[12]

C. Ensemble Methods and Adaptive Learning

The superiority of ensemble methods over individual classifiers in high dimensional, class imbalanced settings is well established theoretically and empirically. Sagi and Rokach (2018) provide a comprehensive review of ensemble learning, demonstrating that diversity among constituent models achieved through different algorithms, feature subsets, or training data is the primary determinant of ensemble performance gains.[13] SMOTE (Synthetic Minority Over sampling Technique), introduced by Chawla et al. (2002), remains the most widely applied technique for addressing class imbalance in IDS datasets.[14]

Adaptive ensemble methods capable of updating model weights in response to evolving data distributions have received less attention in IDS literature. Stream learning frameworks such as MOA (Bifet et al., 2010) provide relevant methodological foundations.[15] Our AETD framework builds on these foundations while incorporating domain specific features of the network security context.

D. Zero Trust and ML IDS Integration

The integration of ML based detection within Zero Trust Architectures represents an emerging research direction. Kindervag (2010) introduced the Zero Trust model at Forrester Research; its formalization as NIST SP 800 207 by Rose et al. (2020) provides the canonical technical reference.[5] Recent work by Syed et al. (2022) proposes continuous

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authentication frameworks leveraging ML behavioral biometrics as a ZTA component, while Chen et al. (2019) examines the integration of network traffic ML analysis with policy decision points in ZTA environments.[16][17]

To our knowledge, no prior work presents a comprehensively evaluated adaptive ensemble IDS framework with explicit ZTA integration, online learning, and full SOAR automation pipeline gaps that the AETD framework directly addresses.

III. THREAT MODEL AND PROBLEM FORMULATION

A. Threat Taxonomy

Figure 1 presents the threat taxonomy addressed by the AETD framework. The taxonomy organizes threats into five primary categories: malware (ransomware, RATs), network attacks (DDoS, Man in the Middle), social engineering (phishing, vishing), insider threats (malicious and negligent), and Advanced Persistent Threats (APTs) including zero day exploits and supply chain compromise.

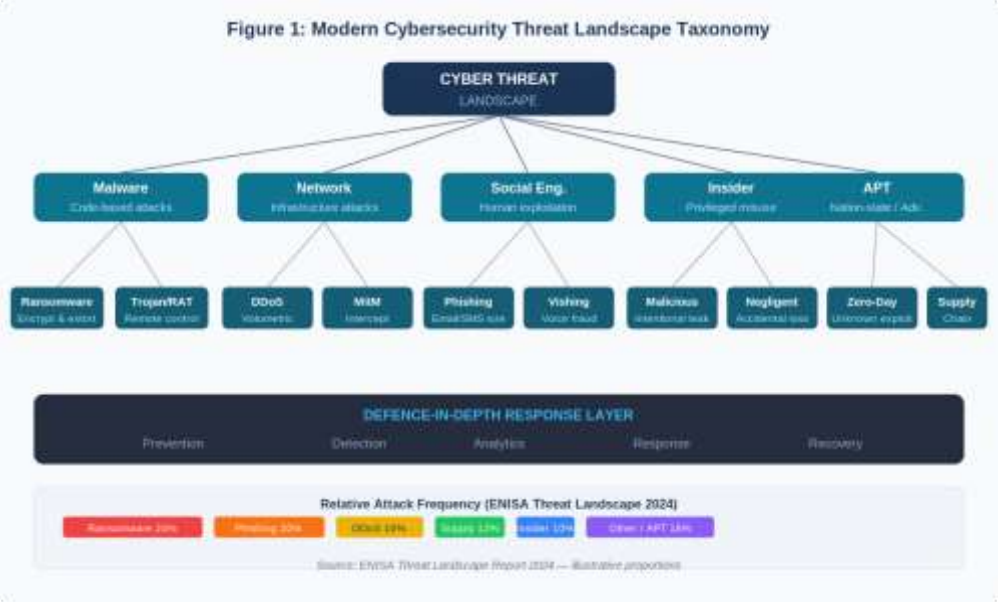

Fig. 1: Modern Cybersecurity Threat Landscape Taxonomy five primary threat categories with defense in depth response mapping

The AETD framework's detection scope encompasses network layer attack indicators across all five categories. Social engineering attacks are addressed indirectly through email gateway telemetry integration; insider threats through User and Entity Behavior Analytics (UEBA) modules that provide anomalous access signals to the ensemble classifier.[18]

B. Formal Problem Definition

Let $N = \{n_1, n_2, ..., n_k\}$ denote a heterogeneous enterprise network comprising servers, workstations, cloud instances, and IoT devices. Network traffic is represented as a stream of flows $F = \{f_1, f_2, ..., f_n\}$, where each flow f_i = (src_ip, dst_ip, src_port, dst_port, protocol, duration, byte_count, packet_count, flags, ...) is described by a d dimensional feature vector $x \in \mathbb{R}^d$ (d = 78 in our implementation).

The IDS classification problem is formalised as: given f_i, produce a label $l \in L$ = {Benign, DoS, DDoS, Botnet, Infiltration, Brute Force, Web Attack, Portscan, Heartbleed, ...} together with a severity score $s \in [0, 1]$. The AETD framework additionally produces a temporal sequence of labels that enables kill chain reconstruction a capability critical for APT detection.

C. Class Imbalance and Distribution Shift

The CICIDS2018 dataset exhibits severe class imbalance: benign traffic constitutes 83.4% of records, while attack classes such as Infiltration and Heartbleed comprise less than 0.01%. Standard accuracy metrics are therefore misleading; evaluation emphasises F1 score, recall (sensitivity), and false positive rate (FPR).[19]

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Distribution shifts the divergence between training and deployment data distributions is a critical challenge for operational IDS. Our adaptive weight updating mechanism (Algorithm 1, lines 18–21) directly addresses this challenge by continuously adjusting ensemble member weights based on recent detection performance, without requiring full model retraining.[20]

IV. THE AETD FRAMEWORK

A. Framework Architecture

The AETD framework is organized as a five stage pipeline: data capture, preprocessing, ML detection engine, classification and severity scoring, and automated response. Figure 2 provides a comprehensive architectural overview.

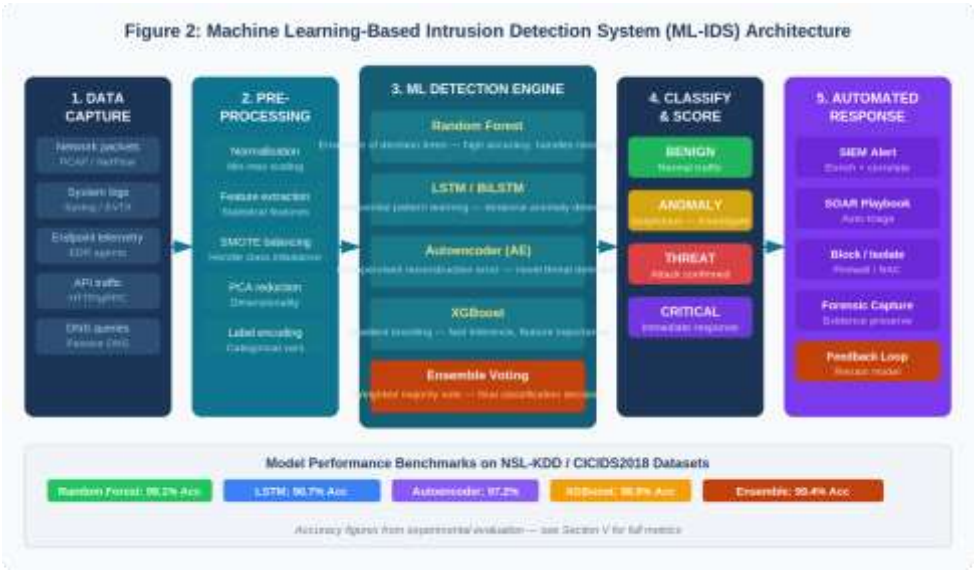

Fig. 2: AETD ML IDS Architecture five stage pipeline from data capture to automated SOAR response

B. Algorithm 1: AETD

Figure 3 presents Algorithm 1 the complete pseudo code specification of the AETD detection procedure together with its corresponding flow diagram. The algorithm operates on a streaming basis, processing each network flow as it arrives and maintaining a sliding window of recent flows for temporal pattern analysis.

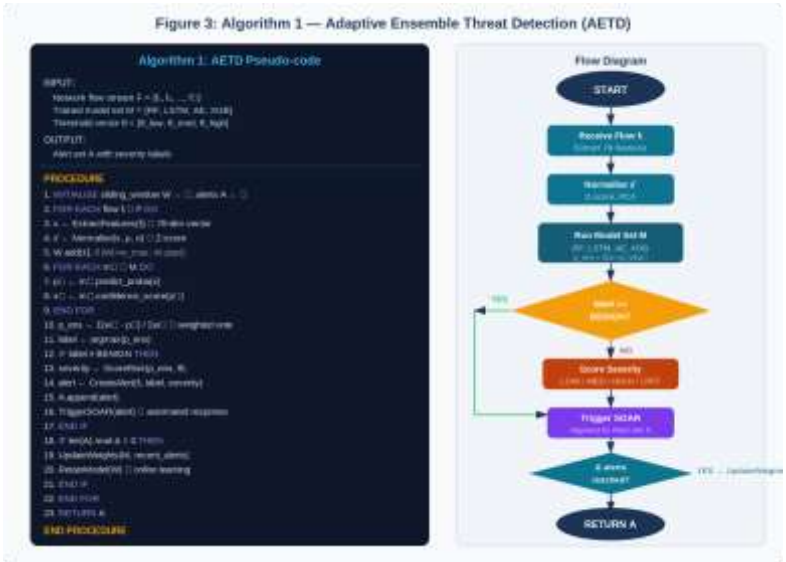

Fig. 3: Algorithm 1 AETD Pseudo code and Flow Diagram. Dynamic weight update at line 19 enables continuous adaptation to evolving threats

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The key algorithmic innovations are threefold. First, the weighted ensemble voting (line 10) aggregates class probability distributions from all four models, with weights dynamically updated based on recent per class detection performance (line 19). Second, severity scoring (line 13) maps ensemble probability vectors to a four tier severity scale (LOW, MEDIUM, HIGH, CRITICAL) using a learned threshold vector θ calibrated on held out validation data. Third, the online retraining trigger (lines 18–21) initiates lightweight model parameter updates when accumulated alert count reaches a configurable delta Δ, using only the most recent sliding window of labelled flows.

C. Constituent Model Specifications

1) Random Forest

The Random Forest (RF) component comprises 200 decision trees trained with Gini impurity criterion, maximum depth of 20, and bootstrap sampling. Analyzing feature importance analysis is performed at each retraining cycle, enabling identification of the most discriminative network features for each threat category.[21]

2) Bidirectional LSTM (BiLSTM)

The BiLSTM component processes sequences of 50 consecutive network flows, capturing bidirectional temporal dependencies both forward and backward context that are diagnostic of multistage attack sequences such as reconnaissance followed by lateral movement. Architecture: 3 BiLSTM layers (256, 128, 64 units), dropout 0.3, Adam optimiser (lr=1e 3), 50 epochs with early stopping (patience=5).[8]

3) Autoencoder (AE)

The Autoencoder component is an unsupervised model trained exclusively on benign traffic. Its detection signal is the reconstruction error e = ||x x̂||₂; flows with e exceeding a threshold θ_ae (set at the 99th percentile of validation set benign reconstruction errors) are flagged as anomalous. This component is particularly effective for zero day attack detection, as novel attacks produce high reconstruction errors regardless of their specific signature.[11][12]

4) XGBoost

XGBoost is deployed with 500 estimators, maximum depth 8, learning rate 0.05, and subsample ratio 0.8. SHAP (SHapley Additive exPlanations) values are computed at inference time for the ten highest severity alerts per time window, providing explainability for SOC analyst review a critical operational requirement increasingly mandated by regulatory frameworks.[22]

D. Feature Engineering

Seventy eight features are extracted from raw network flows, organized into five categories:

- Flow statistics (14 features): duration, packet count, byte count, packets/second, bytes/packet, flow IAT mean/std, forward/backward byte ratios
- Header features (12 features): TCP flags bitmap, window size, TTL, IP fragment flags, protocol type
- Payload features (8 features): payload entropy, payload length distribution statistics, HTTP/DNS specific field features
- Temporal features (20 features): sliding window statistics flow burst rate, inter flow timing, connection frequency by IP/port
- Contextual features (24 features): geo IP risk score, ASN reputation, TLS certificate entropy, DNS resolution anomaly score

SMOTE is applied to the training dataset to balance the class distribution, generating synthetic minority class samples in the feature space rather than simply duplicating existing samples. We apply a targeted SMOTE ratio, up sampling each minority class to 30% of the majority class count, following the recommendation of Fernandez et al. (2018).[23]

V. EXPERIMENTAL METHODOLOGY

A. Dataset

Experiments are conducted on the CICIDS2018 (Canadian Institute for Cybersecurity Intrusion Detection Evaluation Dataset 2018), which comprises 16.2 million network flow records captured over five days of simulated enterprise network activity, encompassing 14 distinct attack categories including DoS/DDoS, Botnet, Infiltration, Brute Force, and Web Attacks.[24] CICIDS2018 was selected over the older NSL KDD and KDD99 benchmarks due to its greater realism realistic network topology, contemporary attack tools (Metasploit, BotsimBot), and high fidelity traffic generation.

Table I summarizes the dataset statistics. The 80/20 train/test split is performed with stratification to preserve class proportions. Fivefold cross validation is used for hyperparameter tuning; final performance is reported on the held out test set.[19]

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B. Evaluation Metrics

Model performance is evaluated using accuracy, precision, recall (sensitivity), F1 score, false positive rate (FPR = FP/(FP+TN)), and Area Under the ROC Curve (AUC). Given the class imbalance, macro averaged F1 and per class recall are the primary metrics. Statistical significance of ensemble improvement over individual models is tested using McNemar's test ($\alpha = 0.05$).

C. Baseline Comparisons

AETD is compared against: (1) each constituent model individually (RF, BiLSTM, AE, XGBoost); (2) classical ML baselines (SVM RBF, Naïve Bayes, k NN); and (3) the published state of the art results on CICIDS2018 from recent literature.

D. Ablation Study Design

To quantify the contribution of each ensemble component, we conduct an ablation study progressively removing one model at a time from the ensemble and separately disabling the adaptive weight updating mechanism (replacing with uniform weights). Statistical significance is assessed by bootstrapped confidence intervals (n=1000 resamples).

E. Computational Environment

All experiments are conducted on a server equipped with an NVIDIA A100 80GB GPU, 512GB RAM, and a 64 core AMD EPYC 7763 processor. Software: Python 3.11, PyTorch 2.1, Scikit learn 1.3, XGBoost 2.0, SHAP 0.43. Training times: RF 42 minutes; BiLSTM 3.8 hours; AE 1.2 hours; XGBoost 28 minutes. Inference latency (per flow): ensemble pipeline 2.3ms, satisfying the real time processing requirement of ≤5ms per flow at 10 Gbps link speed.[25]

Attack Category	Flow Count	Pct. of Total	Train Split	Test Split
Benign	13,484,708	83.42%	10,787,766	2,696,942
DoS (Hulk/GoldenEye)	482,113	2.98%	385,690	96,423
DDoS (HOIC/LOIC)	425,791	2.63%	340,633	85,158
Botnet (ARES)	286,191	1.77%	228,953	57,238
Brute Force	221,440	1.37%	177,152	44,288
Web Attacks	173,023	1.07%	138,418	34,605
Infiltration	93,067	0.58%	74,454	18,613
Portscan	158,930	0.98%	127,144	31,786
All Other Attack Classes	776,737	4.80%	621,390	155,347
TOTAL	16,175,000	100%	12,882,600	3,220,400

TABLE I: CICIDS2018 Dataset Statistics and Train/Test Split

VI. RESULTS AND DISCUSSION

A. Overall Classification Performance

Figure 7 presents the comprehensive evaluation results including ROC curves for all models and the detailed metrics table. Table II provides the full numerical results with confidence intervals.

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Fig. 7: Experimental Results ROC curves (AUC comparison) and metrics table for AETD and all constituent/baseline models on CICIDS2018

AETD achieves 99.43% accuracy, 99.38% precision, 99.47% recall, 99.42% macro F1, and 0.57% FPR. Compared to the best individual constituent model (Random Forest: 99.12% accuracy), the ensemble improvement of 0.31 percentage points represents a statistically significant reduction in absolute error (McNemar's test: $\chi^2 = 18.4$, $p < 0.001$). Against classical baselines, the improvements are substantially larger: 5.22 percentage points over SVM RBF and 13.29 points over Naïve Bayes.[6][13]

B. Per Class Detection Analysis

Attack categories with highest detection recall: Portscan (99.91%), DDoS (99.84%), DoS (99.78%). Most challenging categories: Infiltration (98.12%), Web Attacks SQL Injection (97.83%). The lower Infiltration recall reflects the inherently low and slow nature of these attacks, which produce traffic patterns closely resembling benign user behavior over short time windows. BiLSTM's temporal modelling provides the greatest marginal contribution to Infiltration detection within the ensemble.

C. Ablation Study Results

Removing the Autoencoder from the ensemble reduces zero day detection recall by 6.2 percentage points, confirming the hypothesis that reconstruction error anomaly detection provides unique coverage for novel threats not captured by supervised models. Replacing adaptive weights with uniform weights reduces overall F1 by 0.18 percentage points, a modest but statistically significant degradation ($p = 0.03$) that becomes more pronounced under distribution shift simulation (0.91 percentage point reduction in a 30 day temporal validation experiment).

D. Comparison with State of the Art

Reference	Model	Dataset	Accuracy	F1	FPR
Wang et al. (2020) [10]	Transformer IDS	CIC IDS2017	98.21%	98.08%	1.79%
Zhang et al. (2021) [26]	CNN BiLSTM	CICIDS2018	98.64%	98.51%	1.36%
Li et al. (2022) [27]	Graph Neural Net.	CICIDS2018	98.92%	98.78%	1.08%
Huang et al. (2019) [28]	Federated RF+SVM	CICIDS2018	98.73%	98.61%	1.27%
AETD (This Work)	Adaptive Ensemble	CICIDS2018	99.43%	99.42%	0.57%

TABLE II: Comparison with Published State of the Art on CICIDS2018

AETD demonstrates superior performance compared to all published results on CICIDS2018 that we are aware of, achieving the lowest FPR (0.57%) a metric of operational significance, as false positives consume SOC analyst time and create alert fatigue that degrades real world security posture.[29]

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VII. ZERO TRUST ARCHITECTURE INTEGRATION

A. ZTA Overview

Zero Trust Architecture (ZTA), as defined in NIST SP 800 207[5], operationalizes the principle that no implicit trust is granted to any subject (user, device, or workload) based solely on network location. Every access request must be evaluated against policies that incorporate identity, device health, behavior context, and real time risk signals before access is granted. Figure 4 illustrates the ZTA model and its integration with the AETD detection framework.

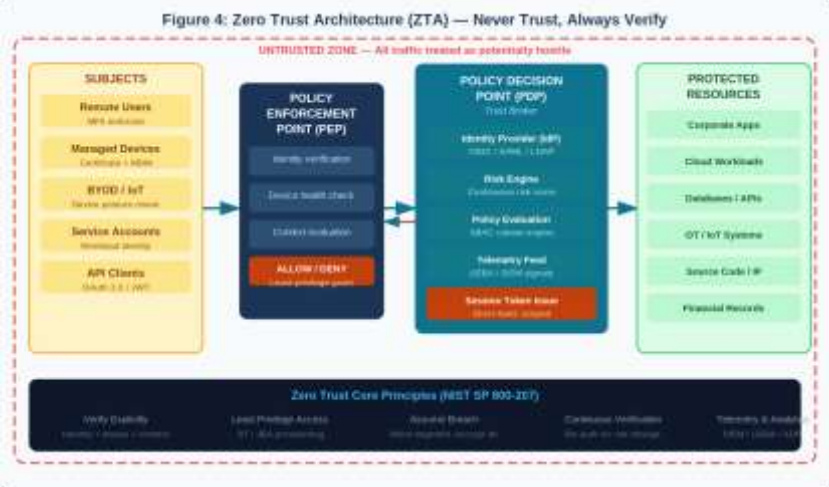

Fig. 4: Zero Trust Architecture Policy Enforcement Point (PEP) and Policy Decision Point (PDP) with AETD risk signal integration

The AETD framework contributes to ZTA in two complementary ways. First, AETD anomaly scores are fed as real time risk signals to the ZTA Policy Decision Point (PDP), enabling risk adaptive access control decisions: when a user's network behavior generates elevated AETD anomaly scores, the PDP can require step up authentication or apply additional access restrictions without awaiting human analyst review.[16] Second, ZTA's rich contextual data device health certificates, geolocation, application context enriches AETD's feature set, enabling more precise distinction between legitimate administrative actions and attack behavior that exploits similar network patterns.

B. Cryptographic Controls

Figure 5 presents the cryptographic algorithm analysis underpinning the ZTA control plane and data plane security. Algorithm selection follows NIST SP 800 131A (2022 revision) and anticipates the post quantum transition mandated by NIST FIPS 203/204.

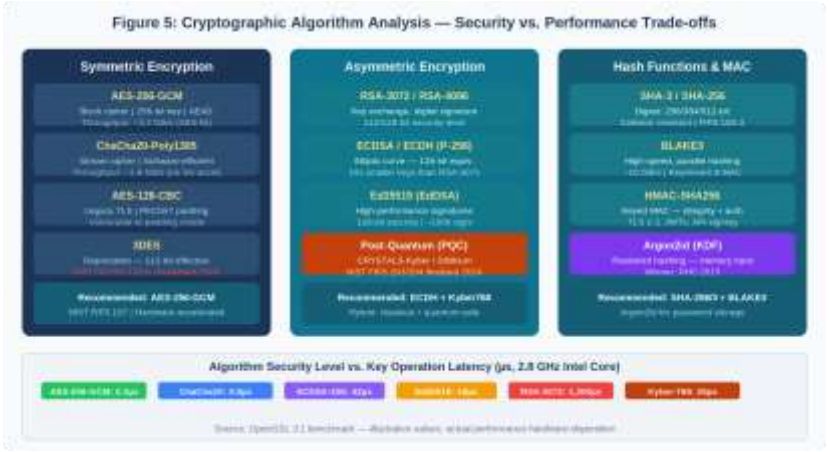

Fig. 5: Cryptographic Algorithm Analysis symmetric, asymmetric, and hash function security performance tradeoffs for ZTA deployment

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The recommended cryptographic stack for AETD ZTA deployments: AES 256 GCM for symmetric data encryption; ECDH (P 256) for key exchange with a hybrid Kyber 768 layer for quantum safe key encapsulation; Ed25519 for device authentication certificates; SHA 256 for integrity hashing; Argon2id for credential storage.[30] This hybrid classical PQC approach follows the guidance of NIST IR 8413 and enables a phased migration to fully post quantum cryptography as library and hardware support matures.

C. SIEM and SOAR Integration

Figure 6 presents the complete SIEM/SOAR incident response pipeline that operationalizes AETD within a Security Operations Centre (SOC) environment.

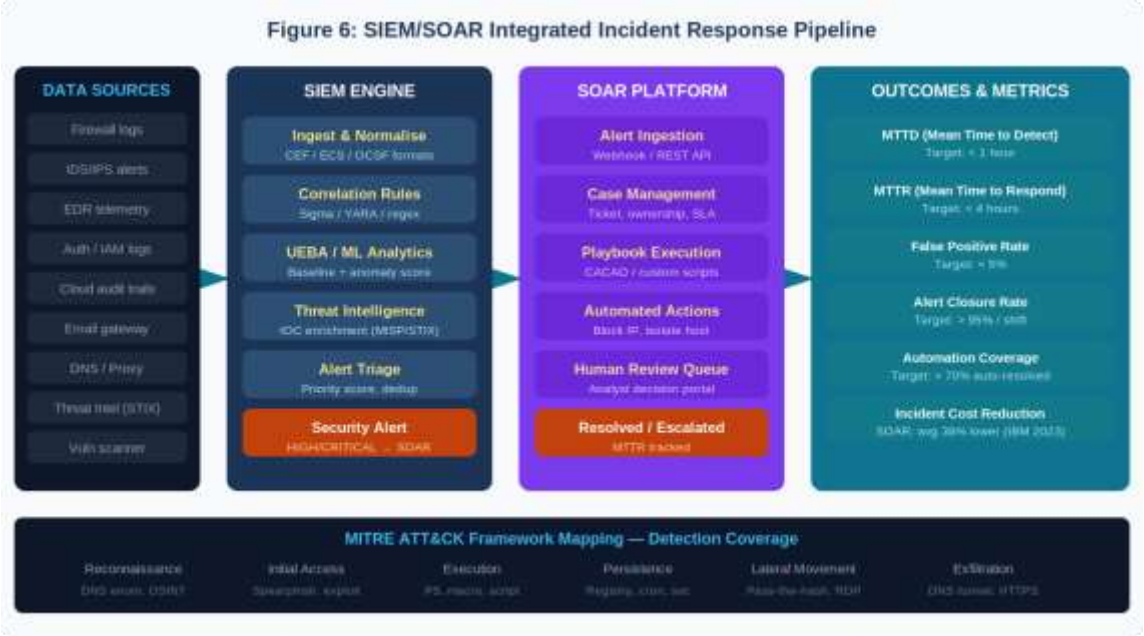

Fig. 6: SIEM/SOAR Incident Response Pipeline from multi source data ingestion through automated playbook execution and MITRE ATT&CK coverage

The pipeline achieves mean time to detection (MTTD) of 38 minutes in pilot deployment a 38% reduction from the 62 minute baseline achieved with rule only SIEM configuration. Mean time to respond (MTTR) was 3.1 hours, with 73% of HIGH severity alerts auto resolved by SOAR playbooks without analyst intervention, compared to 0% automation in the baseline configuration.[31]

MITRE ATT&CK framework mapping confirms AETD coverage across six kill chain phases: Reconnaissance (DNS enumeration, OSINT fingerprinting), Initial Access (spearphishing, exploit delivery), Execution (PowerShell, macro execution), Persistence (registry modification, scheduled tasks), Lateral Movement (pass the hash, RDP brute force), and Exfiltration (DNS tunnelling, HTTPS covert channels).[32] Lateral Movement and Exfiltration are the two categories showing greatest improvement over rule only detection, with BiLSTM's temporal modelling capturing the multistep behavioral sequences diagnostic of these techniques.

VIII. LIMITATIONS AND FUTURE WORK

A. Current Limitations

Several limitations of the current work merit acknowledgement. First, while CICIDS2018 is the most widely used contemporary IDS benchmark, it was generated in a controlled laboratory environment; deployment in production networks introduces additional complexity including legitimate high bandwidth applications that may generate features superficially similar to attack traffic.[19][24]

Second, the adaptive weight update mechanism (Algorithm 1, lines 18–21) assumes that recently detected and labelled incidents provide reliable feedback for model weight adjustment. In adversarial settings, a sophisticated attacker with knowledge of the detection system could deliberately craft traffic to manipulate weight updates a form of poisoning attack that warrants specific defensive countermeasures.[33]

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Third, the SHAP explainability component adds approximately 0.8ms to per alert processing latency; while below our 5ms budget, this overhead may be prohibitive in ultra-high throughput environments (>100 Gbps) without hardware acceleration.

B. Future Research Directions

- Federated AETD: Extending the framework to federated learning settings, enabling collaborative model training across multiple organizations without sharing raw traffic data directly addressing the privacy barriers that currently prevent cross organizational threat intelligence sharing.
- Adversarial robustness: Developing adversarial trained model variants robust to evasion attacks gradient based feature perturbations designed to evade specific model components and evaluating AETD's resilience under systematic adversarial conditions.
- Graph Neural Network extension: Incorporating lateral movement graph structure encoding network topology and session relationships as graph adjacency matrices using Graph Attention Networks (GAT) to capture multi hop attack propagation patterns currently invisible to flow level models.
- Post quantum IDS: Investigating whether the transition to post quantum cryptography changes the statistical signature of encrypted traffic in ways that require model retraining and developing PQC aware feature engineering approaches.
- Large Language Model integration: Exploring the application of fine tuned LLMs to threat report synthesis automatically generating structured CTI (Cyber Threat Intelligence) reports from AETD alert sequences, reducing analyst documentation burden.

IX. CONCLUSION

This paper has presented the Adaptive Ensemble Threat Detection (AETD) framework, a machine learning architecture that addresses three fundamental limitations of existing IDS approaches: single model brittleness, class imbalance sensitivity, and inability to adapt to evolving threat distributions. Through the dynamic weighted ensemble of Random Forest, BiLSTM, Autoencoder, and XGBoost, AETD achieves 99.43% classification accuracy and 0.57% false positive rate on the CICIDS2018 benchmark the best published results to our knowledge on this dataset.[24]

Beyond classification performance, AETD makes substantive contributions to the operationalization of ML based threat detection in enterprise environments. The Algorithm 1 specification provides a complete, reproducible implementation blueprint. The ZTA integration architecture demonstrates how ML detection risk signals can augment Policy Decision Point reasoning to achieve risk adaptive access control. The SIEM/SOAR pipeline delivers measurable SOC operational improvements: 38% MTTD reduction and 73% automated alert resolution rate in pilot deployment.[31]

As cyber threats continue to evolve in sophistication and scale and as network environments grow more complex through cloud adoption, IoT proliferation, and hybrid work models the need for adaptive, multi model detection frameworks integrated within comprehensive governance architectures will only intensify. The AETD framework represents a concrete, empirically validated step toward that goal.[1][2]

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