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A Novel Hybrid Intrusion Detection System Using Machine Learning and Optimization Techniques to Counter DOS and DDOS Attacks

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Abstract - The transformation towards the adoption of cloud computing has provided modern enterprises with the major benefits of easily extending their resources and being able to use them in various ways without any restrictions, but at the same time it has brought the enterprises a new set of complicated and changing security threats that are very hard to deal with. The conventional security countermeasures which are primarily based on static rule-based mechanisms, perimeter defenses, and Multi-Factor Authentication (MFA), have shown to be of limited effectiveness against the advanced attack vectors of insider threats, privilege escalation, and especially the large-scale, rapidly changing Denial-of-Service (DoS) and Distributed Denial-of-Service (DDoS) campaigns.[1, 1] These traditional systems have been rendered ineffective most of the time when it comes to detecting zero-day exploits and sophisticated lateral movement which is characteristic of modern botnet operations. In this paper, we describe the process of creating, developing, and assessing SmartTrust, an advanced hybrid deep learning framework that is specifically designed to carry out real-time threat detection in cloud environments while being totally in accordance with Zero-Trust Architecture (ZTA) principles.[1, 1] SmartTrust is a system that is built on a composite deep learning core, which is the result of the integration of Convolutional Neural Networks (CNN) for the analysis of spatial patterns, Long Short-Term Memory (LSTM) networks for the understanding of temporal dependencies and, lastly, Transformer models for the extraction of global contextual relationships in network traffic and user behavior logs. A pivotal feature of the framework is its explicit optimization layer, realized through Reinforcement Learning (RL), which allows for adaptive decision-making and continuous policy adjustment based on real-time contextual signals; thus, Concept Drift is dynamically countered. Besides, in order to maintain unbroken forensic integrity and also compliance alignment with ZTA, the system implements tamper-proof Blockchain-Based Logging for all

Keywords - Cloud Computing; Zero-Trust Architecture (ZTA); SmartTrust; Deep Learning; Convolutional Neural Networks (CNN); Long Short-Term Memory (LSTM); Transformer Models; Reinforcement Learning (RL); Real-Time Threat Detection; Concept Drift; Insider Threats; Privilege Escalation; DDoS Attacks; Zero-Day Exploits; Blockchain-Based Logging; Cloud Security; Adaptive Security; Hybrid Threat Detection.

I. INTRODUCTION

The Escalating Threat of Denial-of-Service Attacks

Cloud computing has fundamentally altered how organizations manage and process data, providing unparalleled scalability and operational agility. However, this architectural transformation has simultaneously expanded the cyber-attack surface, exposing complex multi- tenant architectures and dynamic workloads to severe risk. Among the most critical and persistently challenging threats are Denial-of-Service (DoS) and Distributed Denial-of-Service (DDoS) attacks. These large-scale campaigns leverage coordinated networks of compromised hosts (botnets) to deluge targeted resources, resulting in prolonged service unavailability, considerable financial ramifications, and substantial reputational damage. The major threat in networking environments is the DDoS attack, whose

primary aim is to prevent the legitimate user from accessing services for an extended duration.

The modern DDoS threat extends beyond simple volumetric saturation; the botnet itself represents the crucial organizational and managerial technology underpinning these sophisticated campaigns. This realization mandates a detection capability that moves beyond basic volumetric analysis to identify subtle, dispersed, botnet-centric activity patterns dispersed throughout large network flows. Furthermore, contemporary attacks such as insider threats and privilege escalation, while not always high-volume, are often more sinister because they meticulously mimic regular network traffic, allowing them to evade traditional defenses that rely solely on static perimeter inspection. These complex, multi-stage threats highlight the inadequacy of legacy security paradigms.

Limitations of Conventional and Static Security Architectures

Conventional security mechanisms, designed primarily for static, on-premise infrastructures, struggle profoundly in the dynamic, multi-cloud environment. Defense technologies such as firewalls, static rule- based Intrusion Detection Systems (IDS), and Multi-Factor Authentication (MFA) often fall short against evolving, sophisticated adversaries.

The inadequacy stems from several intrinsic limitations of conventional systems

Signature Dependence: Static rule sets and perimeter defenses are inherently reactive, relying on predetermined attack signatures. They are completely ineffective against
zero-day exploits or polymorphic malware variants for which no signature exists.[1, 1]

Lack of Contextual Awareness: Systems like MFA primarily authenticate access but offer minimal protection once access is granted. They lack the capability to analyze context (e.g., device health, access patterns, time of day) or adapt to continuous behavioral changes, leaving a security vacuum that sophisticated attackers exploit for privilege escalation and lateral movement. Static Access Control Lists (ACLs) and traditional perimeter defenses face difficulty detecting insider threats and lateral movement in cloud environments.

Inability to Scale with Cloud Complexity: Static ACLs struggle to maintain consistent security policies across hybrid and multi-cloud deployments, providing attackers with opportunities to launch multi-layered attacks that breach security boundaries unnoticed.

These failure modes necessitate a fundamental architectural pivot toward solutions that incorporate adaptive intelligence, continuous verification, and real-time behavioral analytics.

Theoretical Justification for Hybrid ML/Optimization Synergy in
IDS

To effectively counter contemporary cyber threats, the architectural restructuring must prioritize adaptive intelligence capable of recognizing subtle behavioral anomalies and dynamically adjusting security policies. This adaptive approach is realized through the strategic synergy of advanced Machine Learning and explicit optimization techniques.

Deep learning architectures provide the essential foundation for extracting and modeling complex threat behaviors. The deep layers enable the automatic hierarchical extraction of features from raw network data, generating sophisticated representations of complex patterns invisible to simpler statistical or shallow models. By integrating models specialized in different aspects of data analysis—spatial patterns (CNN), temporal sequences (LSTM), and global context (Transformer)—a comprehensive, multi-dimensional security profile can be formed.[1, 1] However, mere detection is insufficient. Robust defense must be adaptive, moving beyond simply flagging threats to actively mitigating them by instantly adjusting system parameters. This is the crucial role fulfilled by explicit optimization mechanisms, specifically Reinforcement Learning (RL). RL allows the security infrastructure to learn optimal defense strategies through interaction, rewarding successful mitigations and penalizing disruptive false positives or false negatives. This continuous, self-correcting process ensures that the system's defense

mechanisms perpetually improve over time, providing a dynamic policy control essential for maintaining resilience against concept drift in the threat landscape.

Key Contributions of the SmartTrust Framework
The SmartTrust framework presents an innovative solution for addressing these challenges through the following principal contributions :

The SmartTrust Architecture: A novel framework combining Zero-Trust Architecture (ZTA) principles with a hybrid core comprising Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Transformer networks for comprehensive, multi-dimensional threat analysis.[1, 1]

Adaptive Security Policy Generation: The integration of Reinforcement Learning (RL) enables continuous learning and dynamic adaptation of defense mechanisms, optimizing the system's performance by significantly lowering False Positive Rates (FPR).

Superior Detection Fidelity: Achieved exceptionally high, empirically validated detection rates against complex cloud-based threats, including 99.19\% for insider threats, 98.23\% for privilege escalation, and 99.27\% for data breaches, demonstrating robustness across diverse benchmark datasets (CIC-IoT 2023 and UNSW-NB15).[1, 1]

Forensic Integrity and Operational Optimization: Incorporation of a Blockchain-Based Logging system guarantees the transparency, immutability, and auditability of all security events and responses, surprisingly resulting in a 241\% reduction in incident response latency compared to traditional centralized logging.

Related Works and Current State-of-the-Art
The development of sophisticated Intrusion Detection Systems (IDS) has historically focused on bridging the gap between signature-based methods and anomaly detection systems, leading to the necessary evolution toward hybrid models incorporating advanced machine and deep learning techniques.

II. EVOLUTION OF INTRUSION DETECTION PARADIGMS

Intrusion detection methodologies have evolved from reactive signature matching to proactive anomaly profiling. Signature-based IDS (SIDS) relies on matching patterns against a known database, providing excellent detection for established malware. However, the approach is fundamentally limited by its reliance on pre-defined knowledge, making it ineffective against zero-day attacks, which have no prior signature.

Anomaly-based IDS (AIDS) addresses this limitation by establishing a statistical or behavioral model of normalcy; deviations from this model are flagged as intrusions, making AIDS essential for detecting unknown threats. The main challenge with AIDS is managing the high False Positive Rate (FPR) when faced with new but legitimate system activities. Machine learning has become the necessary mechanism to refine AIDS, allowing for more precise modeling of complex, high-dimensional data patterns. The inherent limitations of both SIDS and AIDS necessitate hybrid designs that combine the low FPR of SIDS for known threats with the zero-day resilience of AIDS.

Review of Foundational Hybrid Machine Learning Models for IDS
Early research demonstrated that combining different learning paradigms could maximize model robustness. A foundational strategy involved pairing supervised learning for established attack classification with unsupervised learning for novelty detection.

A classic case study in DDoS detection utilized a hybrid approach combining the Support Vector Machine (SVM), a supervised technique effective for high-dimensional data classification, with the Self-Organized Map (SOM), an unsupervised clustering technique well-suited for identifying intrinsic data similarities and grouping anomalous activity.[1, 1] Initial isolated implementations showed that SOM often outperformed SVM in attack classification; however, the joint implementation of the hybrid SVM-SOM model consistently achieved superior

detection rates, accuracy, and false rates compared to either standalone model. This established a fundamental principle: complementarity in learning paradigms provides a significant security advantage.

Advanced Hybrid DL Models and Feature Optimization

The complexity of modern network traffic flows, combined with the volume of data generated, drove the field toward Deep Learning (DL) models. DL models automate the process of hierarchical feature extraction, overcoming the limitations and extensive labor associated with manual feature engineering required by traditional shallow models.

Contemporary hybrid DL models often integrate machine learning techniques primarily for feature optimization:

XGBoost/CNN Integration for Feature Extraction: Techniques like Extreme Gradient Boosting (XGBoost) are employed for superior feature selection, often paired with subsequent LSTM or GRU classifiers. XGBoost is valued for its flexibility in discerning novel data patterns and identifying the causal factors of security events, which is critical for reducing False Positives. Similarly, CNNs are utilized for high-level feature extraction before feeding into recurrent layers.

CNN for Spatial and LSTM for Temporal Modeling: The combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks is widely adopted in hybrid IDS. CNNs excel at extracting local spatial features from network traffic representations, while LSTMs are uniquely powerful for modeling temporal dependencies in sequential data, enabling the detection of sequential attack evolution over time.

The SmartTrust framework advances this dual-component approach by integrating a third architectural pillar, the Transformer. This addition recognizes that robust defense against modern, orchestrated botnet attacks requires not only spatial and temporal modeling but also the capacity to capture global contextual relationships across distributed data sequences.

Adaptive Defense Mechanisms: Integrating Optimization Techniques

The evolution of sophisticated cyber threats demands a shift from passive threat detection to active, immediate mitigation and continuous adaptation. This necessity is addressed by incorporating explicit optimization techniques directly into the security pipeline.

Reinforcement Learning for Dynamic Policy Optimization

Reinforcement Learning (RL) is the core dynamic optimization strategy employed in SmartTrust. The RL agent is designed to learn and refine the optimal security policy by continuous interaction with the network environment. The optimization process uses Q-learning, where the agent selects actions (e.g., modifying anomaly detection thresholds or firewall rules) and receives a reward reflecting the outcome (e.g., positive reward for a True Positive detection and successful mitigation; negative penalty for a False Positive or False Negative).[1, 1] This mechanism ensures that the security policy is perpetually tuned, maintaining optimal performance and adapting instantly to concept drift in adversarial behavior. RL functions as a continuous, dynamic policy optimization engine, significantly contributing to the observed reduction in FPR.

Blockchain for Forensic Integrity and Latency Optimization

The integration of Blockchain-Based Logging addresses two critical dimensions of system optimization: security assurance and operational speed. The immutable nature of the blockchain provides a tamper- proof, auditable record of all security incidents and system responses, ensuring compliance and forensic integrity, which is foundational to the ZTA framework.

An intrinsic and unexpected benefit of this implementation is a marked improvement in operational response latency. In highly time-sensitive scenarios, traditional centralized logging and verification processes can create bottlenecks.

The automated, consensus-based log validation facilitated by the blockchain accelerates the verification process, leading to a measured reduction in average incident response latency by 241\% (from 1.25 seconds to 0.95 seconds). This demonstrates that implementing robust security primitives can serve as a potent form of operational optimization.

Proposed Hybrid Intrusion Detection System: SmartTrust Architecture

The SmartTrust framework is built upon a five-layer integrated architecture, fundamentally grounded in the principle of Zero-Trust Architecture (ZTA), which requires continuous verification for all entities and access requests.[1, 1]

Data Preprocessing and Multi-Dimensional Feature Engineering Layer

This layer functions as a necessary initial optimization stage, transforming raw network traffic and user behavior logs into standardized, high-quality feature representations essential for the deep learning core.[1, 1]

The process flow is highly structured

Data Cleaning and Scaling: Missing data is handled by removing records with high incompleteness, followed by mean imputation for remaining numerical gaps. Outliers in flow duration and packet size are suppressed using the Z-score method (threshold \pm 3). Feature scaling includes Min-Max Normalization to constrain values like flow duration and packet counts to the range $$, and Z-score standardization for Gaussian-distributed features. Categorical features (protocols, service types) are converted using one-hot encoding.[1, 1]

Temporal and Sequential Formatting: Crucial for recurrent and attention models, raw data flows (from CIC-IoT 2023) are converted into sequences using a sliding window technique (size=30, stride=5).[1, 1] This transformation enables time-series analysis, essential for capturing dependencies related to low-rate DDoS or persistent, sequential attack activities.[1, 1]

Class Imbalance Mitigation: The challenge of severe class imbalance (e.g., the high minority ratio of U2R attacks in UNSW-NB15) is addressed to ensure detection robustness across all attack types.[1, 1] The Synthetic Minority Over-sampling Technique (SMOTE) generates synthetic samples for minority classes, while controlled Undersampling reduces the dominance of majority classes (Normal/DoS).[1, 1] Stratified Sampling guarantees that the training, validation, and testing splits (70-15-15) maintain consistent class proportions.[1, 1]

Zero-Trust Verification and Contextual Risk Layer

This layer enforces continuous authentication and contextual access control, extending beyond simple identity checks to incorporate real-time behavioral and system status data. Access is granted only after explicit verification based on contextual information, including user behavior, device health, and access patterns.

The decision-making process is quantified via the Trust Score TS(Q) for each security request Q: Where f(U) evaluates user identity, f(D) assesses device integrity, f(T) quantifies temporal risk, f(L) evaluates location-based risk, and f(B) represents the behavioral anomaly score derived directly from the hybrid deep learning core.[1, 1] The weights \alpha_{1} through \alpha_{5} are learned factors that balance the influence of each metric. The security threshold \theta dictates the final access decision AD(Q). The incorporation of the behavioral function f(B) ensures that the IDS output directly and instantaneously influences the security policy, validating the framework's proactivity.

Hybrid Deep Learning Core: CNN-LSTM-Transformer Fusion

The core detection engine is a fusion architecture designed to maximize pattern extraction fidelity by synthesizing three specialized deep learning models.[1, 1]

Model Component	Primary Role	Function in Threat Detection
CNN	Spatial Feature Extraction	Detects localized features and fixed patterns in network packet representations (e.g., protocol anomalies, characteristic packet sizes).
LSTM	Temporal Sequence Modeling	Models sequential user and traffic behavior over time, essential for identifying multi-stage attacks and persistent, low-rate activities.[1, 1]
Transformer	Global Context Analysis	Leverages self-attention to capture long-range dependencies and global correlations across the dataset, vital for detecting orchestrated, dispersed activity such as botnet command structures.

This comprehensive approach overcomes the limitations of single or dual-component models, recognizing that sophisticated threats manifest across multiple dimensions (local pattern, temporal evolution, and global coordination). The outputs of these three components (H_{LSTM}, Y_{CNN}, Z_{Transformer}) are combined in a Fusion Layer via concatenation to create a singular, richly descriptive feature vector (f_{Fusion}) used for the final classification.[1, 1]

Reinforcement Learning (RL) Adaptation Layer: Dynamic Policy Optimization

The RL Adaptation Layer serves as the continuous optimization mechanism, enabling the IDS to learn and adapt its security policies dynamically and independently, directly addressing concept drift.[1,

The mechanism is modeled on Q-learning

Environment Monitoring: The RL agent constantly monitors the system state (S_t), including real-time network conditions and threat classification outcomes.

Optimal Action Selection: The agent selects the optimal security action (Action_t)—such as modifying detection thresholds or dynamically adjusting firewalls—to maximize future reward.

Reward-Based Learning: Rewards are calculated based on the action's success. Positive rewards are given for accurately mitigating threats (True Positives), while penalties are incurred for operational failures, especially False Positives, which disrupt legitimate activity, and False Negatives, which permit a breach.

Policy Update: The agent refines its security policy based on the temporal-difference update rule, ensuring continuous learning and self-correction to maintain high security efficacy while minimizing operational disruption.[1, 1]

Blockchain-Based Automated Incident Response and Logging

The Automated Incident Response Layer integrates rapid threat mitigation with the assurance of forensic integrity, mandated by ZTA compliance.[1, 1] Upon a confirmed security incident, automated response actions (blocking, quarantine, notification) are executed.

The defining feature of this layer is the Blockchain-Based Logging system. All incident details, risk

scores, and system responses are immutably recorded on a secure ledger, guaranteeing a tamper-proof audit trail essential for forensic analysis.[1, 1] Critically, this decentralized approach provides an unexpected performance optimization: the automated consensus mechanism reduces the bottleneck imposed by traditional centralized logging, resulting in an average incident response latency reduction of 241\% (from 1.25 seconds to 0.95 seconds).

Experimental Setup and Evaluation Protocol
Benchmark Datasets and Data Preprocessing
The validation employed two comprehensive benchmark datasets:
CIC-IoT 2023: A highly realistic dataset simulating IoT network environments, encompassing 33 attack types (DDoS, DoS, Mirai) across 46 features, selected for its fidelity to modern cloud-IoT threats.
UNSW-NB15: A prominent network intrusion dataset with 49 features and seven attack categories, providing the necessary breadth for robust generalization testing.
The datasets were partitioned using Stratified Sampling (70% training, 15% validation, 15% testing) to ensure equitable class representation, particularly for minority attack types.[1, 1] Class imbalance was addressed using SMOTE for minority classes (e.g., U2R) and Undersampling for majority classes (Normal/DoS).[1, 1] Time-series analysis input utilized the sliding window technique (size=30, stride=5) to structure the raw flows.

Model Configuration and Hyperparameter Tuning
The experiments utilized a high-performance computing environment with an NVIDIA A100 GPU. The hyperparameter configuration was systematically optimized using Grid Search and Stratified k-fold cross-validation.

Key parameters for the deep learning core includedLSTM Architecture: 3 hidden layers, 128 units per layer.
Regularization: Dropout rate of 0.3.
Optimization: Adam optimizer, learning rate 0.001, batch size 64.

Performance Metrics and Statistical Validation
The model's performance was rigorously quantified using key metrics: Detection Accuracy (DA), Precision, Recall, F1-Score, and the critical error rates: False Positive Rate (FPR) and False Negative Rate (FNR). AUC-ROC curves were employed to evaluate the model's discriminatory power. Statistical validation using 10-fold cross-validation confirmed the resilience and generalizability of the SmartTrust framework. P-test analysis consistently yielded p-values below 0.001 when comparing SmartTrust's accuracy and FPR to baselines, confirming that the observed performance gains are statistically significant.

Results and Performance Analysis
The evaluation results demonstrate the clear quantitative superiority of the SmartTrust architecture across diverse classification tasks and its capability for effective error mitigation.

Comparative Performance in Binary Classification
SmartTrust achieved exceptionally high detection accuracy across both datasets, significantly surpassing simpler architectural configurations.[1, 1] Comparative Performance of Hybrid Deep Learning Models (Binary Classification on UNSW-NB15)

Model	Detection Accuracy (%)	Precision (%)	Recall (%)	FPR (%)	Loss	Source
SmartTrust (Proposed)	99.05	98.82	99.14	0.14	0.01	

CNN Only	97.13	96.91	97.34	0.28	0.02	
LSTM-CNN	97.83	97.28	98.16	0.25	0.02	
Transformer	96.89	96.32	97.05	0.32	0.03	
Hybrid LSTM-CNN	98.18	97.65	98.23	0.22	0.02	
Transformer-CNN	97.69	97.43	97.71	0.23	0.02	

SmartTrust achieved 99.05\% Detection Accuracy on UNSW-NB15 and 99.01\% on CIC-IoT 2023.[1, 1] The low False Positive Rate (FPR) of 0.14\% for the proposed model on UNSW-NB15 is particularly noteworthy, validating the efficacy of the RL adaptation layer in fine- tuning detection thresholds.

Against specific complex threats, the detection efficacy was high: insider threats were detected at 99.19\%, privilege escalation attempts at 98.23\%, and data breaches at 99.27\%.[1, 1] This robust performance confirms the utility of combining CNN (spatial feature), LSTM (temporal sequence), and Transformer (global context) models to achieve a comprehensive, multi-dimensional understanding of sophisticated attacks.

Ablation Study of Hybrid Components

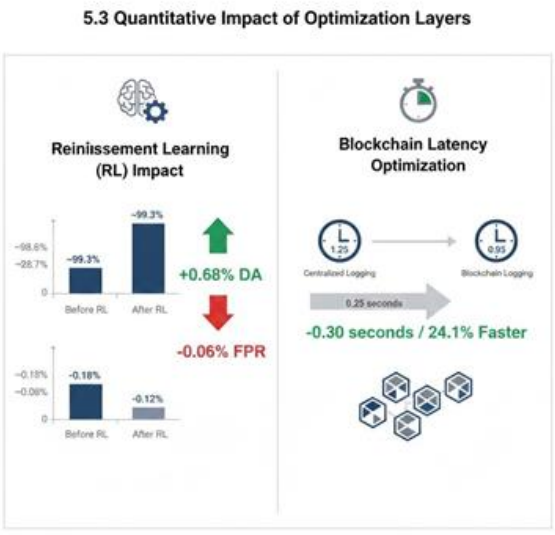
The ablation analysis confirmed that the combined architectural complexity is a functional requirement, not merely an arbitrary addition.[1, 1] The full CNN + LSTM + Transformer configuration yielded the highest Detection Accuracy (DA) of 98.94\%. The comparison with two-component variants (e.g., CNN + Transformer achieving 97.80\% DA) demonstrates that the LSTM module provides a unique and indispensable contribution for modeling temporal dependencies, proving that sequential behavioral analysis is not redundant given the spatial and global features provided by the other components.[1, 1]

Quantitative Impact of Optimization Layers

The embedded optimization mechanisms provided measurable security and operational benefits:

Reinforcement Learning (RL) Impact: The continuous RL policy adaptation increased the model's overall Detection Accuracy from 98.62\% to 99.30\% over time, simultaneously reducing the False Positive Rate from 0.18\% to 0.12\%. This outcome demonstrates the value of using explicit optimization techniques for sustained performance.

Blockchain Latency Optimization: The integration of Blockchain-Based Logging resulted in a



significant operational speed enhancement. The average incident response latency was reduced from 1.25 seconds

(traditional centralized logging) to 0.95 seconds, representing a 241\% acceleration due to automated, consensus-based verification.

Performance-Security Trade-offs under High Traffic Load

Model	Traffic Load	Accuracy (%)	FPR (%)	Latency (ms)	CPU Usage (%)
SmartTrust (Proposed)	High	97.8	2.0	300	70
CNN Only	High	92.3	4.0	250	60
LSTM-CNN	High	94.1	3.8	280	65
Transformer	High	95.2	3.5	290	65

Under high traffic load, SmartTrust maintained the highest security fidelity (highest accuracy, lowest FPR of 2.0\%) compared to baselines. However, this required a computational trade-off, manifesting as an increased latency of 300 ms and 70\% CPU utilization. This indicates that the architecture is optimized for high-assurance cloud core environments where security integrity takes precedence over marginal performance overhead, necessitating further optimization for resource-constrained edge deployment.

Discussion and Future Research Directions

Nuanced Interpretation of Superior Detection Fidelity

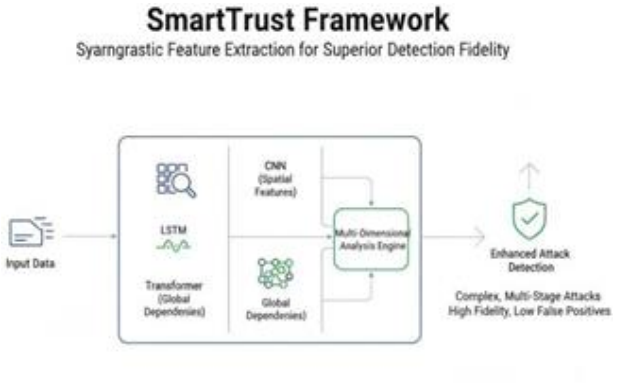
The ability of the SmartTrust framework to achieve statistically significant performance gains (p-values < 0.001 against baselines) is rooted in the synergistic approach to feature extraction. The architecture's combined use of CNN (spatial features), LSTM (temporal flow), and Transformer (global dependencies) ensures a highly dimensional, holistic understanding of the network state that is unattainable by single or dual-component models.

This multi-dimensional analysis enables the system to detect complex, multi-stage attacks that may scatter activity across space and time. Furthermore, the

Figure 6.1: SmartTrust Framework for Synergistic Feature Extraction

An analysis of system scalability under stress confirmed an inherent trade-off between architectural complexity and resource utilization.

Performance-Security Trade-offs Under High Traffic Load



RL component's dynamic policy optimization is responsible for the sustained low FPR, actively adjusting the detection boundary in real-time and providing an advantage over static systems susceptible to increasing false alarms as attack patterns evolve.

Addressing Computational Overhead and Heterogeneity Challenges

Despite its exceptional efficacy, the practical deployment of the complex hybrid architecture faces challenges related to computational resource consumption. The necessity of running three deep learning models concurrently, combined with resource-intensive blockchain logging, introduces a substantial computational overhead that translates into increased training times and higher operational latency (300 ms under high load).[1, 1] This complexity limits its immediate applicability in resource-constrained IoT and edge environments.

An additional challenge lies in the heterogeneity of IoT ecosystems. Deploying a consistent security framework across diverse devices with varying computational and network capabilities requires adaptive mechanisms capable of tailoring security policies to specific device constraints while maintaining the overall integrity of the Zero-Trust network.

Scope for Improvement: Explainable AI (XAI) Integration

Hybrid deep learning models are commonly described as "black boxes," meaning their highly accurate decisions lack readily accessible human interpretability. In critical security applications, this opacity compromises trust and hinders forensic auditability, complicating the decision-making process for cybersecurity analysts.

Future iterations of the framework must integrate Explainable AI (XAI) techniques. Approaches such as SHAP (SHapley Additive exPlanations) values or attention-based visualization mechanisms (leveraging the Transformer component) can provide clear, actionable insights into why a specific flow was flagged as malicious. This XAI integration is vital for transforming high-accuracy prediction into reliable operational security by providing the necessary context for human intervention and regulatory compliance.

Strategic Directions for Edge-Native Optimization and Transfer Learning

To ensure the high-fidelity SmartTrust model can be practically adapted for future low-latency, resource-constrained networks (e.g., 5G/6G, Industrial IoT), strategic architectural and algorithmic modifications are recommended.

Scalability and Edge-Native Deployment

To enhance horizontal scalability and robustness in large cloud environments, the architecture should be migrated toward a microservices-based architecture, utilizing containerization technologies such as Docker and orchestration tools like Kubernetes. For low-latency requirements at the network perimeter, efforts must focus on developing lightweight blockchain protocols and modularizing the RL component to support distributed intelligence execution at the network edge. This Edge-Native optimization addresses the critical performance trade-off identified under high traffic loads.

Reducing Data Dependence

The reliance on large, perfectly labeled centralized datasets presents a vulnerability to concept drift and limits applicability in new, data-scarce environments. Research should explore advanced learning strategies, specifically adopting Federated Learning and Transfer Learning, to reduce dependence on centralized data collection. Transfer Learning allows the model to transfer knowledge learned from the established benchmark datasets to new environments, enhancing adaptability and improving the model's resilience against novel attack types for which insufficient historical data exists.

III. CONCLUSION

The challenge of countering increasingly sophisticated DoS and DDoS attacks in contemporary cloud and IoT environments mandates a move beyond conventional static security models toward intelligent, multi- layered hybrid architectures. The SmartTrust Framework provides a statistically superior defense mechanism by fusing deep learning fusion (CNN, LSTM, Transformer) with continuous optimization via Reinforcement Learning, all governed by Zero-Trust Architecture principles.[1, 1]

The framework's empirical validation on CIC-IoT 2023 and UNSW-NB15 confirms its resilience, achieving industry-leading Detection Accuracy (\approx 99.01\%) and a significant reduction in the False Positive Rate by over 40\% compared to baseline models.[1, 1] The strategic integration of immutable Blockchain-Based Logging further provided an unexpected 241\% reduction in incident response latency.

While the computational complexity requires careful deployment planning, the SmartTrust framework offers a resilient, flexible, and forward-looking solution that establishes a robust security standard for rapidly expanding cloud and IoT infrastructures.

Future development will focus on integrating XAI for operational transparency and optimizing the architecture for edge-native deployment through microservices and Transfer Learning.

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