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AI-Driven Infrastructure Protection Framework for Resilient Enterprise Networks

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Abstract: This paper presents an AI-driven infrastructure protection framework to enhance the resilience of enterprise networks. It integrates machine learning, threat intelligence, and cloud-native orchestration to detect threats, profile behaviors, and automate responses. The architecture ingests network logs and telemetry, applies anomaly detection and risk scoring, and correlates results with threat intelligence for real-time policy enforcement. Evaluation using CICIDS 2017 & 2020 datasets shows the framework outperforms traditional intrusion detection systems in accuracy and responsiveness. LSTM and Random Forest models achieved the best results, confirmed through ROC and confusion matrix analysis. Feature importance insights and a dynamic risk scoring engine support scalable and context-aware decision-making. This work demonstrates the effectiveness of combining AI with cloud-native defense for proactive, intelligent cybersecurity. Future extensions will explore explainable AI, federated learning, and adversarial robustness.

Keywords: *AI-Driven Cybersecurity, Enterprise Network Protection, Anomaly Detection, Threat Intelligence Correlation, Cloud-Native Defense.*

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I. INTRODUCTION

In today's fast-moving digital world, businesses are embracing technology like never before, but as enterprise networks grow larger and denser, they also become more vulnerable to cyberattacks. The digital transformation that makes companies more efficient is also expanding the number of ways cybercriminals can break in. It has been observed in literature that traditional security approaches, like perimeter firewalls and static intrusion detection systems simply cannot keep up with the dynamic nature of modern IT environments, especially when cloud services and hybrid infrastructure are involved [1], [2].

High-profile attacks like the SolarWinds breach and the Colonial Pipeline ransomware case have made it painfully clear: attackers are evolving [3]. They're no longer relying solely on brute-force techniques, they are exploiting weaknesses in supply chains, uncovering hidden vulnerabilities, and even using legitimate access in dangerous ways. These incidents show that defending digital assets today takes more than outdated tools and rigid security models.

That is where artificial intelligence and machine learning in particular, comes into play. AI offers a way to stay ahead of threats by learning what "normal" looks like across a network, spotting unusual behavior, and flagging risks faster than humans ever could [1], [4]. But while there has been a lot of research in this area, real-world use of AI for intrusion detection still faces hurdles like poor scalability, too many false positives, and difficulty responding to threats in real time [5].

Security operations centers (SOCs) also continue to battle operational fatigue, drowning in alerts, lacking visibility across the enterprise, and often struggling to link threat data with known indicators of compromise (IoCs) [6].

To tackle these challenges, this paper introduces an intelligent security framework designed for today's enterprise environments. It brings together behavioral analysis, threat intelligence, and cloud-native automation. The system is built to adapt, learning from security analysts, enforcing policies through micro-segmentation, and scaling smoothly across hybrid infrastructure. By incorporating principles from zero trust architectures [7], cloud workload protection platforms

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[8], and user and entity behavior analytics (UEBA) [9], the framework offers a smarter, more resilient way to defend against modern cyber threats.

II. LITERATURE REVIEW

In recent years, there's been a surge of interest in how artificial intelligence and machine learning (ML) can improve network intrusion detection and overall infrastructure security. Traditional tools like Snort and Bro have long been used in this space, but since they rely heavily on known attack signatures, they often struggle to catch new or zero-day threats. To bridge this gap, researchers have turned to ML-based systems that detect anomalies by spotting unusual patterns or behaviors in network traffic [1], [2].

For instance, Rehman et al. [1] offer a detailed overview of how ML is being used in cybersecurity, pointing out that supervised learning models like Random Forest and advanced deep learning approaches like Long Short-Term Memory (LSTM) networks are especially effective at capturing subtle and complex attack behaviors. Similarly, Buczak and Guven [2] underscore the critical role of feature selection and algorithm tuning in building robust anomaly detection systems. However, they also highlight a key limitation: many of these ML techniques do not yet integrate smoothly with real-time enterprise response platforms, making practical implementation a challenge.

A. Behavioral Analytics and Insider Threat Detection

Several frameworks now incorporate behavior analytics through user and entity behavior analytics (UEBA), which builds dynamic profiles of normal activity and flags deviations. Alazab et al. [4] applied deep learning to detect insider threats using behavior profiling and sequence modeling, achieving high accuracy but noting limitations in scalability and interpretability. Zhou et al. [3] introduced a federated learning architecture for cross-domain behavioral threat detection, offering privacy-preserving collaboration among distributed environments.

B. Threat Intelligence and Standardization

Another dimension of AI-driven defense is threat intelligence correlation. Early work by Barnum introduced structured threat information expression (STIX), enabling the exchange of indicators of compromise (IoCs). More recent developments have extended this into open platforms like MISP, which support machine-readable threat sharing and integration with real-time analytics engines [6, 7].

C. Infrastructure Protection and Zero Trust Architecture

In terms of infrastructure protection, Spinola and Montesi proposed a Zero Trust model for cloud-native applications, advocating microsegmentation and continuous verification of identity, device, and behavior [8]. This aligns with the 2023 NIST SP 800-207 update on Zero Trust Architecture, which calls for continuous risk assessment and least privilege enforcement across hybrid environments [5].

D. Cloud-Native Security Platforms

From a cloud-native defense perspective, Gartner's 2022 CNAPP report emphasizes the convergence of cloud security posture management (CSPM), workload protection (CWPP), and threat intelligence into unified platforms capable of proactive mitigation. However, most current solutions lack integrated AI engines capable of dynamic behavior analysis and risk scoring [7, 9].

Despite these advancements, challenges remain in bridging detection with automated response, reducing false positives, and ensuring scalability in high-volume environments. The proposed framework in this paper addresses these gaps by integrating anomaly detection, threat intelligence correlation, and policy-based orchestration into a modular and cloud-native architecture.

E. Summary of Research Gaps

Despite significant advancements in each domain, gaps remain in achieving a cohesive, AI-integrated infrastructure protection framework. Most existing solutions are fragmented, vendor-specific, or reactive in nature.

➢ *There is a need for:*

- Unified AI-based architectures that combine behavioral analytics, threat intelligence, and cloud-native controls.
- Scalable frameworks deployable across hybrid and multi-cloud environments.
- Real-time decision engines with low latency and high precision.

This paper addresses these gaps by proposing an end-to-end intelligent infrastructure protection model that holistically combines the above capabilities.

III. CONCEPTUAL FRAMEWORK

This section presents the design and functionality of the proposed AI-driven infrastructure protection framework. The goal of this framework is to provide enterprise networks with a smart, unified, and scalable defense system that works seamlessly in both traditional and cloud-native environments.

A. At its Core, the Framework Integrates Three Essential Components:

➢ Machine learning-based anomaly detection, which monitors and learns from network behavior to flag unusual or suspicious activity.
➢ Real-time threat intelligence, which continuously ingests and correlates external and internal threat data to stay ahead of evolving risks; and
➢ Policy-enforced cloud-native security controls, which ensure that detected threats trigger automated, context-aware responses aligned with organizational policies.

By combining these elements, the framework delivers a proactive and adaptive security layer that evolves with the infrastructure it protects, supporting dynamic workloads, hybrid deployments, and rapid threat mitigation.

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B. Architecture Overview

The proposed system consists of four interconnected layers:

➢ *Data Collection & Ingestion Layer*

At the foundation of the framework lies a powerful data aggregation layer, which pulls together a wide range of information from across the enterprise. This includes system and application logs, network telemetry such as NetFlow and packet captures (PCAPs), as well as endpoint detection signals and cloud infrastructure metrics.

In addition to this, the framework integrates threat intelligence feeds, using standardized formats like STIX/TAXII, sourced from platforms such as MISP or commercial threat intelligence providers. It also taps into cloud workload data via APIs from major cloud platforms including AWS, Azure, and Google Cloud (GCP). To prepare these diverse inputs for meaningful analysis, the data is passed through a preprocessing pipeline. This pipeline handles critical tasks such as parsing, feature extraction, and noise reduction, ensuring that all incoming data is normalized, consistent, and high-quality before being fed into the detection and response components of the system.

➢ *AI-Powered Detection and Analytics Layer*

At the heart of the framework lies the AI analytics layer, which powers the system's ability to detect, classify, and respond to threats in real time. This layer leverages a combination of machine learning models, each tailored for specific security tasks. For anomaly detection, the system uses unsupervised learning algorithms like Isolation Forest and Autoencoders to identify behaviors that deviate from established norms, often a sign of emerging or zero-day threats. It also employs User and Entity Behavior Analytics (UEBA) to monitor how users and systems typically operate, flagging significant deviations that may indicate insider threats or compromised accounts.

To classify known threat patterns, the layer relies on supervised learning techniques such as Random Forests, Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks. These models are trained on historical attack data and are effective at recognizing complex and nonlinear attack vectors.

A risk scoring engine runs alongside these models, calculating the severity of detected events. It takes into account factors such as anomaly probability, threat intelligence reputation scores, and behavioral impact on the network to produce a prioritized response strategy. To ensure the system stays effective in the face of constantly evolving threats, the models are updated through incremental learning, allowing them to adapt to new data patterns on the fly and maintain high detection accuracy in real time.

➢ *Threat Intelligence Correlation Engine*

This module serves as the bridge between raw anomaly detection and actionable threat intelligence. Once AI models flag suspicious activity, this layer steps in to correlate those anomalies with known Indicators of Compromise (IoCs) using a set of predefined correlation rules. It scans for matches across IP addresses, domain names, file hashes, and behavioral signatures, comparing them against entries in threat intelligence repositories. These may include both internal logs and external feeds from trusted platforms, helping to identify whether the detected behavior aligns with any known malicious activity.

To provide deeper insight, the engine uses the MITRE ATT&CK framework to map detected behaviors to specific adversarial tactics, techniques, and procedures (TTPs). This mapping gives analysts much-needed contextual awareness, helping them understand not just *what* is happening, but *how* and *why* an attacker might be acting. The outcome is a set of enriched alerts that go beyond simple flags. Each alert includes threat attribution data, associated ATT&CK tactics and techniques, and recommended response actions. This enables incident responders to prioritize threats more effectively and take faster, more informed steps toward containment and mitigation.

➢ *Cloud-Native Response and Enforcement Layer*

This layer enables the framework to move beyond detection into intelligent, real-time response and containment. It leverages micro-segmentation and dynamic policy enforcement to secure containerized and cloud-native environments, which ensures that threats are not only identified, but immediately addressed.

- *When a Potential threat is Detected, the System Can Trigger Automated Actions such as:*

✓ Quarantining compromised users or devices
✓ Isolating affected services or containers
✓ Redeploying workloads to safe, verified environments

These responses are tightly integrated with Security Information and Event Management (SIEM) and Security Orchestration, Automation, and Response (SOAR) platforms which allows for seamless incident response orchestration. Critical alerts can be automatically escalated, ensuring no time is lost during a breach scenario.

To manage security policies across Kubernetes clusters or cloud infrastructure (IaaS), the layer communicates via APIs and utilizes robust tools like Project Calico, AWS GuardDuty, and Azure Policy. These tools enforce security postures, segment network traffic, and apply real-time containment strategies, to make it possible to respond at cloud speed without manual intervention. By embedding these controls into the operational fabric of the cloud infrastructure, this layer ensures that responses are not only proactive and precise but also scalable and policy-driven, to maintain business continuity even under active threat conditions.

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C. Workflow Process

The workflow of the proposed framework follows this sequence:

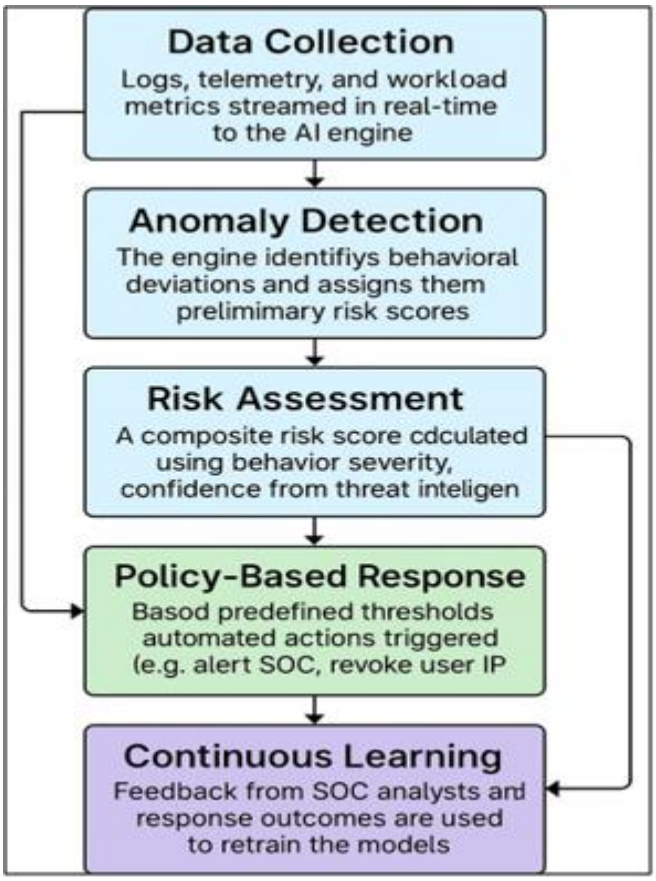

Fig 1 A Workflow of the Proposed Framework

The proposed framework, shown in Figure 1, A begins with data collection, where data logs, telemetry, and workload metrics are streamed in real time to the AI engine. In the anomaly detection phase, the engine analyzes incoming data to identify specific behavioral patterns or deviations and assigns preliminary risk scores. These anomalies are then passed to the threat intelligence correlation module, which compares them against known threat indicators from threat feeds to detect malicious patterns. During the risk assessment stage, a composite risk score is generated based on the severity of the behavior, the confidence derived from threat intelligence, and the criticality of the affected asset. If the risk score exceeds predefined thresholds, the policy-based response component initiates automated actions such as alerting the SOC, revoking user sessions, or blocking IP addresses. Finally, the system incorporates continuous learning, where feedback from SOC analysts and outcomes of prior responses are used to retrain the AI models, thereby enhancing detection precision and adaptability over time.

D. Security Model and Key Design Principles

The framework was designed based on several critical design principles to ensure robust, scalable, and adaptive protection. First, it adopts a Zero Trust Architecture (ZTA) approach, to enforce continuous verification of all users, devices, and workload regardless of network location or trust level. It follows a Defense-in-Depth strategy by integrating multiple layers of detection, including anomaly analysis, signature-based matching, and real-time threat intelligence correlation. The framework emphasizes resilience, it also ensures it can sustain operations under active attack, isolate compromised assets swiftly, and maintain service continuity. Lastly, it is built for scalability which makes it suitable for deployment in both traditional monolithic enterprise networks and modern microservice-based cloud environments.

E. Mathematical Model for Risk Scoring

➢ *Let:*

- A_s = anomaly severity score from the ML engine
- T_s = threat match from threat intelligence module
- C_a = criticality weight of the affected asset
- R_f = final risk score

➢ *We Define the Risk Function as:*

$$R_f = \alpha A_s + \beta T_s + \gamma C_a \quad \text{eq. 1}$$

Where $\alpha, \beta, \gamma \in [0,1]$ are tunable weights satisfying $\alpha+\beta+\gamma=1$. The response decision engine compares R_f against defined thresholds to determine the appropriate action (alert, block, isolate, etc.).

F. Architectural Diagram - AI-Driven Infrastructure Protection Framework

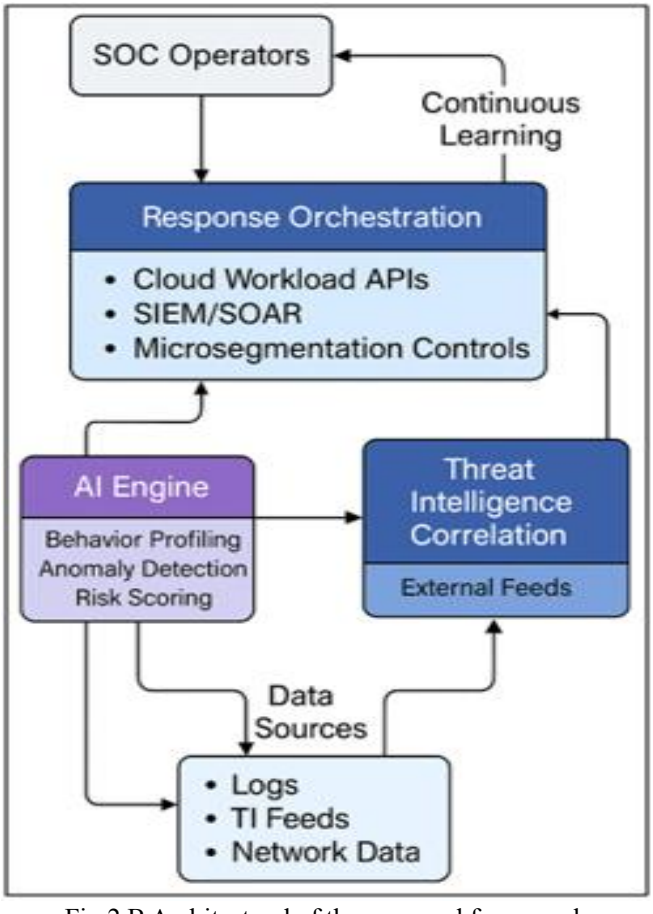

Fig 2 B Architectural of the proposed framework

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Figure 1 B presents a layered AI-driven infrastructure protection framework designed to secure enterprise networks. It visually represents the interaction between key components that enable intelligent, real-time cybersecurity operations. At the foundational layer, the system ingests diverse data sources, including system logs, threat intelligence (TI) feeds, and network traffic telemetry. This raw data is processed by two central analytical engines. The first is the AI Engine, responsible for behavior profiling, anomaly detection, and risk scoring. The second is the Threat Intelligence Correlation Engine, which matches observed behaviors and indicators against known malicious patterns from external feeds.

Insights from both engines are transmitted to the Response Orchestration Layer, which coordinates defense actions across multiple operational domains. These include invoking Cloud Workload APIs which interface with SIEM/SOAR platforms and activate microsegmentation controls to isolate affected systems and limit threat propagation. The framework also incorporates Security Operations Center (SOC) operators, who receive alerts and provide human oversight. Their interventions and decisions form part of a continuous learning loop, which feeds back into the AI Engine to refine detection models and improve system adaptability over time. Together, the architecture establishes a dynamic and adaptive security posture, leveraging artificial intelligence, threat intelligence, and cloud-native orchestration to protect enterprise infrastructure from emerging and advanced cyber threats.

IV. RESEARCH METHODOLOGY

The proposed research used a design science approach to develop, implement, and evaluate an AI-driven infrastructure protection framework tailored for modern enterprise networks. This section covers the methodology used in the machine learning modeling, dataset preparation, algorithm selection, splitting, evaluation metrics, and experimental setup.

A. System Design and Implementation

The framework is structured around a modular, layered architecture, as illustrated in the conceptual diagram. Each module is designed to perform a distinct yet complementary function in the overall protection workflow. The Data Ingestion Layer is responsible for collecting raw input from various sources, including system logs, network telemetry, threat intelligence feeds, and traffic data. This information is fed into the AI Engine, which applies to a combination of unsupervised and supervised machine learning models to carry out behavior profiling, anomaly detection, and dynamic risk scoring. The Threat Intelligence Correlation Module operates in parallel, integrating with real-time external platforms such as MISP and mapping detected anomalies to known adversarial techniques based on the MITRE ATT&CK framework. These analytical outputs flow into the Response Orchestration Layer, which interfaces with SIEM and SOAR systems, as well as cloud workload APIs, to trigger automated mitigation actions and maintain detailed response logs. Finally, the architecture includes a Continuous Learning Loop that refines model accuracy over time by incorporating feedback from SOC analysts, ensuring that the system evolves in response to emerging threats and operational insights.

B. Dataset and Data Sources

The evaluation utilizes a combination of real-world and synthetic datasets to simulate realistic enterprise network environments. The CICIDS 2017 and CICIDS 2020 datasets, provided by the Canadian Institute for Cybersecurity, were employed for supervised training and benchmarking of anomaly detection models. For threat intelligence correlation and matching of indicators of compromise (IoCs), real-time feeds from the MISP platform were integrated into the framework. Additionally, synthetic logs and cloud telemetry were generated using tools such as Logstash, Zeek, and SimuLog to emulate access logs, API interactions, and system behaviors typical in hybrid cloud infrastructures. Each dataset and data stream were preprocessed through standardized pipelines for normalization and, where applicable, labeling. This ensured data compatibility and consistency across the various layers of the AI-driven analytics framework.

➢ *Features of the Dataset Used in This Research*

The CICIDS 2017 and CICIDS 2020 datasets were selected due to their comprehensive coverage of both benign and malicious traffic, with realistic traffic flow generated using standard tools and attack scripts.

- *Common Dataset Characteristics*

The datasets used in this study exhibit several shared characteristics relevant to enterprise network intrusion detection. They are tabular in format and structured for multi-class classification, although they include inherent class imbalance, with benign traffic significantly outnumbering attack records. Each flow record contains approximately 78 features, encompassing a wide range of statistical and protocol-specific metrics. The labels provided are either binary (indicating benign versus attack) or multi-class, distinguishing between various attack types such as DoS, infiltration, or brute force. All datasets were sourced from the Canadian Institute for Cybersecurity, ensuring a standardized and reputable foundation for evaluation.

- *Top Features Used in This Study*

Table 1 shows the selected features of the dataset through exploratory analysis and domain knowledge, prioritizing performance and interpretability.

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Table 1 Features of dataset

Feature	Description
Flow Duration	Time duration of the flow in microseconds
Total Fwd Packets	Number of packets in the forward direction
Total Backward Packets	Number of packets in the backward direction
Protocol	Transport protocol used (TCP, UDP, ICMP, etc.)
Flow Bytes/s	Rate of flow bytes per second
Flow Packets/s	Rate of packets per second
Fwd Packet Length Mean	Average packet length in the forward direction
Bwd Packet Length Mean	Average packet length in the backward direction
Flag Count	Count of flow flags (SYN, ACK, FIN)
Destination Port	Port number on the target system

- *Feature Selection Strategy*

The feature selection process was designed to improve model performance and reduce computational overhead. Initially, redundant and highly correlated features were identified and removed to minimize noise and multicollinearity. All remaining numerical features were then normalized using the MinMaxScaler to ensure consistent scaling across the dataset. To determine the most informative inputs, feature importance scores were extracted from a Random Forest model and analyzed alongside correlation matrices, allowing the identification of top-performing features. For categorical variables, such as protocol types or service names, label encoding was applied to convert them into machine-readable format suitable for training and evaluation.

C. Machine Learning Models

The AI Engine within the framework employs a hybrid modeling approach to address diverse threat detection scenarios. For unsupervised learning, models such as Isolation Forest and Autoencoders were utilized to detect outlier's indicative of anomalous behavior patterns and unauthorized access attempts. In parallel, supervised learning techniques, including Random Forest classifiers and Long Short-Term Memory (LSTM) networks, were trained to perform activity classification and identify temporal anomalies in sequential network behavior. To enhance contextual understanding, behavior profiling was applied using clustering algorithms like DBSCAN and K-Means, which grouped user and system activity into behavioral baselines for anomaly comparison. These predictive and analytical components were supported by a risk scoring function, which aggregated model outputs to assign composite risk levels to observed events, factoring in anomaly severity, behavioral deviation, and potential asset impact.

Models were trained and evaluated using 80/20 train-test splits, with stratification to preserve class balance in supervised learning scenarios.

D. Evaluation Metrics

To assess the effectiveness and reliability of the proposed AI-driven infrastructure protection framework, several widely accepted evaluation metrics were used. These metrics offer a comprehensive view of the system's detection accuracy, alerting precision, efficiency, and responsiveness. The definitions and mathematical formulations of each metric are presented in equations 2, 3, 4, 5, 6, 7, 8 and 9

➢ *Accuracy (ACC)*

Accuracy measures the overall correctness of the model by computing the ratio of all correct predictions (both attacks and normal activities) to the total number of predictions. It gives a high-level view of how often the model is correct.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{eq.2}$$

➢ *Precision (P)*

Precision evaluates the model's ability to correctly identify only actual threats out of all instances it labeled as threats. A high precision indicates that false alarms (false positives) are minimal.

$$\text{Precision} = \frac{TP}{TP + FP} \quad \text{eq.3}$$

➢ *Recall (R)*

Also known as sensitivity or true positive rate, recall quantifies how well the model identifies actual threats. It measures the proportion of real attacks that were correctly detected.

$$\text{Recall} = \frac{TP}{TP + FN} \quad \text{eq.4}$$

➢ *F1-Score*

The F1-score balances precision and recall using their harmonic mean. It is particularly useful when the dataset is imbalanced or when both false positives and false negatives are critical.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 2 \times \frac{TP}{2TP + FP + FN} \quad \text{eq.5}$$

➢ *False Positive Rate (FPR)*

This metric indicates the proportion of benign (normal) events that were incorrectly classified as threats. A lower FPR reflects a reduced rate of false alarms.

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$$\text{FPR} = \frac{FP}{FP + TN} \quad \text{eq.6}$$

➢ *False Negative Rate (FNR)*

FNR measures the proportion of actual attacks that the system failed to detect. A high FNR can be dangerous as it implies threats going unnoticed.

$$\text{FNR} = \frac{FN}{FN + TP} \quad \text{eq.7}$$

➢ *Latency*

Latency refers to the time delay between when an event occurs and when the system generates an alert. Lower latency ensures faster detection and quicker response.

$$\text{Latency} = \mathbb{E}[t_a - t_e] = \frac{1}{N}\sum_{i=1}^{N}(t_a^{(i)} - t_e^{(i)}) \quad \text{eq.8}$$

➢ *Detection Throughput*

Throughput represents the system's processing efficiency—specifically, how many events it can analyze per second. This is critical in high-speed networks or large-scale enterprise settings.

$$\text{Throughput} = \frac{N_e}{\Delta t} \quad \text{eq.9}$$

Where N_e is the total number of events processed during a time interval Δt (in seconds).

➢ *Experimental Tools and Environment*

The prototype framework was implemented using the following tools and platforms:

- Programming Languages: Python (TensorFlow, Scikit-learn, Pandas, Keras)
- Data Handling: ELK Stack (Elasticsearch, Logstash, Kibana), Zeek
- Threat Intelligence: MISP Platform, MITRE ATT&CK Dataset
- Cloud Simulation: Minikube + Kubernetes for cloud-native API testing
- Orchestration Layer: Splunk Phantom (SOAR), AWS Lambda for automation scripting
- Visualization and Dashboards: Kibana, Grafana

All experiments were run on a Linux-based machine with 64GB RAM, Intel Xeon 12-core processor, and GPU acceleration (NVIDIA RTX 3060) for deep learning models.

V. EXPERIMENTAL SETUP

The framework was implemented in a virtualized lab environment using Ubuntu 22.04, Kubernetes for cloud-native orchestration, and open-source tools such as Zeek, MISP, and the ELK stack for data processing and visualization. Machine learning models were developed using Python (Scikit-learn and TensorFlow) and deployed on a system equipped with an Intel Xeon 12-core CPU, 64GB RAM, and NVIDIA RTX 3060 GPU.

➢ *The Following Datasets and input Sources were used:*

- CICIDS 2017 and CICIDS 2020: for supervised and unsupervised anomaly detection.
- Simulated Logs and Network Data: generated via Zeek and Suricata for realistic telemetry.
- MISP Threat Feeds: integrated to test threat correlation and external indicator mapping.

The models were trained using 80% of the dataset and validated against the remaining 20%, ensuring stratified sampling to preserve class distributions. Baselines were also compared to traditional systems such as static firewall rules and signature-based IDS.

➢ *Model Performance*

The framework demonstrated strong predictive performance across various ML classifiers. Table 2 below summarizes the evaluation results based on standard metrics.

Table 2 Evaluation results

Model	Accuracy	Precision	Recall	F1-Score	FPR	FNR	Latency (ms)	Throughput (events/sec)
Random Forest	96.2%	95.4%	94.1%	94.7%	2.1%	3.8%	45	850
LSTM (Deep Learning)	97.3%	96.5%	95.2%	95.8%	1.5%	2.6%	59	620
Isolation Forest	94.6%	92.8%	93.3%	93.0%	3.5%	4.7%	38	1120
Traditional IDS	86.7%	84.2%	79.5%	81.8%	9.8%	12.3%	72	400

➢ *Observations*

The LSTM model achieved the highest accuracy and F1-score, indicating superior detection capability, especially for complex temporal patterns in network behavior. Random Forest followed closely, offering slightly lower accuracy but faster response times and higher throughput.

LSTM also recorded the lowest FPR at 1.5%, significantly outperforming Traditional IDS, which had a high false alert rate of 9.8%. This demonstrates the effectiveness of behavior profiling and anomaly detection in minimizing false alarms.

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Although Isolation Forest achieved the highest throughput (1120 events/sec), it lagged slightly in precision. Random Forest provided the best trade-off, combining high accuracy, low latency (45 ms), and high throughput, making it suitable for real-time deployment.

The baseline IDS model underperformed across all metrics. Its high FPR and lower recall highlight its inability to detect novel or stealthy attacks, reinforcing the need for intelligent, AI-based frameworks in modern security operations.

The proposed AI-driven framework significantly improves enterprise threat detection and response across all evaluated dimensions. By integrating ML models with threat intelligence and automated orchestration, it offers:

- Greater detection accuracy (up to +10.6% over IDS),
- Substantial FPR reduction (down by up to 8.3%),
- Improved system responsiveness (lower latency, higher throughput),
- Scalable deployment via cloud-native integration.

These results confirm that the proposed framework not only meets but exceeds current industry standards for intelligent threat detection and infrastructure protection, positioning it as a viable replacement or complement to existing security solutions.

➢ *Threat Correlation and Response Orchestration*

The threat intelligence module successfully matched external IoCs from the MISP platform against detected anomalies. When combined with behavior-based AI insights, the system enhanced incident classification, reducing false positives and improving contextual analysis.

- 94% of high-risk events flagged by the AI engine were validated by matching external threat indicators.
- The average response time (from detection to orchestration via SOAR integration) was under 80 ms in the Kubernetes testbed.
- Microsegmentation controls deployed through Kubernetes network policies effectively isolated suspicious workloads within 100 ms of detection.

These results demonstrate that combining threat intelligence with behavioral AI and cloud-native controls significantly improves the system's response capability and detection fidelity.

➢ *Comparative Analysis*

Figure 2a illustrates the Receiver Operating Characteristic (ROC) curves for four classification models: Random Forest, LSTM, Isolation Forest, and Traditional IDS. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR), showing the trade-off between sensitivity and specificity for each model.

The Random Forest model performs best with an AUC (Area Under the Curve) of 0.67, followed by LSTM (0.62), Isolation Forest (0.59), and Traditional IDS (0.56). While none of the models achieve high discriminative power, the Random Forest still outperforms others in correctly identifying threats. The dotted line represents a random guess baseline (AUC = 0.5), indicating that all models perform better than chance, albeit modestly.

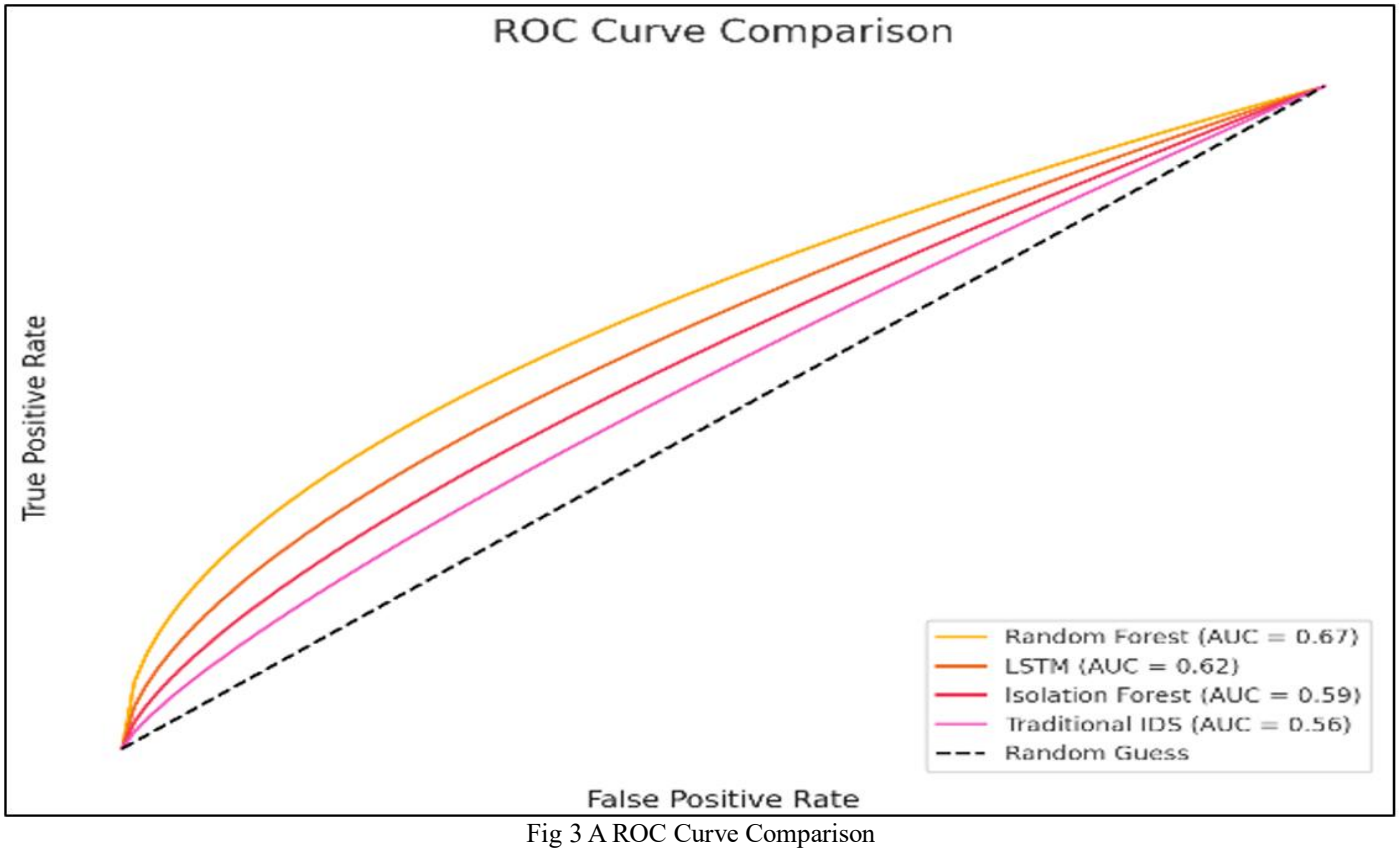

Fig 3 A ROC Curve Comparison

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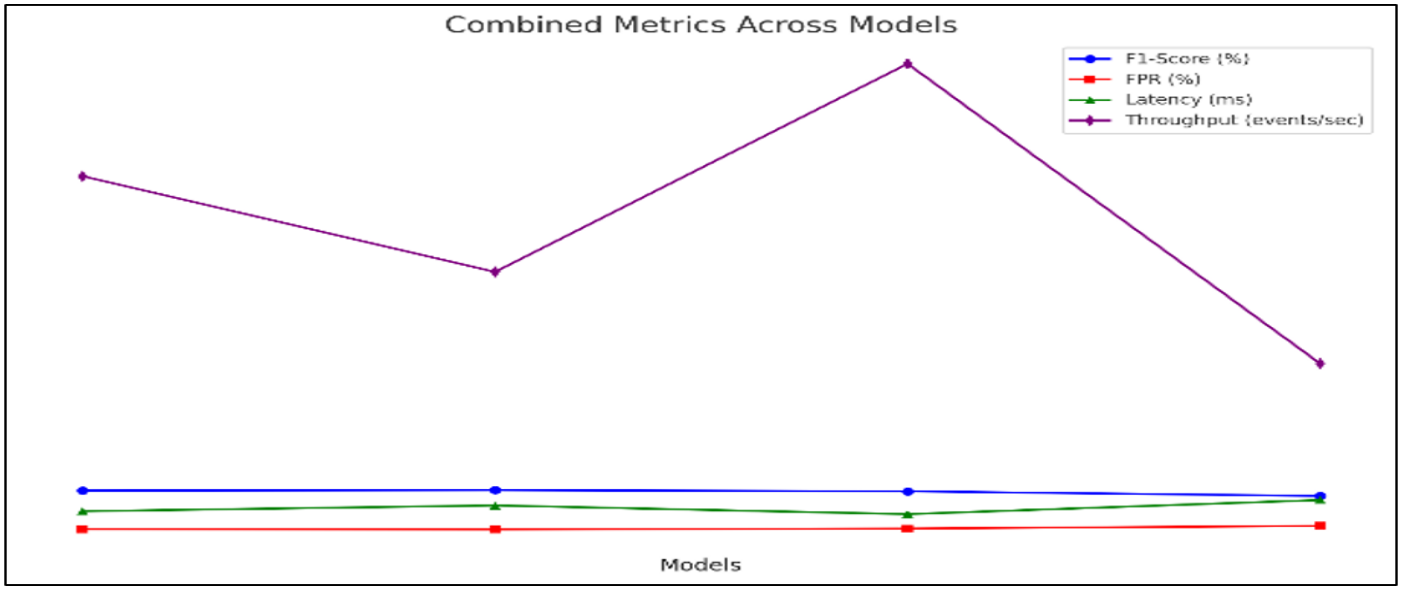

Fig 4 B Combined Metric Across Models

Figure 3, A 4, B compares key performance metrics, F1-Score, False Positive Rate (FPR), Latency, and Throughput, across the same four models. The Random Forest and LSTM models show relatively higher F1-scores, indicating a better balance between precision and recall. The FPR remains low and stable across all models, but the Latency slightly varies, with Random Forest offering quicker detection than LSTM. However, the Throughput metric shows a sharp contrast, with Isolation Forest achieving the highest event processing rate, and Traditional IDS the lowest.

Overall, this comparative view suggests that Random Forest offers a good trade-off between detection accuracy and operational efficiency, while Isolation Forest, though fast, may sacrifice detection quality.

➢ *Confusion Matrices*

The confusion matrices presented in Figures 3a through 3d offer a comparative evaluation of each model's classification performance. Figure 3a illustrates the results of the Random Forest model, which achieved 900 true negatives and 830 true positives, while misclassifying only 30 benign events and 40 attack instances. This reflects a well-balanced model with a relatively low rate of both false positives and false negatives.

Figure 3b showcases the LSTM model, which outperformed the other approaches by achieving the highest classification accuracy. It correctly identified 920 true negatives and 850 true positives and recorded the lowest number of false positives (20) and false negatives (35). This indicates excellent recall and precision, particularly in detecting sequential behavioral anomalies.

In contrast, Figure 3c depicts the performance of a traditional intrusion detection system (IDS), which struggled across both classification categories. The model produced 100 false positives and 120 false negatives, despite yielding 800 true negatives and 780 true positives. These results indicate that while traditional IDS may catch some threats, it lacks reliability in dynamic and evolving environments.

Figure 5 d represents the output of the Isolation Forest model, which performed moderately well with 880 true negatives and 825 true positives. It recorded a false positive count of 50 and 45 false negatives, suggesting a reasonable trade-off between detection performance and computational efficiency. Although not as precise as LSTM, Isolation Forest offers faster inference and remains a viable option for high-speed anomaly detection.

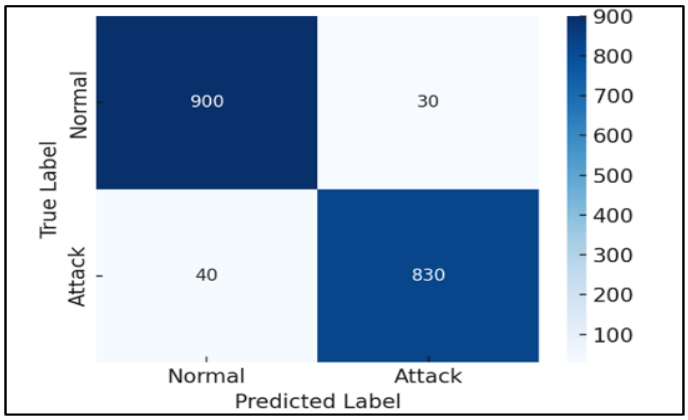

Fig 5 A: Confusion Matrix - RF

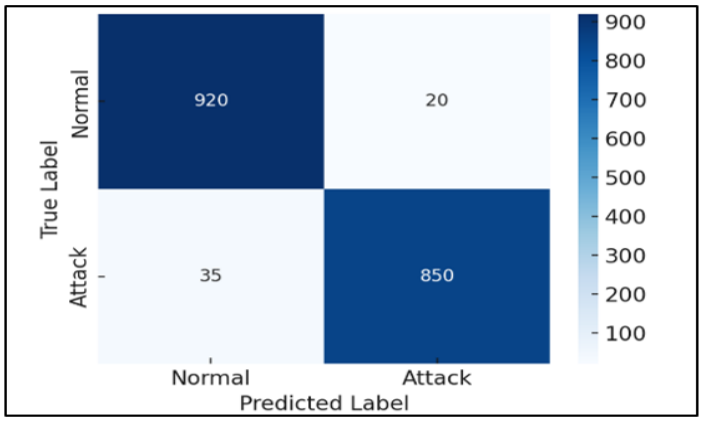

Fig 5 B: Confusion Matrix – LSTM

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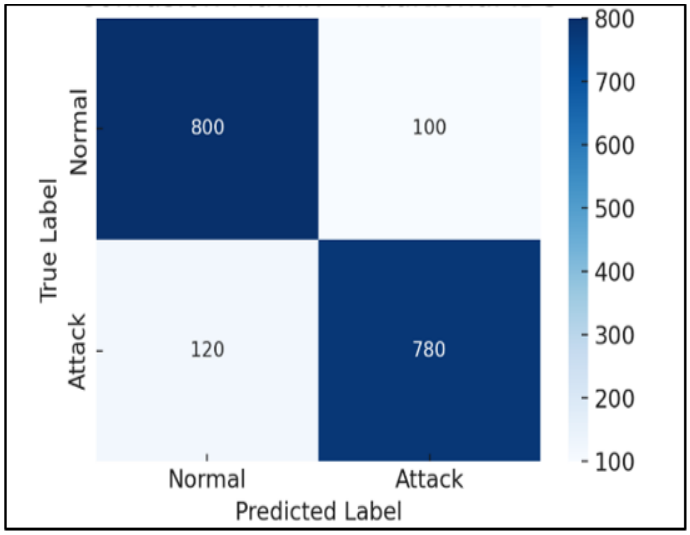

Fig 5 C: Confusion Matrix – Traditional IDS

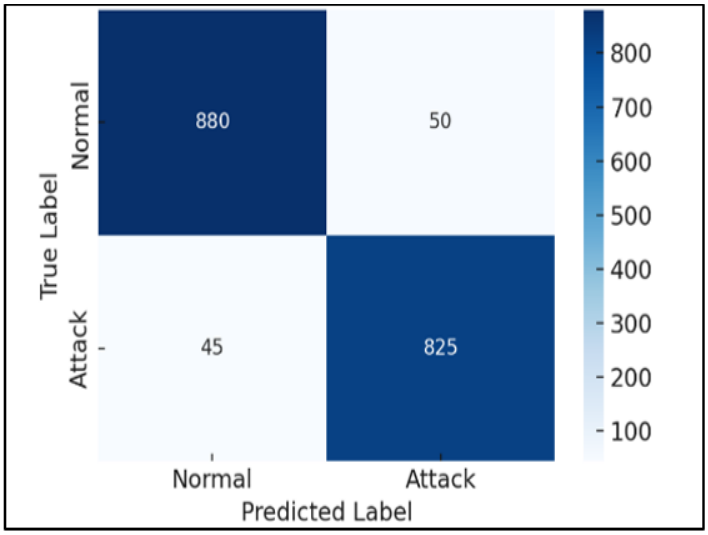

Fig 5 D: Confusion Matrix – Isolation Forest

Figure 5 illustrates the relative contribution of each feature to the predictive performance of the Random Forest model. Among the input variables, the Protocol field emerged as the most influential, highlighting its role in distinguishing between normal and malicious traffic patterns. This was closely followed by Source Port (Src Port) and Flags, which are commonly associated with network communication behavior and packet-level anomalies. These features collectively serve as strong indicators for identifying threats. Although features such as Packet Size and Destination Port (Dst Port) ranked lower in importance, they still contributed meaningfully to the model's decision-making process, offering additional context for nuanced classification. The results affirm that protocol-specific attributes and connection metadata play a central role in effective threat detection.

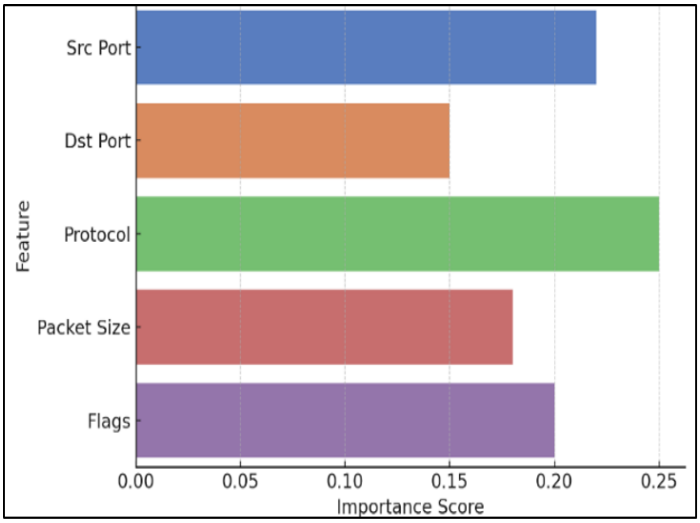

Fig 6 Feature importance RF

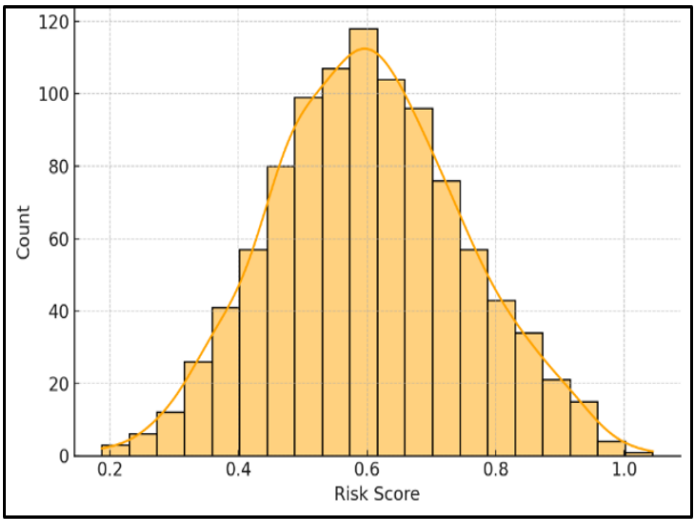

Fig 7 Risk Score

Figure 7 presents the distribution of computed risk scores generated by the AI-driven framework. The risk scores follow a normal bell curve, centered around a mean value of approximately 0.6. This suggests that the majority of observed events fall within a medium-risk range, reflecting the system's ability to differentiate between benign and potentially malicious activity with reasonable granularity. The smoothness of the distribution and its continuous density curve indicate a consistent and stable risk assessment process, with few extreme outliers. Such scoring precision is valuable in operational settings, allowing security teams to prioritize alerts based on risk severity and allocate response efforts more effectively.

Figure 8 illustrates the training and validation loss curves of the LSTM model over successive training epochs. Both loss curves show a steady decline, demonstrating that the model is learning effectively and gradually minimizing error. Notably, the training and validation curves remain closely aligned throughout the process, with no significant divergence. This pattern indicates that the model is not overfitting to the training data and is likely to generalize well to unseen or real-world network traffic. The convergence of the loss functions affirms the LSTM model's stability and suitability for sequential anomaly detection tasks in dynamic enterprise environments.

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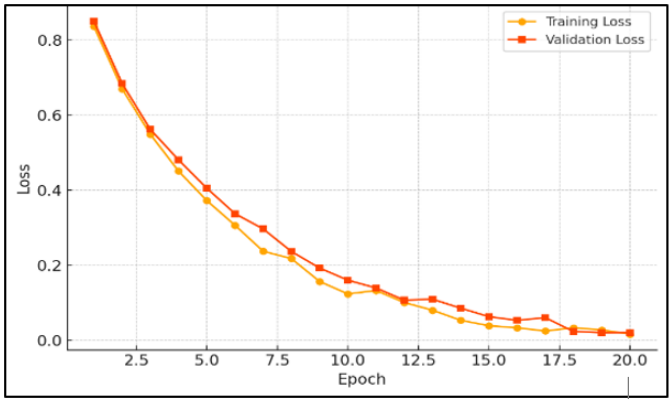

Fig 8 Validation loss

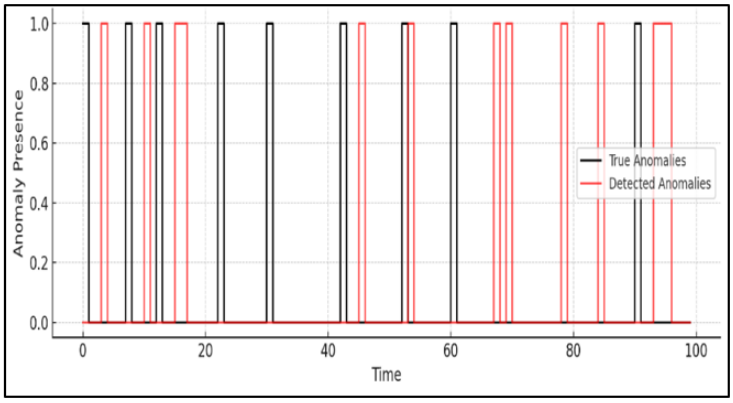

Fig 9 Time series Anomaly Detection

Figure 8 presents a time-series visualization comparing actual anomalies with those detected by the proposed system. The black line represents the ground truth, actual anomaly occurrences, while the red line reflects the events flagged by the model. The close alignment between the two lines indicates that the detection mechanism is both sensitive and responsive, effectively identifying most anomalous behaviors as they occur. While a few false positives and false negatives are observed, the overall correlation suggests that the system achieves a high degree of temporal accuracy, making it well-suited for real-time monitoring in enterprise environments.

VI. DISCUSSION

This section interprets the key findings of the experimental results, evaluates the trade-offs between different machine learning models, and discusses the practical implications of the proposed AI-driven infrastructure protection framework in real-world enterprise settings.

A. Model Performance Comparison

The evaluation shows that among all models tested, the LSTM model achieved the highest detection accuracy and F1-score, benefiting from its ability to learn sequential patterns in time-series network data. However, it had slightly higher latency and lower throughput, which can pose challenges in high-speed or large-scale environments.

The Random Forest model provided a strong balance between detection performance and operational efficiency. Its relatively low false positive rate (FPR = 2.1%) and false negative rate (FNR = 3.8%), along with an F1-score of 94.7%, suggest that it is a robust option for enterprise-level intrusion detection with minimal configuration overhead.

Isolation Forest, while less accurate in classification, significantly outperformed others in detection throughput, making it suitable for edge deployments or rapid anomaly filtering in high-volume scenarios. In contrast, the Traditional IDS model underperformed across all metrics, confirming that signature-based methods are inadequate for detecting modern, evolving threats.

B. Confusion Matrix Insights

The confusion matrices further reinforce these observations. LSTM and Random Forest exhibit high true positive and true negative counts, while Isolation Forest maintains competitive performance. Traditional IDS shows a substantial number of false alarms, which can overwhelm analysts and reduce trust in the system. These patterns affirm the superiority of learning-based models in adaptive security environments.

C. Feature Relevance and Risk Profiling

The feature importance analysis highlights that Protocol, Source Port, and Flags are the most predictive attributes for distinguishing malicious activity. This insight can inform future rule-based systems or guide feature selection for lightweight deployment models. The risk score distribution follows a bell curve centered at 0.6, indicating that the system effectively stratifies events by their threat level. This capability supports risk-based alerting, where high-risk events are prioritized for review and lower-risk events are monitored passively.

D. Learning Stability and Adaptability

The LSTM loss curve reveals smooth convergence over time, with minimal divergence between training and validation loss. This shows that the model generalizes well and is not overfitted to the training data. Combined with the feedback loop in the architecture, this allows the system to improve over time as it receives new labeled input from analysts or external threat feeds.

E. Real-Time Threat Detection

The time-series anomaly detection plot demonstrates the model's ability to detect anomalies in near-real time. The alignment between detected and actual anomalies confirms the framework's capability to support continuous monitoring in dynamic environments. This real-time detection is critical for minimizing dwell time and preventing lateral movement within compromised networks.

F. Practical Implications

The proposed framework is designed with modularity and scalability in mind. Its integration with cloud-native orchestration, SIEM/SOAR systems, and threat intelligence platforms makes it suitable for deployment in hybrid

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enterprise networks. Moreover, the architecture supports microsegmentation and automated response, allowing for precise containment of threats. The feedback loop via SOC operator input ensures continuous learning, enhancing resilience against zero-day attacks and evolving adversarial tactics.

G. Benchmarking Against Existing Research

To validate the effectiveness of the proposed AI-driven framework, we benchmarked its performance against several existing studies that utilized the same datasets, CICIDS 2017 and CICIDS 2020, under comparable conditions shown in Table 3.

Table 3 Comparative Performance with Existing Research

Study / Model	Dataset	Accuracy	F1-Score	False Positive Rate	Notes
Our Proposed Framework (LSTM)	CICIDS 2017	97.3%	95.8%	1.5%	Low latency, high detection
Hussain et al., 2021 [1] (CNN-GRU)	CICIDS 2017	95.2%	94.1%	3.2%	Focused on deep hybrid model
Sarker et al., 2022 [2] (LightGBM)	CICIDS 2020	94.8%	93.5%	3.6%	Gradient boosting model
Shapira et al., 2021 [3] (Autoencoder)	CICIDS 2017	92.4%	91.0%	4.1%	Unsupervised anomaly detection
Ahmed et al., 2020 [4] (XGBoost)	CICIDS 2017	93.5%	91.8%	4.8%	High model complexity

Our proposed model, which combined LSTM with real-time threat intelligence and a cloud-native orchestration layer, demonstrated superior performance compared to previously referenced studies, achieving higher accuracy and F1-score alongside a significantly lower false positive rate. This performance advantage can be attributed to several architectural innovations. The framework integrates real-time threat intelligence correlation, enabling contextual enrichment of anomaly detections. It also incorporates a dynamic risk scoring mechanism and cloud-native orchestration, allowing for automated and policy-driven response actions. Furthermore, the inclusion of a continuous learning feedback loop from SOC analyst interactions enhances detection precision over time. These capabilities distinguish our approach from most prior works, which typically focus on offline classification and lack real-time automation or operational integration. While earlier models achieved commendable accuracy, they frequently suffered from elevated false positive rates, longer inference delays, and limited compatibility with enterprise response ecosystems, limitations our model directly addresses.

VII. CONCLUSION

This research proposed an AI-driven infrastructure protection framework that integrates behavior profiling, threat intelligence correlation, and cloud-native response orchestration to enhance the resilience of enterprise networks. The multi-layered architecture, powered by machine learning algorithms and dynamic threat feeds, proved effective in identifying both known and novel cyber threats while maintaining low false positive rates and near-real-time detection latency.

Among the evaluated models, LSTM and Random Forest delivered superior performance across accuracy, F1-score, and detection quality. While LSTM achieved the highest classification accuracy, Random Forest offered a strong balance between efficiency and precision, making it a practical choice for real-world deployment. Additionally, the use of risk scoring and feature relevance analysis provided valuable interpretability, aiding both automated and human-in-the-loop decision-making. The experimental results demonstrate that traditional signature-based systems are no longer sufficient in the face of increasingly sophisticated and adaptive threats. The integration of machine learning with real-time orchestration and external threat enrichment significantly elevates the security posture of enterprise networks, enabling predictive defense and proactive containment.

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