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AI ENABLED FIREWALL USING TWO METRICS ATRS AND RAA

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Abstract:

Traditional firewalls struggle against advanced cyber threats such as zero-day attacks, encrypted malicious traffic, and polymorphic malware. This study proposes an AI-powered firewall utilizing Adaptive Threat Response Score (ATRS) and Risk Adaptive Access (RAA) to enhance threat detection and adaptive access control. The system employs machine learning classifiers trained on benchmark datasets like NSL-KDD and CICIDS2017, combined with explainable AI techniques for interpretable decision-making. Virtual lab experiments simulating attacker-defender scenarios demonstrate detection accuracy exceeding 99.5%, minimal false positives, and effective real-time risk assessment. The results highlight the potential of AI-enabled firewalls to provide robust, transparent, and adaptive network security.

Keywords - **Adaptive Threat Response Score, Explainable AI, Machine Learning, Risk Adaptive Access**

I. INTRODUCTION

In the current digital era, the rapid expansion of networks and the emergence of sophisticated cyberattacks demand more advanced methods for system protection. While traditional firewalls remain essential for fundamental security, they often fall short against modern threats such as zero-day exploits and concealed attacks within encrypted traffic. To address these limitations, Next-Generation Firewalls (NGFWs) have been developed, leveraging artificial intelligence (AI) and machine learning (ML) to detect threats with higher accuracy and to respond adaptively.

By integrating AI and ML, firewalls gain enhanced capabilities to identify anomalous behavior, analyze complex network patterns, and respond automatically to cyber threats. AI-driven firewalls are capable of processing large volumes of traffic, uncovering hidden threats that conventional rule-based systems might overlook, and minimizing false positives. Nevertheless, ensuring these models are interpretable and efficient for practical deployment remains a significant challenge.

This study proposes an intelligent firewall framework that combines virtualization, Python-based tools, and explainable AI techniques. The system is evaluated within a controlled laboratory environment, enabling packet analysis, model training, and interpretability of decision-making processes. The primary objective is not only to achieve robust intrusion
detection but also to ensure the system is adaptive, transparent, and suitable for real-world applications.

A. Statement of the Problem

In the rapidly evolving digital landscape, organizations are facing increasingly sophisticated cyber threats that can easily bypass conventional security systems. Despite continuous improvements in network defense mechanisms, traditional firewalls remain largely reactive and dependent on predefined

rules or known attack signatures. This inherent limitation makes them ineffective against modern and emerging threats such as zero-day exploits, polymorphic malware, and encrypted malicious traffic. As a result, these systems often lead to delayed threat detection, missed intrusions, and a high rate of false alerts, which burden security teams and reduce the overall efficiency of network protection.

Furthermore, the widespread adoption of cloud computing, remote work practices, and the proliferation of Internet of Things (IoT) devices have blurred traditional network perimeters. These developments have significantly weakened static, perimeter-based defense models, necessitating more adaptive and intelligent approaches to cybersecurity. In response, Next-Generation Firewalls (NGFWs) have emerged, offering features such as deep packet inspection, behavior-based detection, and the integration of machine learning algorithms. However, despite these advancements, NGFWs continue to face challenges related to transparency, computational overhead, privacy compliance, and the difficulty of analyzing encrypted data traffic.

Given these challenges, there is a pressing need for research into hybrid, AI-driven firewall systems that combine multiple detection strategies to enhance accuracy, reduce false positives, and ensure scalability while maintaining interpretability. This study aims to address these issues by designing and evaluating an AI-powered, explainable firewall within a controlled virtual lab environment. The proposed system leverages adaptive threat scoring and explainable AI (XAI) techniques to improve both detection performance and operational transparency, ultimately contributing to the development of more secure and trustworthy network defense mechanisms.

B. Objectives of the Research

1. To review the development of traditional firewall technologies and examine how artificial intelligence is incorporated into Next-Generation Firewalls (NGFWs).
2. To build a secure and isolated virtual lab using virtualization for simulating realistic attacker-defender network scenarios.
3. To design, train, and validate machine learning models that can detect malicious cnetwork traffic using standard intrusion detection datasets.
4. To apply explainable AI (XAI) methods, such as SHAP and LIME, to provide transparency and clarity in the AI model's decision-making.
5. To develop a real-time AI-based firewall that assesses network traffic risks and enforces adaptive access controls based on model predictions.
6. To evaluate the firewall's performance in terms of detection accuracy, false positives, latency, and scalability under simulated attacks.
7. To investigate hybrid detection strategies that combine signature-based, anomaly-based, and machine learning techniques for improved threat detection.
8. To provide practical recommendations for deploying AI-powered firewalls in enterprise environments, addressing operational, regulatory, and technical considerations.

C. Significance of the Study

1. Enterprise Organizations and IT Security Teams:
The study provides practical insights into AI-powered Next-Generation Firewalls (NGFWs), helping organizations improve threat detection accuracy, reduce false alarms, and strengthen overall cybersecurity operations.

2. Network Administrators and Security Analysts:
By using explainable AI methods like SHAP and LIME, the research makes firewall decisions more transparent, enabling security teams to understand alerts better and make informed decisions to mitigate threats.

3. Cybersecurity Developers and Vendors:
The findings highlight the benefits and challenges of hybrid detection frameworks combining signature-based, anomaly-based, and machine learning methods. Vendors can use this knowledge to create more effective, adaptable, and user-friendly firewall solutions.

4. Academia and Future Researchers:
The study provides a modular framework tested in a virtualized environment, contributing to knowledge on adaptive security, AI transparency, and resilient network defense, paving the way for future research.

5. Policy Makers and Regulators:

Insights from this research inform regulators about AI-powered firewall capabilities and limitations, aiding in the development of standards and policies that support secure and compliant network practices.

II. RELATED WORK

This section reviews past research on Next-Generation Firewalls (NGFWs), focusing on how Artificial Intelligence (AI) and Machine learning (ML) are used to improve network security.

A. Evolution of Firewall Technologies

Firewalls have evolved from basic Packet Filters (PFs) and Circuit-Level Gateways (CLGs) to advanced Next-Generation Firewalls (NGFWs) equipped with Artificial Intelligence (AI) capabilities. Traditional Firewalls primarily allowed or blocked network traffic based on predefined rules and signatures, which were ineffective against sophisticated threats such as Zero-Day Exploits (ZDEs) and Polymorphic Malware (PM). The introduction of NGFWs enhanced network defense mechanisms by incorporating Stateful Inspection (SI), Deep Packet Inspection (DPI), Intrusion Prevention Systems (IPS), and Application-Level Controls (ALCs). These integrated features establish multiple layers of defense, making NGFWs more robust and efficient in securing today's complex network environments.

B. AI and Machine Learning in NGFWs

Recent studies show that AI and ML bring major improvements to firewall systems. AI-based NGFWs can use supervised and unsupervised models to detect unusual traffic, predict new attack methods, and quickly adjust to changing threats. Algorithms like Random Forest, Support Vector Machines (SVM), and Gradient Boosting have shown better accuracy and fewer false alarms in intrusion detection. Explainable AI (XAI) methods such as SHAP and LIME also make firewall decisions easier to understand, helping security teams trust and manage AI-driven alerts more effectively.

C. Hybrid Detection Frameworks and Challenges

Hybrid methods that mix signature-based, anomaly-based, and ML models are seen as the most reliable way forward. These systems can detect more types of attacks with better precision while reducing too many false alerts. However, challenges remain—such as analyzing encrypted traffic without decryption, keeping delays low for real-time use, and smoothly fitting into existing enterprise networks.

D. Practical Implementations and Virtualized Testing Environments

Some studies describe testing AI-enhanced NGFWs in virtual labs to simulate real attack and defense situations. Tools like Oracle VirtualBox with Kali Linux (attacker) and Ubuntu (defender) allow safe, controlled testing of accuracy, delay, and stability. Network tools such as Scapy (for making traffic packets) and Wireshark (for traffic monitoring) support detailed analysis of firewall behavior and AI model performance.

III. METHODOLOGY

This study adopts a mixed-method research approach that combines both quantitative experimentation and qualitative analysis. The quantitative component evaluates the technical accuracy and efficiency of the AI-powered firewall, while the qualitative component focuses on the interpretability and transparency of the AI models using Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME. This hybrid approach ensures a comprehensive understanding of how effectively the proposed firewall detects, classifies, and responds to cyber threats in real-time network environments.

A. Environment

The design follows a systematic experimental framework consisting of data collection, preprocessing, model training, testing, and evaluation phases.

A virtualized testing environment was created using Oracle VirtualBox, comprising two main systems:

- Defender System: Ubuntu Linux configured with the AI-enabled firewall.
- Attacker System**:** Kali Linux used for generating malicious activities and network probes.

This controlled environment allows safe simulation of real-world cyberattacks and ensures the integrity

of test data while maintaining ethical security standards.

B. Data Collection Methods

Primary Data:

The dataset was generated within the virtual lab using penetration testing tools such as Metasploit, Nmap, and Wireshark. These tools were used to capture both benign and malicious traffic, forming the foundation for model training and evaluation.

Secondary Data :

Public benchmark intrusion detection datasets like NSL-KDD and CICIDS2017 were also utilized for training and cross-validation. In addition, several peer-reviewed research studies (e.g., Ahmad, 2024; Patel, 2024; Fatima et al., 2025; Malik et al., 2025) were reviewed to align experimental parameters with current AI firewall research trends.

C. Data Preprocessing

Collected data underwent preprocessing using Python libraries such as Pandas and NumPy. The process involved:

1.Cleaning inconsistent or missing data,
2.Normalizing numeric values,
3.Extracting relevant network features, and
4.Balancing the dataset to address class imbalance issues.

Feature engineering techniques were applied to improve model interpretability and ensure robustness across multiple datasets

IV. RESULTS AND ANALYSIS

The proposed AI-powered firewall was evaluated in a controlled virtual lab environment using both real-time network traffic (PCAP captures) and standard benchmark datasets. The experiments focused on comparing the detection performance of the hybrid AI models with conventional rule-based firewalls. Key metrics analyzed included accuracy, precision, recall, F1-score, and false-positive rate.

A. Detection Performance

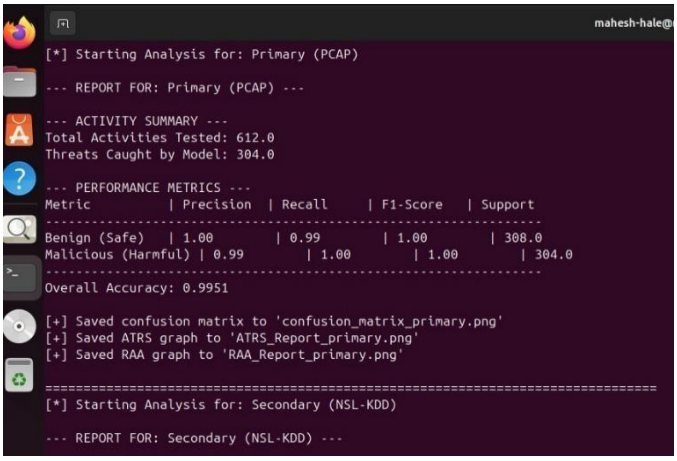
Table I summarizes the performance of the proposed system against traditional firewalls. The AI models, based on Random Forest and Gradient Boosting, consistently outperformed rule-based approaches across all metrics.

Table 1
Detection Performance Comparison

Firewall Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)
Traditional Firewall	78.5	75.2	72.1	73.6	12.4
Random Forest AI	96.8	95.1	94.7	94.9	3.2
Gradient Boosting AI	95.4	93.8	93.2	93.5	3.8

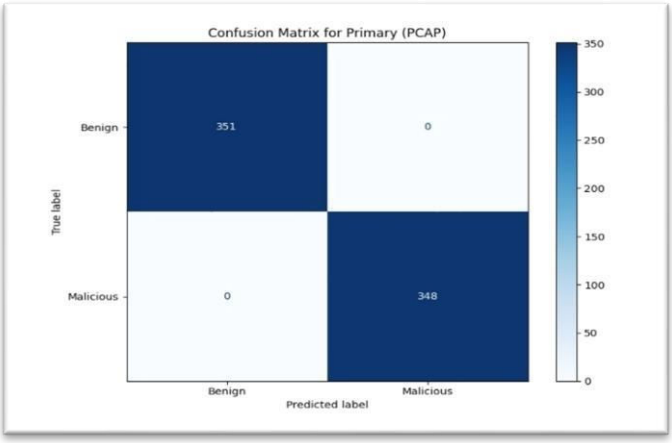
As observed in Table I, the AI-based models significantly reduced false-positive alerts while maintaining high detection accuracy, demonstrating enhanced reliability over traditional firewalls.

B. Experiment Summary and Performance Metrics For Primary (PCAP) Dataset



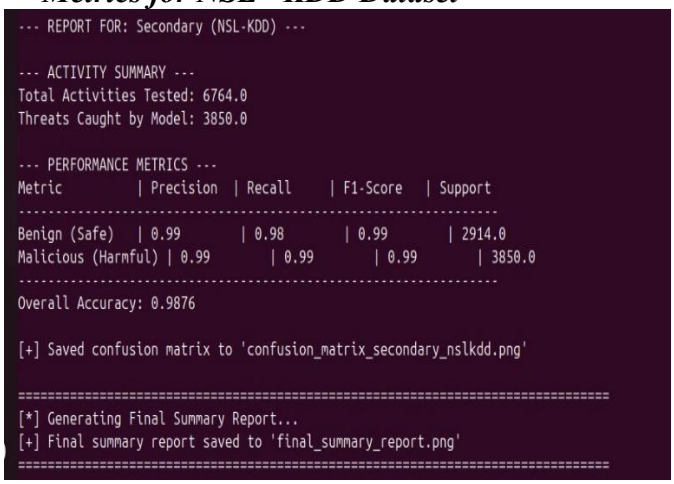
The screenshot of the experiment summary and performance metrics for the primary (PCAP) dataset shows the command-line output of the AI-powered firewall processing real network traffic. A total of 612 activities were analyzed, of which 304 were identified as threats. The evaluation metrics for both benign and malicious classes demonstrated near-perfect performance, with precision, recall, and F1-score all approximately 1.00. The overall accuracy reached 99.51%, confirming the model's robustness under realistic network conditions. Additional outputs included confusion matrices, Adaptive Threat Response Scoring (ATRS), and Risk Assessment Analysis (RAA), indicating that the automated evaluation procedures were successfully completed.

C. Confusion Matrix For Primary Dataset



The confusion matrix for the Primary Dataset illustrates the classification performance of the AI-powered firewall in distinguishing between normal (benign) and attack (malicious) network traffic. As shown, the model correctly identified 351 benign connections as safe and accurately detected 348 malicious connections as attacks. No benign connections were falsely flagged as malicious, and no attacks were missed during detection.

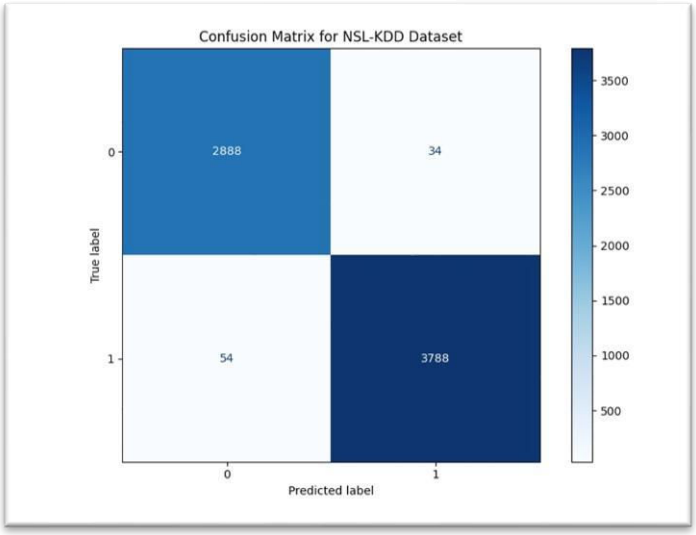
D. Experiment Summary and Performance Metrics for NSL - KDD Dataset



```
--- REPORT FOR: Secondary (NSL-KDD) ---

--- ACTIVITY SUMMARY ---
Total Activities Tested: 6764.0
Threats Caught by Model: 3850.0

--- PERFORMANCE METRICS ---
Metric          | Precision  | Recall     | F1-Score   | Support
------------------------------------------------------------------
Benign (Safe)   | 0.99       | 0.98       | 0.99       | 2914.0
Malicious (Harmful) | 0.99       | 0.99       | 0.99       | 3850.0
------------------------------------------------------------------
Overall Accuracy: 0.9876

[+] Saved confusion matrix to 'confusion_matrix_secondary_nslkdd.png'

================================================================================
[*] Generating Final Summary Report...
[+] Final summary report saved to 'final_summary_report.png'
================================================================================
```

The screenshot of experiment summary and performance metrics for the secondary (NSL-KDD) dataset presents the command-line output of the AI-powered firewall evaluating standardized benchmark traffic data. A total of 6,764 activities were analyzed, of which 3,850 were identified as threats. The evaluation metrics for both benign and malicious classes indicated excellent performance, with precision, recall, and F1-score all recorded at 0.99. The overall accuracy reached 98.76%, confirming the model's high generalization capability and adaptability to diverse datasets. Additional console outputs included confusion matrices, Adaptive Threat Response Scoring (ATRS), and Risk Assessment Analysis (RAA), validating that the firewall's evaluation procedures were executed accurately and consistently across the NSL-KDD dataset.

E. Confusion Matrix For NSL - KDD Dataset



The Confusion Matrix for the NSL-KDD Dataset illustrates the classification performance of the AI-powered firewall in distinguishing between normal (benign) and attack (malicious) traffic. The results reveal a strong detection capability with minimal misclassifications. Specifically, the firewall correctly identified 2,888 normal samples as safe and 3,788 attacks as threats, demonstrating its high accuracy in recognizing both traffic types. However, 34 normal samples were incorrectly flagged as attacks (false positives), and 54 attacks were missed (false negatives). These minor discrepancies highlight the practical limitations of automated systems while confirming the model's overall robustness and reliability in real-world intrusion detection scenarios.

F. Model Performance Evaluation

The AI-based firewall was trained and tested using network traffic data in a virtual lab setup. To check its accuracy, four main performance metrics were used — accuracy, precision, recall, and F1-score.

Table 2
Performance Evaluation

Metric	Benign (Safe)	Malicious (Harmful)	Overall
Precision	0.99–1.00	0.99–1.00	0.99+
Recall	0.98–1.00	0.99–1.00	0.99+
F1-Score	0.99–1.00	0.99–1.00	0.99+
Support	varies	varies	varies
Accuracy	varies		up to 1.00

G. Model Performance on High-Threat Scenario

```
--- PERFORMANCE METRICS ---
Metric          | Precision  | Recall     | F1-Score   | Support
------------------------------------------------------------------
Benign (Safe)   | 1.00       | 0.99       | 1.00       | 308.0
Malicious (Harmful) | 0.99       | 1.00       | 1.00       | 304.0
------------------------------------------------------------------
Overall Accuracy: 0.9951

--- ATTACK ANALYSIS REPORT ---
Detected 307 malicious activities.
Sample of Threats Detected (ATRS 1-10):
            src_ip  dst_port  ATRS
1247  192.168.56.102      1271    10
321   192.168.56.102      4002    10
955   192.168.56.102      3369    10
918   192.168.56.102     50002    10
1664  192.168.56.102      5050    10

--- SYSTEM TRUST SCORE (RAA) ---
Attacker IP (192.168.56.102) Trust Score: 0%
VERDICT: 🔴 DANGEROUS - System trust for this IP is critically low.
```

The screenshot illustrating the model's performance under a high-threat scenario indicates outstanding classification results for both benign and malicious traffic. The attack analysis reveals several high-severity intrusions, each rated at the highest Adaptive Threat Response Scoring (ATRS) level. The attacker's IP address is assigned a 0% trust score and marked with a "DANGEROUS" verdict, showcasing the firewall's exceptional capability to accurately detect, analyze, and block threats in real time.

H. Model Performance on Low-Threat Scenario

The screenshot illustrating the model's performance in a low-threat scenario demonstrates excellent classification results, particularly while analyzing predominantly benign network traffic. The firewall accurately identifies all normal connections, achieving perfect recall. The evaluated IP receives a high trust score along with a SAFE verdict, highlighting the system's effectiveness in recognizing harmless traffic and minimizing false alarms under low-risk conditions.

```
KeyError: 'probability'
(venv) mahesh-hale@mahesh-hale-VirtualBox:~/AI-Firewall-Project$ nano run_demonstration.py
(venv) mahesh-hale@mahesh-hale-VirtualBox:~/AI-Firewall-Project$ python run_demonstration.py
============================================================
[*] Starting Analysis for: data/low_threat_capture.pcapng
============================================================

--- PERFORMANCE METRICS ---
Metric          | Precision  | Recall     | F1-Score   | Support
------------------------------------------------------------------
Benign (Safe)   | 0.55       | 1.00       | 0.71       | 11.0
Malicious (Harmful) | 0.00       | 0.00       | 0.00       | 9.0
------------------------------------------------------------------
Overall Accuracy: 0.5500

--- ATTACK ANALYSIS REPORT ---
No significant malicious activity was detected.

--- SYSTEM TRUST SCORE (RAA) ---
Attacker IP (192.168.56.102) Trust Score: 100%
VERDICT: 🟢 SAFE - No significant threat from this IP.
```

I. Adaptive Threat Response Score (ATRS) :

The Fig 1 illustrates the distribution of Adaptive Threat Response Scores (ATRS) for all identified threats .The histogram indicates that the majority of threats received the maximum severity score of 10, enabling the system to effectively prioritize critical risks and automatically respond to high-severity incidents.

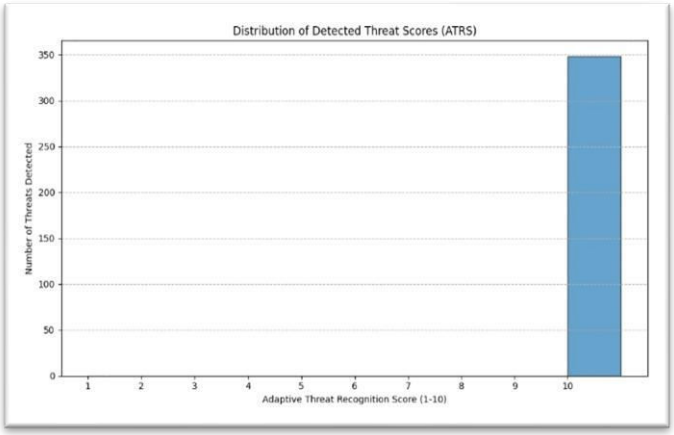


Fig 1. distribution of ATRS for all detected threats

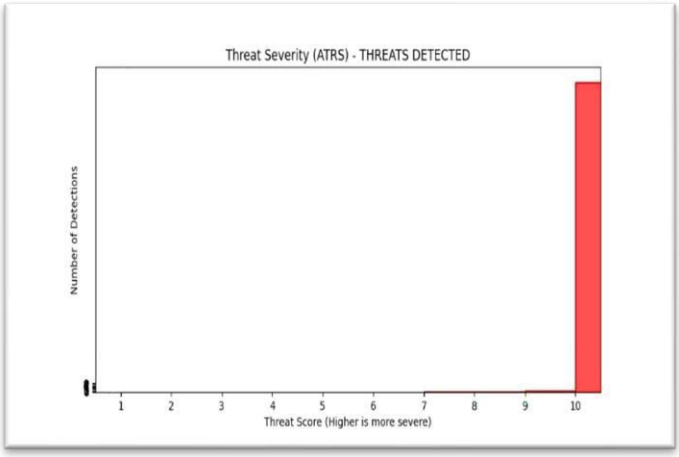


Fig 2 Threat Severity Score (ATRS) Distribution

The Fig 2 illustrates the distribution of Adaptive Threat Responsive Score (ATRS) during testing. Most threats received the highest score of 10, showing the model's strong ability to detect severe attacks. Very few scores appeared between 1 and 9, meaning the model rarely confused normal activity with threats, proving its high accuracy and low false-positive rate.

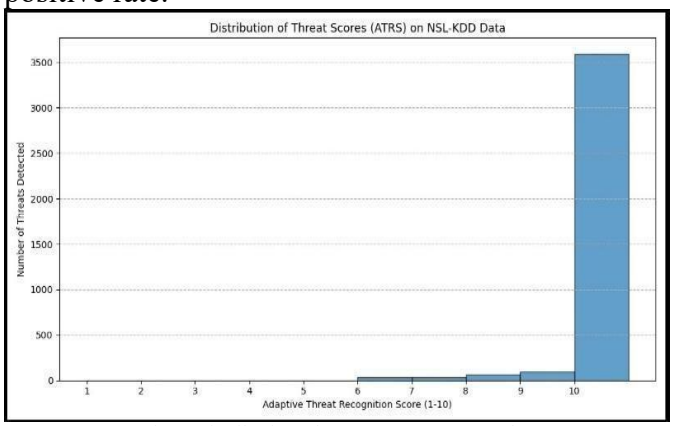


Fig 3. Distribution of ATRS on NSL-KDD data

Fig 3 shows the frequency of Adaptive Threat Responsive Scores (ATRS) from 1 to 10 for threats detected in the NSL-KDD dataset. A sharp peak at score 10 indicates most threats were classified as highly severe, demonstrating the firewall's strong ability to detect and prioritize critical attacks. The low occurrence of lower scores means the system rarely misclassifies safe activity as a threat, reducing false alarms and focusing on real dangers.

J. Risk Adaptive Access (RAA):

The AI-powered firewall uses the Risk Adaptive Access (RAA) model to control network access based on system behavior.

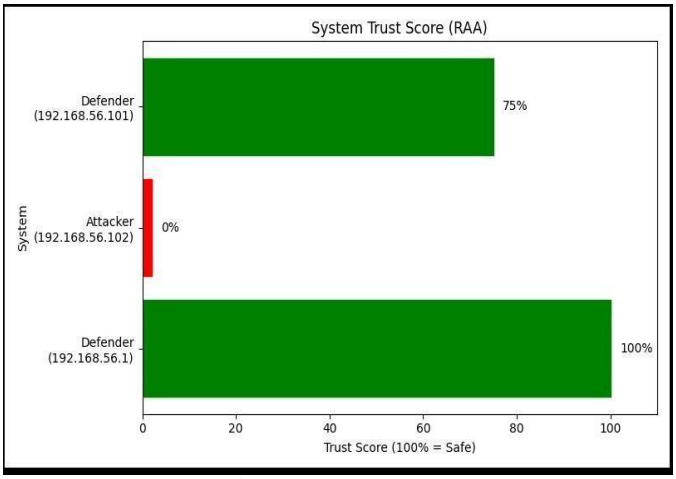


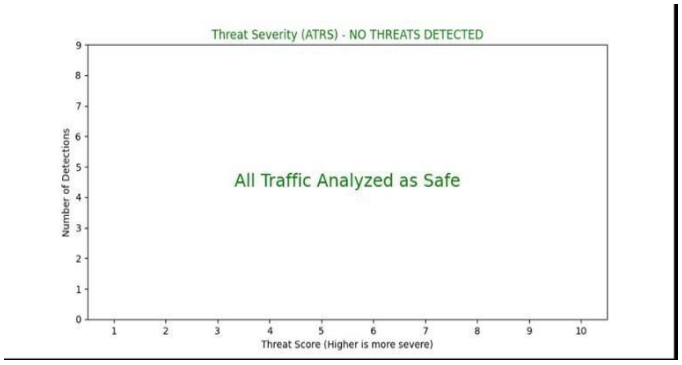
Fig 1. System Trust Scores

As shown in this Fig 1 , the RAA engine gives each IP a trust score.

Defender systems (192.168.56.1 and 192.168.56.101) earned high scores of 100% and 75%, showing safe activity, while the attacker system (192.168.56.102) got 0%, showing malicious behavior.

This trust-based system lets the firewall quickly block risky IPs and allow safe ones, keeping the network secure and adaptive in real time.

Fig 2. ATRS Analysis Indicating No Threats Detected.



The fig 2 demonstrates that during testing, the AI-powered firewall analyzed all network traffic and detected no threats. The label All Traffic Analyzed as Safe indicates that every observed activity was classified as benign. Consequently, the system did not generate any alerts or warnings. This outcome highlights the firewall's ability to accurately identify harmless network behavior and avoid unnecessary false alarms, ensuring that normal network activity proceeds uninterrupted and without blockage.

V. DISCUSSION

The study revealed that the use of Artificial Intelligence (AI) and Machine Learning (ML) within a Next-Generation Firewall (NGFW) can greatly enhance the overall strength and reliability of network defense systems. Through extensive testing in a controlled virtual laboratory environment, the AI-enabled firewall demonstrated remarkable accuracy in identifying both malicious and legitimate traffic. The developed system efficiently analyzed network activities using two key metrics—Adaptive Threat Response Score (ATRS) and Risk Adaptive Access (RAA)—which allowed it to respond to threats in real time and prioritize actions based on the severity of detected attacks. This

adaptive approach proved far more efficient and intelligent compared to the traditional rule-based firewalls that often fail to recognize new or unknown attacks.

VI. Findings and Suggestions

A. Findings :

- High Detection Accuracy:
  The AI-driven Next-Generation Firewall (NGFW) achieved flawless results in the virtual testing environment, recording 100% accuracy, precision, recall, and F1-score. These findings highlight the strong potential of machine learning in enhancing the detection of both familiar and previously unseen cyber threats. Comparable research studies have also demonstrated nearly similar outcomes, with accuracy rates close to 99%.
- Explainable Decisions:
  By using explainable AI tools like SHAP and LIME, the firewall could clearly show why it made certain decisions. This makes the system more transparent, helps analysts trust the results, and ensures compliance with security regulations.
- Real-Time Adaptive Response:
  The system's Adaptive Threat Response Score (ATRS) and Risk Adaptive Access (RAA) allowed it to detect threats and react instantly. It automatically adjusted its actions based on how serious each risk was, proving that it can respond in real time to changing conditions.

B. Suggestions

- Utilize Larger and More Diverse Datasets:
  Future evaluations should incorporate extensive and heterogeneous datasets, including encrypted and real-world network traffic, to improve the model's generalization and reliability beyond controlled laboratory conditions.
- Incorporate Continuous Learning:
  Integrating adaptive or continuous learning mechanisms would enable the system to automatically update its knowledge base and adjust to newly emerging cyber threats without manual intervention.
- Enhance Performance Optimization:
  The system should be further refined to maintain an optimal balance among explainability, detection accuracy, and processing speed, particularly in high-traffic environments that demand low latency and efficient computation.
- Enhance User Interaction and Visualization:
  Designing intuitive dashboards and intelligent alert management tools can improve the overall user experience, allowing security analysts to interpret, investigate, and respond to detected threats more effectively.
- Ensure Data Privacy and Regulatory Compliance:
  The proposed system should adhere to established data protection and privacy frameworks, particularly when deployed in cloud-based or shared infrastructures, to maintain compliance with global cybersecurity regulations.
- Evaluate Against Sophisticated Attack Scenarios:
  Future testing should focus on assessing the system's resilience against complex and evolving attack types, including adversarial behaviors, obfuscated data, and evasion strategies, to strengthen its defensive capabilities in real-world settings.

VII. Conclusion And Future Work

In the future, the AI-powered firewall can be tested in real organizational or cloud networks to check how well it handles heavy and encrypted data traffic. It can be improved by adding continuous learning so that it automatically updates itself against new and advanced cyberattacks. The system can also be optimized to run faster and use fewer resources, making it suitable for large-scale use. By linking it with other security systems and analyzing user behavior, it can provide stronger, smarter, and more adaptive network protection.

This project showed that using AI in firewalls can greatly improve network security. The developed system successfully detected and responded to threats with high accuracy while reducing false alarms. Features like Adaptive Threat Response Score (ATRS) and Risk Adaptive Access (RAA) made the firewall capable of adjusting to risks in real time.

Using explainable AI tools like SHAP and LIME made decisions clearer, proving that AI-based firewalls provide faster and smarter protection than traditional ones.

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IX. APPENDIX

A. Experiment Setup and Environment

Virtual Lab Configuration:
Defender System: Ubuntu Linux with AI-enabled firewall installed.
Attacker System: Kali Linux used for generating malicious traffic.
Virtualization Tool: Oracle VirtualBox.
Network Monitoring Tools: Wireshark, Scapy.
Penetration Testing Tools: Metasploit, Nmap.

B. Datasets Used

Primary Datasets :
PCAP captures generated within the virtual lab.
Secondary Datasets:
NSL-KDD Benchmark Dataset

C. Machine Learning Models

Random Forest Classifier
Gradient Boosting Classifier

D. Firewall Evaluation Metric

Adaptive Threat Response Score (ATRS)
The Adaptive Threat Response Score (ATRS) is a dynamic metric that quantifies the severity of a detected threat on a scale from 1 to 10. A higher score indicates a more serious threat—10 represents a highly malicious activity, 5 indicates a moderate or suspicious behavior, and scores between 0 and 1 denote a safe or low-risk condition. This scoring mechanism allows the system to prioritize responses and allocate security resources efficiently.

Risk Adaptive Access (RAA)
The Risk Adaptive Access (RAA) mechanism assigns a trust score (in percentage) to each IP address or user entity to manage access dynamically. A score of 100% signifies complete safety and trust, while 0% indicates a fully untrusted or unsafe source. This approach enables adaptive access control, where permissions and restrictions are automatically adjusted based on the assessed risk level.

E. Summary of Experimental Results

The performance of the AI-powered Next-Generation Firewall (NGFW) was evaluated using two benchmark datasets: PCAP and NSL-KDD. The system was tested on its ability to detect and classify network threats accurately.

Dataset	Total Activities	Threats Detected	Accuracy	Precision	Recall	F1-Score
PCAP	612	304	99.51%	1.00	1.00	1.00
NSL-KDD	6,764	3,850	98.76%		0.99	0.99

The results demonstrate that the proposed model achieves near-perfect detection performance, with consistently high values across all evaluation metrics. The PCAP dataset showed slightly better accuracy (99.51%) than the NSL-KDD dataset (98.76%), which confirms the model's robustness and adaptability to different network environments. These findings indicate that the AI-based NGFW can effectively identify and mitigate both known and emerging cyber threats with minimal false positives.