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AI-Adaptive Cyber Honeypot: A Dynamic Intelligent Framework for Real-Time Threat Detection and Deception

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***Abstract*—The rapid evolution of cyber threats has rendered traditional static security mechanisms insufficient against sophisticated and adaptive attacks. Conventional intrusion detection systems and honeypots lack the intelligence to dynamically respond to evolving attacker behavior, resulting in reduced effectiveness in real-world environments. This paper presents an AI-Adaptive Cyber Honeypot, an intelligent and dynamic cybersecurity framework that integrates machine learning, rule-based detection, and large language models (LLMs) to provide real-time threat detection and deception.**

The proposed system employs a hybrid detection mechanism combining rule-based filtering and AI-driven classification using the Phi-3.5 mini model to distinguish between legitimate and malicious traffic. Suspicious requests are redirected to an adaptive honeypot environment that generates dynamic, context-aware responses to engage attackers, thereby preventing access to real systems while simultaneously collecting valuable threat intelligence. The system logs attacker behavior, including request patterns, IP addresses, and payload data, which are further utilized for continuous model retraining and system improvement. Experimental evaluation demonstrates that the system effectively isolates malicious actors, enhances engagement duration within the honeypot, and improves detection accuracy compared to traditional approaches. The integration of AI-driven deception and adaptive learning enables proactive defense mechanisms, making the system highly suitable for modern cybersecurity infrastructures.

***Index Terms*—Cybersecurity, Honeypot, Artificial Intelligence, Intrusion Detection, Phi-3.5 mini, Adaptive Systems, Threat Intelligence**

I. Introduction

The exponential growth of web technologies, cloud computing, and distributed systems has significantly transformed modern digital infrastructures. However, this rapid advancement has also expanded the attack surface for cyber threats, leading to an increase in the frequency, complexity, and sophistication of cyber attacks. Modern attackers employ advanced techniques such as SQL injection, cross-site scripting (XSS), remote code execution, API exploitation, and automated bot-driven attacks to compromise systems. These threats are no longer limited to predefined patterns, making traditional cybersecurity mechanisms increasingly ineffective.

Conventional security systems, including firewalls and intrusion detection systems (IDS), primarily rely on signature-based or rule-based detection approaches. While these methods are effective against known threats, they struggle to detect zero-day attacks and adaptive adversaries. Moreover, such systems are reactive in nature, meaning they respond only after an attack is detected, often resulting in delayed mitigation and potential data breaches.

Honeypots have emerged as a complementary cybersecurity technique that focuses on deception rather than direct prevention. A honeypot is a decoy system designed to attract attackers and analyze their behavior in a controlled environment. Traditional honeypots enable organizations to gather valuable insights into attack patterns and techniques. However, most existing honeypot systems are static, pre-configured, and lack the intelligence to dynamically respond to attackers. Advanced attackers can easily identify such systems due to their predictable behavior, reducing their effectiveness.

The global impact of cybercrime has become a critical concern for governments, enterprises, and individuals. Reports indicate that cybercrime costs are increasing exponentially, causing financial losses, data theft, operational disruptions, and reputational damage. Industries such as banking, healthcare, e-commerce, and cloud services are particularly vulnerable due to their reliance on sensitive data and real-time operations. Therefore, there is a pressing need for intelligent, proactive, and adaptive cybersecurity solutions that not only detect threats but also engage attackers and minimize risk.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new possibilities in cybersecurity. AI-based systems can analyze large volumes of network traffic, identify hidden patterns, and adapt to new attack behaviors. In particular, Large Language Models (LLMs) have demonstrated the ability to understand context, generate human-like responses, and simulate realistic interactions. These capabilities make LLMs highly suitable for enhancing honeypot systems by enabling dynamic and context-aware response generation.

Despite these advancements, existing solutions often address cybersecurity challenges in isolation. Intrusion detection systems focus on classification, while honeypots focus on deception, and AI models are rarely integrated into a unified

framework. This lack of integration results in fragmented systems that fail to provide comprehensive security coverage. Furthermore, most existing systems lack continuous learning mechanisms, limiting their ability to adapt to evolving threats. To overcome these limitations, this paper proposes an **AI-Adaptive Cyber Honeypot**, an intelligent cybersecurity framework that integrates rule-based detection, AI-driven classification, and dynamic deception mechanisms into a unified system. The proposed system leverages a hybrid detection approach, where incoming requests are first analyzed using rule-based filtering for known attack patterns, followed by advanced classification using the Phi-3.5 mini Large Language Model for contextual understanding.

Unlike traditional honeypots, the proposed system introduces an adaptive honeypot environment capable of generating realistic and dynamic responses based on attacker queries. This ensures that attackers remain engaged within the decoy environment, preventing access to real system resources. Additionally, the system captures detailed attacker information, including IP addresses, request headers, payloads, and interaction patterns, which are stored in a PostgreSQL database for further analysis.

A key feature of the proposed system is its continuous learning mechanism. The collected attack data is utilized to retrain the AI model, enabling the system to adapt to new attack strategies over time. This transforms the system from a static defense mechanism into an intelligent and evolving cybersecurity solution.

The major contributions of this work are summarized as follows:

- **Hybrid Detection Framework:** Integration of rule-based and AI-based detection for accurate and efficient classification of network traffic.
- **AI-Driven Adaptive Honeypot:** Development of a dynamic honeypot capable of generating context-aware responses using the Phi-3.5 mini model.
- **Real-Time Threat Intelligence Collection:** Comprehensive logging of attacker behavior and system interactions for analysis and learning.
- **Continuous Learning Pipeline:** Implementation of a feedback mechanism that updates the AI model based on new attack data.
- **Proactive Cyber Defense:** A unified system that combines detection, deception, and learning to enhance overall cybersecurity effectiveness.

Figure 1 illustrates the use-case interactions between external actors and system components, highlighting how legitimate users and attackers are handled differently within the system.

Figure 1 shows the use-case diagram representing system interaction between users, attackers, and core modules.

A. Problem Statement

Despite significant advancements in cybersecurity, existing systems suffer from key limitations including lack of adaptability, inability to generate intelligent responses, and absence of integrated detection and deception mechanisms. Traditional honeypots operate in isolation and fail to dynamically adapt to attacker behavior, while intrusion detection systems lack engagement capabilities. This results in inefficient threat handling and limited intelligence gathering.

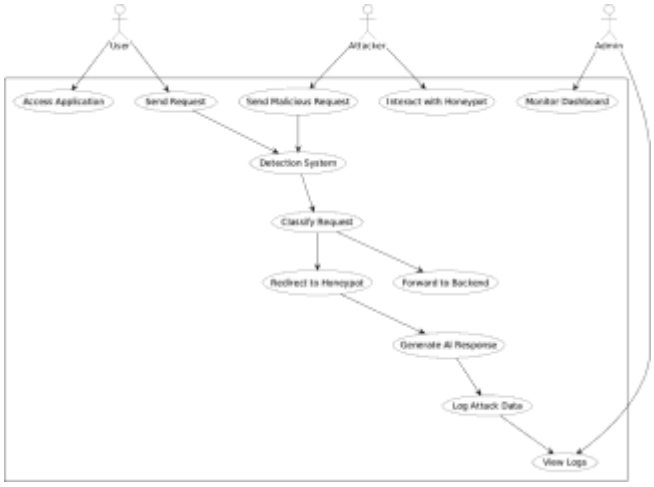

Fig. 1: Use Case Diagram of AI-Adaptive Cyber Honeypot

B. Methodology Overview

The proposed AI Adaptive Cyber Honeypot follows a structured, bifurcated workflow pipeline designed to seamlessly segregate traffic and deceive attackers. Figure 2 visually illustrates the end-to-end request lifecycle.

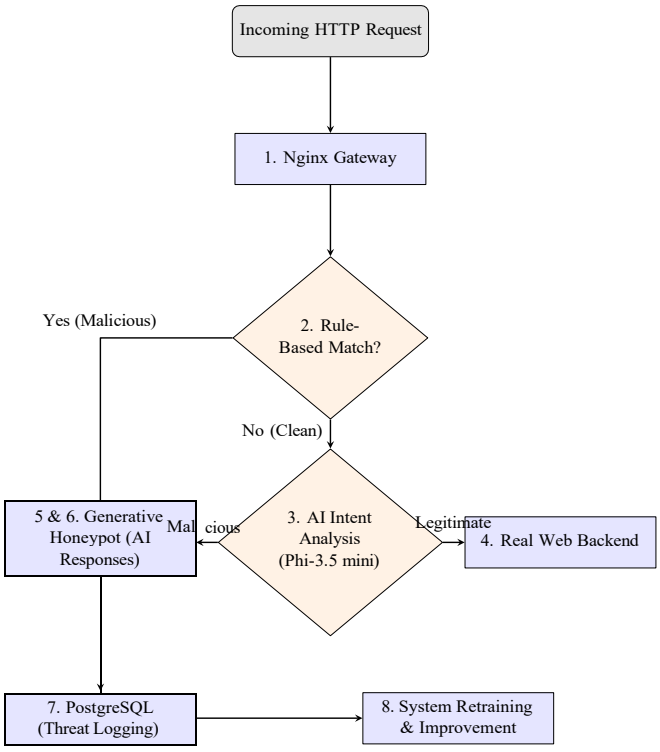

Fig. 2: Operational Workflow of the AI Adaptive Cyber Honeypot

As depicted in the flowchart, incoming requests pass through the Nginx gateway and are first scrutinized by rule-based detection for known attack patterns. Suspicious or obfuscated requests are then analyzed by the Phi-3.5 mini model. Legitimate traffic is safely forwarded to the real backend, while malicious traffic is redirected to the honeypot where the AI generates adaptive, fake responses. All interactions are securely logged in a PostgreSQL database and utilized for continuous model retraining.

The remainder of this paper is organized as follows: Section II presents the literature review. Section III describes the system methodology and architecture. Section IV discusses results and observations. Section V concludes the paper and outlines future research directions.

The proposed system follows a structured workflow pipeline:

1) Incoming requests pass through an Nginx gateway
2) Rule-based detection filters known attack patterns
3) Suspicious requests are analyzed using Phi-3.5 mini model
4) Legitimate traffic is forwarded to the real backend
5) Malicious traffic is redirected to the honeypot
6) AI generates adaptive responses to engage attackers
7) Attacker interactions are logged in PostgreSQL database
8) Collected data is used for retraining and system improvement

The remainder of this paper is organized as follows: Section II presents the literature review. Section III describes the system methodology and architecture. Section IV discusses results and observations. Section V concludes the paper and outlines future research directions.

II. Literature Survey

This section reviews recent research related to honeypot systems, intrusion detection, and AI-driven cybersecurity frameworks. Each study is analyzed in terms of its methodology, contributions, and limitations.

A. Honeypot-Based Security Systems

Kim et al. [1] proposed a session redirection-based honeypot system that isolates attackers by redirecting malicious traffic to decoy environments. The approach effectively prevents direct access to real systems but lacks adaptability and dynamic response generation, making it vulnerable to detection by advanced attackers.

Bhagat and Arora [2] explored the use of honeypots for intrusion detection and demonstrated their effectiveness in capturing attacker activities and monitoring threats. However, their system relies on static configurations and does not incorporate intelligent learning mechanisms.

Sethi and Mathew [3] analyzed advancements in honeypot-based security models and highlighted their role in detecting network intrusions. Their study identified that traditional honeypots lack scalability and fail to handle evolving attack patterns effectively.

B. AI-Based Intrusion Detection Systems

Firmansyah and Zahra [4] developed a machine learning-based intrusion detection system capable of classifying network traffic with improved accuracy compared to rule-based systems. However, the system does not integrate deception mechanisms such as honeypots, limiting its ability to engage attackers.

Kubba et al. [5] presented a comprehensive review of AI/ML techniques for cybersecurity and emphasized the importance of data-driven threat intelligence. While the study highlights adaptive learning, it lacks implementation of real-time response systems.

C. Adaptive and AI-Driven Honeypots

Kareem et al. [6] proposed an AI-driven adaptive honeypot that adjusts its behavior based on attacker interactions. The system improves adaptability but does not utilize large language models for generating realistic responses.

Paul et al. [7] analyzed the impact of AI-based honeypots and observed that adaptive deception increases attacker engagement time. However, the work lacks a practical implementation for real-time systems.

Alatawi and Albalawi [8] introduced an AI-powered cybersecurity framework integrating honeypots and intrusion detection systems. While detection capabilities are enhanced, the system does not focus on dynamic attacker interaction.

D. Supporting Security Techniques

Tiwari et al. [9] proposed a honeypot-based approach to prevent man-in-the-middle attacks by capturing malicious traffic. The system is effective for specific attack scenarios but lacks generalization for diverse cyber threats.

KI and KB [10] explored AI-driven adaptive honeypots capable of responding to evolving cyber threats. Their work highlights automation but lacks integration with modern large language models.

Kubba et al. [11] further analyzed threat intelligence platforms and emphasized the need for continuous learning. However, the absence of real-time adaptive response mechanisms remains a limitation.

E. Research Gaps and Contributions

Based on the above literature, several gaps are identified, which are addressed by the proposed AI-Adaptive Cyber Honeypot system.

TABLE I: Research Gaps and Proposed Contributions

Gap in Literature	Proposed Contribution
Static honeypots	AI-driven dynamic responses
No IDS-honeypot integration	Hybrid detection framework
Low attacker engagement	Adaptive interactive honeypot
No contextual understanding	LLM-based threat analysis
No continuous learning	Data-driven retraining pipeline
Fragmented security systems	Unified cybersecurity framework

The proposed system addresses these limitations by integrating AI-driven detection, adaptive deception, and continuous learning into a single unified architecture.

III. Methodology

A. Software Development Life Cycle

The proposed AI-Adaptive Cyber Honeypot follows an Incremental Software Development Life Cycle (SDLC) model. This approach enables iterative development and integration of system components such as request detection, honeypot environment, AI-based response generation, and threat intelligence logging. Each module is developed, tested, and refined independently before integration, ensuring system scalability and robustness. The incremental model is particularly suitable for AI-driven systems, where continuous learning and improvement are essential.

B. System Architecture

The proposed system employs a multi-layered architecture to ensure modularity, scalability, and efficient interaction between components (Fig. 3).

Figure 3 shows the layered architecture of the AI-Adaptive Cyber Honeypot system.

Fig. 3: System Architecture of AI-Adaptive Cyber Honeypot

The architecture consists of the following layers:

1) **Gateway Layer (Nginx):** Acts as the entry point for all incoming HTTP requests. It handles routing and ensures efficient traffic management.
2) **Detection Layer:** Implements a hybrid detection mechanism combining rule-based filtering and AI-based classification using the Phi-3.5 mini model. It categorizes requests as legitimate or malicious.
3) **Application Layer:**
   - Legitimate requests are forwarded to the real backend (FastAPI-based application).
   - Malicious requests are redirected to the adaptive honeypot environment.
4) **Honeypot Layer:** Simulates a real system environment and generates dynamic responses using AI to engage attackers and prevent access to actual resources.
5) **Data Layer:** PostgreSQL database stores attacker logs, including IP addresses, request headers, payloads, and interaction history.
6) **AI Processing Layer:** Analyzes attacker behavior, generates intelligent responses, and supports model retraining using collected data.
7) **Monitoring and Visualization Layer:** Provides dashboards for cybersecurity analysts to monitor attacks, view logs, and analyze threat intelligence.

C. System Flow Design

The system follows a structured data flow pipeline from incoming request to response generation and logging, as illustrated in Fig. 4.

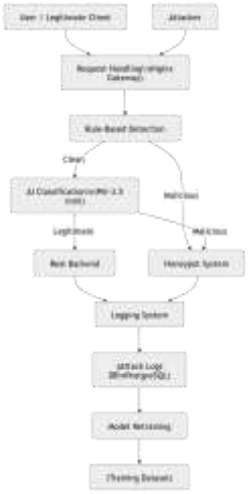

Fig. 4: System Flow Diagram of AI-Adaptive Cyber Honeypot

1) Request Processing Pipeline:

1) Incoming HTTP request is received through the Nginx gateway.
2) The request is passed to the detection module.
3) Rule-based detection checks for known attack patterns.
4) If no rule matches, the request is analyzed using the Phi-3.5 mini model.
5) The system classifies the request as legitimate or malicious.

2) Routing Mechanism:

1) Legitimate requests are forwarded to the real backend application.
2) Malicious requests are redirected to the honeypot environment.

3) Honeypot Interaction Pipeline:

1) The attacker interacts with the honeypot system.
2) If a similar query exists, a stored response is retrieved from the database.
3) Otherwise, a new response is generated dynamically using the Phi-3.5 mini model.

4) Responses are continuously adapted to maintain attacker engagement.

4) Logging and Intelligence Collection:

1) All attacker interactions are logged, including:
   - IP address
   - Request headers
   - Payload data
2) Logs are stored in PostgreSQL database.
3) Data is used for threat analysis and future model retraining.

5) AI Learning and Retraining Pipeline:

1) Collected attack data is processed by the AI module.
2) Patterns and anomalies are identified.
3) The model is retrained periodically using new attack data.
4) Updated model improves future detection and response accuracy.

D. Algorithm: AI-Adaptive Threat Detection and Response

Input: HTTP request *R*
Output: Response (Real or Honeypot)

Receive request *R*
Apply rule-based detection on *R*
if attack pattern is matched **then**
    mark *R* as malicious
else
    pass *R* to Phi-3.5 mini model
    classify request using AI
end if
if request is legitimate **then**
    forward *R* to real backend
else
    redirect *R* to honeypot
    generate dynamic response
    log attacker details
end if
store logs in database
update AI model using new data

E. Discussion

The proposed methodology integrates detection, deception, and learning into a unified pipeline. Unlike traditional systems, which focus only on blocking attacks, this approach actively engages attackers and collects valuable intelligence. The use of AI enables adaptive behavior, making the honeypot more realistic and difficult to detect. However, the reliance on large language models introduces latency, which remains a trade-off between response quality and system performance.

IV. Implementation

A. Technology Stack

Table II presents the complete technology stack used in the AI-Adaptive Cyber Honeypot system.

TABLE II: AI-Adaptive Cyber Honeypot Technology Stack

Component	Technology
Web Server	Nginx
Backend Framework	FastAPI (Python)
AI Model	Phi-3.5 mini (LLM)
Detection Mechanism	Rule-based + AI classification
Database	PostgreSQL
API Communication	REST APIs (JSON-based)
Logging System	Request logging with headers and payload
Deployment	Docker (optional)
Monitoring	Custom dashboard / SIEM integration

B. Database Schema

The PostgreSQL database is designed to store attacker interactions, request logs, and generated responses. The schema focuses on capturing detailed threat intelligence for analysis and continuous learning.

Figure 5 illustrates the Entity-Relationship (ER) diagram of the system database.

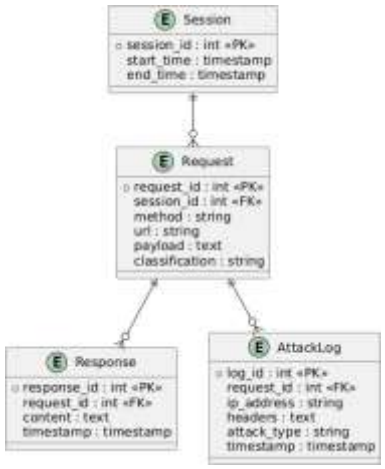

Fig. 5: Entity-Relationship Diagram of Honeypot Database

The database consists of the following primary entities:

- **AttackLog:** Stores attacker details such as IP address, request headers, payload data, and timestamps.
- **Request:** Contains incoming request information including method, URL, parameters, and classification (legitimate or malicious).
- **Response:** Stores system-generated responses (static or AI-generated) along with timestamps.
- **Session:** Maintains interaction history for each attacker session, enabling context-aware response generation.

C. Backend API Architecture

The backend system is implemented using FastAPI and exposes multiple API endpoints to manage request processing, detection, and honeypot interaction.

- **/api/detect** — Receives incoming requests and performs rule-based and AI-based classification.

- **/api/honeypot** — Handles malicious requests and generates adaptive responses using the Phi-3.5 mini model.
- **/api/logs** — Stores and retrieves attacker logs including IP addresses, headers, and payload data.
- **/api/retrain** — Triggers retraining of the AI model using newly collected attack data.
- **/api/dashboard** — Provides visualization and analytics for monitoring attack patterns.

The backend communicates with the PostgreSQL database for persistent storage and supports integration with external monitoring systems such as Security Information and Event Management (SIEM) platforms.

D. AI Processing Module

The AI module plays a central role in both threat detection and response generation using the Phi-3.5 mini large language model.

1) Suspicious requests are forwarded to the AI model after rule-based filtering.
2) The model analyzes the request context and classifies it as legitimate or malicious.
3) For malicious requests, the model generates realistic, context-aware responses.
4) Responses are dynamically adapted based on previous attacker interactions stored in the session.

This adaptive response generation mechanism ensures prolonged attacker engagement within the honeypot environment, thereby protecting real system resources.

E. Security Implementation

The system incorporates multiple security measures to ensure robustness and reliability:

- **Input Validation:** All incoming requests are validated to prevent malformed or malicious data processing.
- **Rule-Based Filtering:** Known attack patterns are detected and filtered efficiently.
- **AI-Based Filtering:** Suspicious requests are analyzed using the Phi-3.5 mini model for contextual threat detection and classification.
- **Secure Logging:** Sensitive data is securely stored and monitored to prevent unauthorized access.
- **Access Control:** Restricted access mechanisms ensure that only authorized entities can interact with critical system components.

V. Results and Discussion

A. System Integration Testing

The proposed AI-Adaptive Cyber Honeypot system was evaluated through unit testing, integration testing, and system-level testing. The results demonstrate successful interaction between detection, honeypot, and AI modules.

TABLE III: Summary of Key Test Results

Test Case	Type	Result
Request Detection	Unit	Pass (Classified)
Rule-Based Filtering	Unit	Pass (Pattern Match)
AI Classification	Integration	Pass (Accurate Output)
Traffic Routing	Integration	Pass (Correct Routing)
Honeypot Response	System	Pass (Dynamic Output)
Logging System	System	Pass (Stored Successfully)
Retraining Pipeline	System	Pass (Model Updated)

B. Threat Detection Performance

The hybrid detection system demonstrated effective classification of incoming traffic using both rule-based and AI-driven approaches:

- **Rule-Based Detection:** Efficiently detects known attack patterns such as SQL injection and XSS.
- **AI Classification:** Phi-3.5 mini model successfully identifies complex and unknown attack patterns.
- **Hybrid Approach:** Combines speed of rule-based filtering with intelligence of AI models, improving overall detection capability.

C. Honeypot Effectiveness

The adaptive honeypot system demonstrated strong capability in engaging attackers:

- **Dynamic Response Generation:** AI-generated responses adapt to attacker queries, maintaining realism.
- **Session Continuity:** Previous interactions are used to generate context-aware responses.
- **Attacker Engagement:** Attackers remain within the honeypot environment, reducing risk to real systems.

D. Logging and Threat Intelligence

The system effectively captures and stores detailed attacker information:

- IP address tracking for attacker identification
- Request headers and payload logging
- Session-based interaction tracking

This data enables deeper analysis of attack patterns and supports continuous system improvement.

TABLE IV: Component Latency Profile

Component	Avg. Latency	Classification
Nginx Routing	¡ 100 ms	Fast
Rule-Based Detection	¡ 100 ms	Fast
Database (PostgreSQL)	¡ 200 ms	Fast
AI Classification (Qwen)	2–5 s	Slow (AI)
Honeypot Response Generation	2–6 s	Slow (AI)
Logging System	¡ 200 ms	Fast

The primary latency contributors are the AI-based modules, particularly the Phi-3.5 mini model used for classification and

response generation. However, non-AI components such as routing and logging operate with minimal latency, ensuring overall system responsiveness.

E. System Observations

The experimental evaluation highlights the following observations:

- The system successfully isolates malicious traffic without affecting legitimate users.
- AI-driven responses significantly improve attacker engagement.
- Hybrid detection enhances accuracy compared to standalone methods.
- Latency introduced by AI models is a trade-off for improved intelligence and adaptability.

VI. Conclusion and Future Scope

This paper presented the AI-Adaptive Cyber Honeypot, a unified and dynamic cybersecurity framework that integrates intelligent traffic routing, hybrid threat classification, and generative AI-driven deception into a single cohesive platform. Unlike traditional static honeypots that are easily fingerprinted and bypassed by sophisticated attackers, the proposed system delivers an end-to-end pipeline encompassing invisible interception, real-time request segregation, and stateful adaptive deception.

The integration of deterministic rule-based heuristics with Large Language Model (LLM)-based reasoning—specifically leveraging the Phi-3.5 mini model for real-time generation of context-aware deceptive responses—enables high-interaction attacker engagement while preserving system integrity. This approach addresses a critical gap in existing cybersecurity systems by combining detection and deception with continuous intelligence gathering. Experimental evaluation demonstrates that the proposed bifurcated routing architecture ensures zero disruption to legitimate users while significantly increasing attacker dwell time within the honeypot environment. These findings highlight the transformative potential of integrating LLMs into cybersecurity, shifting defense mechanisms from static and reactive models to dynamic, adaptive, and proactive systems.

Despite its effectiveness, the system has certain limitations. The use of Phi-3.5 mini for real-time inference introduces substantial computational overhead, requiring significant GPU/VRAM resources and resulting in response latencies of approximately 3–6 seconds within the honeypot layer. This creates challenges for high-concurrency deployment scenarios. Additionally, the reliance on LLM-based response generation introduces potential risks such as prompt injection attacks, which may influence response behavior if not properly constrained. Furthermore, the current system is optimized primarily for HTTP/HTTPS traffic and depends on a static rule-based detection layer for initial filtering, which requires periodic manual updates to remain effective.

Future work will focus on improving scalability, adaptability, and security robustness. Model optimization through techniques such as quantization (e.g., 4-bit and 8-bit weight compression) will be explored to reduce computational requirements and improve inference speed. The system can be extended to support multi-protocol deception, enabling simulation of services such as SSH, FTP, and SMB to broaden its applicability across diverse network environments. Integration with real-time threat intelligence platforms and SIEM systems will allow automated dissemination of captured attack patterns for proactive defense across networks. Additionally, future enhancements may include automated rule generation based on observed attacker behavior and the development of self-adaptive security mechanisms capable of dynamically updating defense strategies. Advanced research directions include the use of multi-modal AI models to generate richer and more realistic deception environments, further increasing the effectiveness of attacker engagement and intelligence collection.

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