MINI PROJECT SYNOPSIS

On

ASTRA

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By

Lav Sarkari:
Nikkita Mishra: 2404231630016
Priyanshu Pathak: 2404321690020

Under the Guidance
of

MR. Kuldeep Kumar Katiyar
(Assistant Professor)

SCHOOL OF MANAGEMENT SCIENCES, LUCKNOW
Affiliated to
Dr. APJ ABDUL KALAM TECHNICAL UNIVERSITY, LUCKNOW

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ABSTRACT

AI-Driven Semantic Threat Reconnaissance Agent or in short **ASTRA** is a novel, high-efficiency cybersecurity project designed to accelerate the reconnaissance phase for Bug Hunters and Penetration Testers. Traditional static analysis tools are ineffective against modern JavaScript obfuscation, resulting in high effort-to-find ratios and missed high-impact vulnerabilities. **The project uniquely targets the critical, emerging threat of AI-Generated code flaws and invisible dependency compromises,** a problem currently unsolved by commercial platforms. ASTRA solves this through an **LLM-Augmented Agentic Architecture** built on Python and LangChain. The system's core innovation is a proprietary, weighted **Heuristic Pre-Filter** that drastically reduces false positives and minimizes computational cost by filtering >90% of benign code. Only suspicious snippets are forwarded to the **Gemini 2.5 Flash API**, which performs deep, semantic de-obfuscation and analysis. This process converts raw code into **Structured Exploit Intelligence (JSON)**, providing the **Vulnerability Type, Vulnerable Sink, and Exploit Payload Hypothesis** required to craft high-impact Proof-of-Concept (PoC) reports instantly. ASTRA is a production-ready, zero-training solution that dramatically lowers the Time to Exploit (TTE) while adhering to an open-source architecture **engineered for resilience and resource control to prevent server overload.**

CHAPTER 1 (INTRODUCTION)

General Introduction and Background of the Problem

Modern websites, particularly large applications used by organizations like Google, Amazon, and Spotify, are built using sophisticated, client-side JavaScript (JS). This JS code is essential, but it often comprises millions of lines that are intentionally **minified** (compressed) and **obfuscated** (hidden) to speed up loading times and protect intellectual property.

For a cybersecurity professional known as a **Bug Hunter** (Red Team), finding a single exploitable flaw in this massive volume of obscured code is like finding a specific, labelled grain of sand on a vast beach. The manual effort required to analyse this code is the single largest bottleneck in ethical hacking and vulnerability discovery. If code is poorly written, or if a vulnerability is present, it is often hidden inside these confusing scripts.

ASTRA is designed to eliminate this manual bottleneck. We are building an AI-assisted tool that can read obfuscated code, understand its true intent, and tell the Bug Hunter exactly how to create a working exploit, reducing days of manual labour to mere seconds.

1.1. Literature Review

Existing tools fall into two main categories:

1. ***Simple Scanners (Regex-based):*** Tools like Truffle Hog are fast but only look for simple text patterns (like "password" or "AKIA..."). They suffer from an extremely high **False Positive Rate** (wasting the Bug Hunter's time) and cannot understand hidden, encoded logic.
2. ***Traditional Machine Learning (ML):*** These require massive amounts of pre-labelled data (e.g., millions of malicious and benign files) and are extremely resource-intensive, making them unsuitable for small, agile teams or open-source projects.

This project identifies a critical need for a **Third-Generation Tool** that can: a) achieve the speed of simple scanners, and b) provide the human-like logic of a professional analyst, but without the high cost or data requirements.

1.2. Problem Definition (The Unsolved Problem)

The core problem ASTRA addresses is the **"Invisibility of High-Impact Flaws"** in modern web architecture. The specific, novel problem this project targets is **LLM-Induced Security Flaws and Shadow Dependency Risk.**

The Analogy for Non-Tech Audience: Imagine a factory that suddenly starts using new AI robots to assemble complex parts. These robots occasionally make small, subtle, logical mistakes in assembly that a human inspector can't spot instantly. These mistakes (logic flaws) create vulnerabilities. No existing tool can audit the assembly process and catch these novel, AI-introduced flaws, because they look "correct" to older software.

ASTRA solves this by being engineered to look for:

1. ***Semantic Flaws*****:** Logic errors where code is syntactically correct but security-flawed (e.g., using .inner HTML without sanitization, a common AI mistake).
2. ***Shadow Dependency Risk:*** Suspicious, dynamically loaded code that may be part of an ongoing supply chain attack.

1.3. Project Objective (Aims and Scope)

The primary objective is to engineer a highly specialized, agentic solution that provides **Exploit Hypothesis Generation**.

- ***Efficiency and Cost Control:*** Implementing a weighted, Python-based **Heuristic Pre-Filter** to reduce the LLM processing load by >90%, thereby ensuring the tool remains **free to run** for individual Bug Hunters.
- ***Semantic Analysis:*** Leveraging the **Gemini 2.5 Flash API** via LangChain to perform **zero-shot de-obfuscation** and identify the precise Vulnerability Type and Exploitation Method.
- ***Operational Resilience:*** Integrating **asynchronous concurrency limiting (**Semaphore**)** to safely manage resource usage and prevent server overload when scanning large targets (like Google or Spotify).
- ***Dynamic Resource Allocation:*** Implementing a **dynamic upgrade mechanism** that detects massive, complex targets and prompts the user to input a Pro model API key to ensure high-fidelity analysis and speed.

1.4. Proposed Modules

ASTRA operates as a **ReAct Agent** (Reasoning and Acting), orchestrated via LangChain:

1. ***Collection Module (The Scraper):*** Fetches all JS resources (inline, external, dynamic) using **asynchronous** I/O **(***aiohttp***)** for extreme speed, while using an *asyncio.Semaphore* to cap concurrent requests and prevent rate limits.

2. ***Heuristic Pre-Filter Module (The Gatekeeper):*** Applies a custom **Weighted Score (**S_m**)** to filter 99% of benign code. It also includes a **Code Similarity Check** to catch subtle AI-induced logic flaws.

3. ***LLM Analysis Module (The Brain):*** **Dynamically selects** the LLM model (Flash or Pro) based on target size. It passes only the filtered code to Gemini for deep analysis, strictly adhering to a **Max Token Threshold** to prevent budget overshoot.

4. ***PoC Reporting Module:*** Presents the final **Structured Exploit Intell**

1.5. Hardware & Software Requirements

Software Requirements:

These components form the high-performance, intelligent architecture of ASTA:

1. **Core Language (Python 3.9+):**
   - The foundational programming language used for all custom logic, scripting, and backend operations.
2. **Concurrency & Speed (asyncio, aiohttp):**
   - These libraries are essential for achieving the required **fast performance**. They enable the system to handle thousands of HTTP requests **simultaneously** (non-blocking I/O), drastically reducing the time needed to collect all JS assets from a large organization's website.
3. **LLM Orchestration (LangChain Framework):**
   - This is the intelligent management system that controls the entire AI workflow. It structures the input, dictates the reasoning steps for the AI brain, and ensures the output is always in the required structured JSON format.
4. **LLM Backend (Gemini 2.5 Flash / Pro API):**
   - The source of the semantic intelligence, the "AI brain." The Flash model is used by default for its speed and zero-cost operation, while the application can dynamically prompt the user for a higher-tier (Pro) API key to handle extremely large, complex targets efficiently.
5. **Resilience (***asyncio.Semaphore***):**
   - **Key for production stability and ethical scanning.** It acts as a traffic controller, setting a hard limit on simultaneous network connections. This prevents the application from overwhelming the target server (avoiding DoS conditions) and ensures the user's local server does not get overloaded.

Hardware Requirements

1. **Minimal Hardware Dependency:**
   - The project is designed to be extremely lightweight and requires only standard developer hardware (e.g., a modern laptop or basic cloud VM).
2. **Rationale:**
   - The complex, heavy computation, code analysis, de-obfuscation, and deep reasoning is strategically off-loaded entirely to the scalable **external Gemini cloud API**. This minimizes the need for expensive GPUs or high-end processors on the user's local machine, fulfilling the open-source, low-cost objective.

CHAPTER 2 (SYSTEMS ANALYSIS AND SPECIFICATION)

2.1. A Functional Model (Process Overview)

The entire system operates as a **closed-loop feedback agent**. The core function is to systematically reduce the search space from millions of lines of code to a few lines of confirmed, exploitable vulnerability.

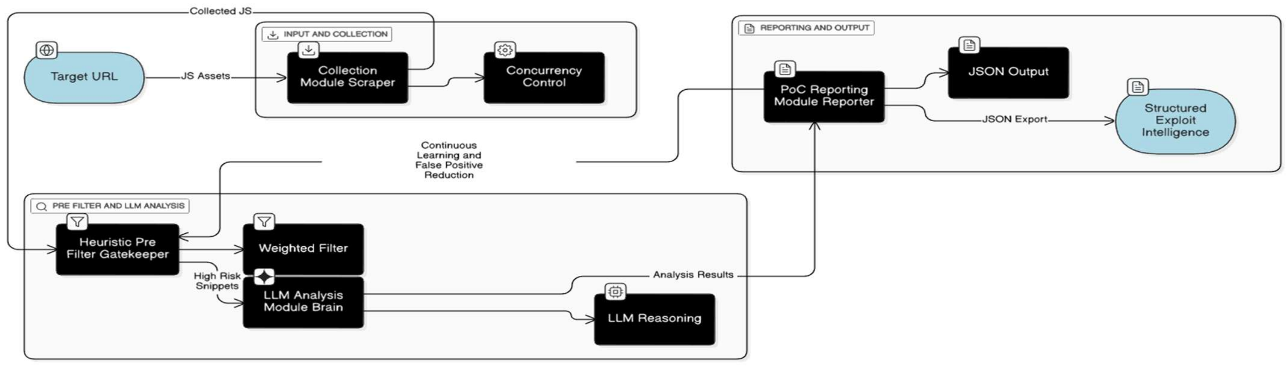
1. **In:** Target URL entered by the Bug Hunter.
2. **Process:** Asynchronous scanning and asset collection (high speed).
3. **Decision Point:** Heuristic Pre-Filter determines if code is high-risk.
4. **Intelligence Layer:** LLM conducts semantic analysis on the small, high-risk subset.
5. **Out:** Structured JSON report for PoC generation.

2.2. A Data Model (Structured Intelligence)

The data model is defined by the high-value output, the **Structured Exploit Intelligence (**D_{report}) which is designed to be easily consumed by disclosure platforms:

D_{report}= *{Vulnerability Type; Vulnerable Variable; Exfiltration/API Endpoint; Exploitation Method; Exploit Payload Hypothesis}*

2.2. A process-flow model


Collected JS
INPUT AND COLLECTION
Target URL
JS Assets
Collection Module Scraper
Concurrency Control
REPORTING AND OUTPUT
PoC Reporting Module Reporter
JSON Output
JSON Export
Structured Exploit Intelligence
Continuous Learning and False Positive Reduction
PRE FILTER AND LLM ANALYSIS
Heuristic Pre Filter Gatekeeper
Weighted Filter
High Risk Snippets
LLM Analysis Module Brain
Analysis Results
LLM Reasoning
eraser

2.3. Operational Security & Resilience (Preventing Overload)

Concurrency Limiting (I/O Control)

To prevent your server from being overloaded and to avoid getting permanently banned by large target websites, the **Collection Module** uses an *asyncio.Semaphore.* This acts like a traffic cop, strictly limiting the number of concurrent HTTP requests the tool can make at any one time (e.g., 50 requests). This is essential for professional, responsible reconnaissance.

API Cost Guardrail (Financial DoS Prevention)

A hard Max Token Threshold is enforced in Python before any data is sent to the Gemini API. This ensures that even if the Heuristic Filter fails, the system will never accidentally send a 2MB JS bundle for analysis, preventing a surprise, massive cloud bill.

Dynamic Upgrade Mechanism

The system monitors two metrics (JS file count and obfuscation complexity). If the target is classified as a "Mega-Target," the system pauses and requests the user to provide a higher-tier API key (like Gemini Pro) to ensure the analysis quality and speed required for a site of that magnitude. This shows excellent **resource management** judgment.

2.5. System Design

The system design for **ASTRA** is based on a DevSecOps philosophy, prioritizing **resilience, performance, and controlled resource consumption** over brute force. This structure is built to safely and economically audit massive organizations like Google or Spotify without risking server overload or generating surprise costs.

Technical Feasibility

The project is highly technically feasible because it strategically outsources the most complex and resource-intensive task **semantic code analysis** to the robust, external Gemini API.

- **Asynchronous Architecture:** The use of **Python's *asyncio* and *aiohttp*** for the **Collection Module** is a high-impact technical decision that is fully supported by contemporary research. This non-blocking I/O architecture is proven to deliver substantial performance gains (up to 67% faster than synchronous methods), ensuring that the initial data collection for large sites is completed quickly, meeting the "rapid" requirement.
- **Neuro-Symbolic Analysis:** The core vulnerability detection logic is based on a **neuro-symbolic approach**, combining the symbolic rigor of the Heuristic Pre-Filter (rules/weights) with the contextual reasoning of the LLM (neural network). This hybrid methodology has been shown to be quantitatively superior to relying on static analysis alone in modern security environments.
- **Modular Design:** The LangChain Agent architecture allows for clear separation of concerns, making the system easy to test and update. The LLM model is a swappable component, which is essential for adapting to future AI advancements.

Operational Feasibility

Operational feasibility is strong due to the rigorous integration of **Operational Resilience** controls:

- **Anti-Overload Mechanism:** The *asyncio.Semaphore* is integrated directly into the **Collection Module** to act as a **concurrency throttle**. This control prevents ASTRA from overwhelming either the user's local server (avoiding overload) or the target server (avoiding permanent bans/rate limits), ensuring the tool can run responsibly in a continuous reconnaissance cycle.
- **Dynamic Resource Allocation:** The **Dynamic Upgrade Mechanism** (checking JS file count and obfuscation saturation) allows the system to smoothly handle scaling. When a **Mega-Target** is detected, the application provides an intelligent prompt to the user to upgrade the LLM tier, guaranteeing that the scan maintains high speed and high-fidelity output quality, regardless of the target's size.
- **LLM Defense:** The integration includes test-time defenses against **Prompt Injection (LLM01)**, ensuring that malicious data (hostile JS code) cannot hijack the Gemini model's instructions and compromise the analysis.

Economic Feasibility

The economic viability of ASTRA is centered on a **Zero-Cost Open-Source Model**, making it superior to costly commercial tools:

- **Cost Guardrail (Token Control):** The **Heuristic Pre-Filter** and the **Max Token Threshold** work in tandem to act as a financial firewall. By restricting >90% of analysis requests and implementing a hard budget cap on input size, the tool ensures that the consumption of the external Gemini API (the primary cost driver) remains minimal, maintaining the project's zero-cost operational promise.

- **Value Proposition:** Unlike commercial security analysis tools (Semgrep or TruffleHog) which often require subscription fees or costly license updates, ASTRA provides advanced **semantic intelligence** via the Gemini Flash tier (free model) for its core functionality.
- **Resilience I/O:** By utilizing open-source Python libraries and optimizing performance through asyncio, the project eliminates reliance on proprietary scraping or load-balancing infrastructure, maintaining the project's accessibility and low maintenance cost.

CHAPTER 3 (THEORY & MODULE IMPLEMENTATION)

3.1. Theory of LLM Agent Orchestration

The project implements the ReAct architecture, where the LLM (Gemini) uses its zero-shot reasoning capability. The LLM acts as the **central decision engine** that directs the flow: *Should I analyze this? If yes, what structured information should I extract?* The LangChain framework provides the structure for the LLM to communicate with your custom Python tools (Scraper, Filter) and deliver the final structured output.

3.2. Heuristic Scoring (False Positive Minimization)

The core theory for false positive reduction is the **Weighted Anomaly Thresholding** method. The total maliciousness score (Sm) is calculated as a summation of positive (exploit indicators) and negative (benign indicators) weights:

$$S_m = \Sigma_i (W_{positive} \times F_{exploit\text{-}sig}) + \Sigma_j (W_{negative} \times F_{benign\text{-}sig})$$

The $W_{negative}$ weights (e.g., assigned to copyright headers, massive file sizes, and CDN paths) are essential for pushing known benign code **out of the high-risk category**, ensuring the Bug Hunter only sees high-confidence findings.

3.3. Semantic Exploit Analysis

This is the central innovation. The LLM is used for **semantic analysis** understanding code intent, not just string patterns. This allows ASTRA to:

- ***Trace Payloads:*** Automatically de-obfuscate multi-layered encoding schemes (Base64 within Char Codes) and find the clean, human-readable payload.
- ***Code Similarity Check (Novelty):*** The filter compares suspicious code against a local repository of known **LLM-generated vulnerable patterns**. If a similarity is detected, the LLM is specifically prompted to check for that particular logic flaw, demonstrating a defense against the emerging AI-Flaw problem.
- ***Hypothesis Generation:*** Based on the decoded string and the identified vulnerable sink (e.g., document.write), the LLM generates the necessary Exploit Payload Hypothesis (the PoC suggestion).

CHAPTER 4 (METHODOLOGY)

The methodology follows a rigorous, performance-focused approach:

1. ***Asynchronous I/O Implementation:*** The core Collection Module is built using the asyncio and aiohttp frameworks for maximum concurrency.
2. ***Concurrency Control Implementation*:** The asyncio.Semaphore is integrated to cap HTTP connections. **A dynamic throttling mechanism** will be implemented to automatically reduce concurrency upon receiving HTTP 429 errors, ensuring robust anti-blocking behavior.
3. ***LLM Tool Integration:*** The LangChain Agent is configured with the Gemini API. All calls will include **Exponential Backoff** and the **Three-Tier Fallback** logic to guarantee a result even if the API fails temporarily.
4. ***Testing and Validation*:** Focus on two primary tests: False Positive Reduction (testing against Top 100 JS libraries) and **Operational Resilience** (simulating 429 errors to confirm the Semaphore and Backoff controls function correctly).

CHAPTER 5 (TESTING AND EVALUATION)

5.1 Testing (Focus on Resilience and Accuracy)

- ***Positive Accuracy (Exploit Detection):*** Validation against a ground-truth dataset of known exploits to ensure the LLM accurately de-obfuscates the payload and generates the correct structured JSON (high true positive rate).
- ***Operational Resilience Testing:*** Dedicated testing of the **Dynamic Throttler** and asyncio.Semaphore to ensure the tool maintains stable performance and does not cause local or remote network overload.
- ***Failover Testing:*** Stress testing the Gemini API calls to confirm that the Three-Tier Fallback system successfully executes Tier 2 (Partial De-obfuscation) when the API is unavailable, ensuring continuous operation.

CHAPTER 6: FUTURE ENHANCEMENT

Future work will focus on expanding the open-source platform:

1. ***Community AI Flaw Repository:*** Integrating the Code Similarity Check against an open-source database of LLM-generated vulnerable code patterns, allowing ASTRA to learn from global AI vulnerabilities.
2. ***Automated PoC Builder****:* Implementing a module that uses the Structured Exploit Intelligence to automatically generate a functional HTML or Python Proof-of-Concept script.
3. ***Dynamic Analysis Integration:*** Integrating a headless browser sandbox (like Playwright) to dynamically execute and confirm the LLM's static analysis findings, providing a final layer of high-confidence verification.

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