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A Mid-term Final Year Project Report

On

Red Sentinel: Transformer-Based Generation and Obfuscation of Context-Aware XSS Payloads

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ABSTRACT

Cross-Site Scripting (XSS) remains a persistent web vulnerability, and traditional scanners, dependent on signatures and manually crafted payloads, struggle with modern filtering mechanisms and diverse injection contexts. This project introduces Red Sentinel, a transformer-based, machine learning–driven system that automatically generates context-aware XSS payloads. Built on a microservice architecture, it includes modules for extracting injection contexts, generating and obfuscating payloads, and orchestrating end-to-end testing workflows. By using byte-level tokenization and an encoder–decoder transformer, the system captures syntactic and semantic nuances across HTML, JavaScript, event handlers, and URL parameters.

Red Sentinel's generator produces syntactically valid, execution-ready payloads tailored to specific contexts, while an obfuscation layer applies encoding and structural mutations to evade modern WAFs. Early experiments show the model generates more diverse and effective payloads than manually created ones, with evaluation mechanisms that measure both success rates and filter evasion. This report summarizes the system architecture, dataset preparation, and results from GRU, LSTM, and transformer baselines, and concludes with challenges, progress to date, and future work including enhanced obfuscation, real-world benchmarking, and integration into penetration testing workflows.

Keywords: Cross-Site Scripting, XSS, Machine Learning, Transformer Models, Adversarial Payload Generation, Web Security, Automated Penetration Testing, Obfuscation, Context-Aware Attack Generation

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LIST OF ABBREVIATIONS

AI Artificial Intelligence

API Application Programming Interface

AWS Amazon Web Services

CI/CD Continuous Integration/Continuous Deployment

CVE Common Vulnerabilities and Exposures

DDQN Double Deep Q-Network

DOM Document Object Model

DQN Deep Q-Network

DVWA Damn Vulnerable Web Application

GRU Gated Recurrent Unit

HTML HyperText Markup Language

LSTM Long Short-Term Memory

ML Machine Learning

mTLS Mutual Transport Layer Security

NLP Natural Language Processing

OWASP Open Web Application Security Project

RL Reinforcement Learning

RNN Recurrent Neural Network

SVG Scalable Vector Graphics

WAF Web Application Firewall

XSS Cross-Site Scripting

1. INTRODUCTION

Web applications today play a central role in handling sensitive information for individuals and organizations. Despite advances in secure software engineering, these systems continue to face long-standing vulnerabilities. Cross-Site Scripting (XSS) remains one of the most persistent and widely exploited threats and consistently appears in the OWASP Top Ten rankings. XSS attacks occur when adversaries inject malicious scripting code into web content that is later delivered to end users, potentially enabling credential theft, unauthorized session access, malware distribution, or manipulation of displayed data.
Modern web pages integrate multiple languages,including HTML, CSS, JavaScript, and SVG, within the same document structure. Because each injection point follows different syntactic and execution rules, attackers must tailor payloads to the specific context in which the code will run. Research has shown that a payload effective inside a script block may fail entirely when placed within an HTML attribute. This context sensitivity is a major reason why XSS detection and prevention remain difficult even after decades of research.

1.1 Problem Statement

Although XSS scanners and WAFs can identify many basic vulnerabilities, they lack the adaptive intelligence required to generate valid and context-aware payloads. Their reliance on predefined signatures limits their ability to detect new, obfuscated, or context-specific attack vectors. There is a clear need for a system that can automatically generate intelligent, adaptable, and context-sensitive XSS payloads using modern machine learning techniques, thereby improving the depth and reliability of security testing.
These challenges have motivated the use of artificial intelligence and machine learning to support offensive security research. Recent work demonstrates that generative models, especially transformer-based architectures, are capable of producing diverse and novel XSS payloads that surpass human-crafted examples. Systems such as GenXSS and fine-tuned language models like GPT-2 and CodeT5 show promising results in automating adversarial payload creation, thereby increasing coverage and uncovering weaknesses that rule-based tools fail to detect.

1.2 Objectives

1. To develop a machine learning–based system capable of generating context-aware XSS payloads.
2. Integrate payload generation with a modular testing framework.

1.3 Project Feasibility

The Red Sentinel project is feasible due to the maturity of ML frameworks, availability of datasets, and growing interest in automated offensive security methods.

1.3.1 Technical Feasibility

1. Modern ML frameworks such as TensorFlow and PyTorch support transformer architectures and byte-level tokenizers, making implementation highly achievable.
2. Hardware requirements for training a medium-sized transformer model are modest and achievable using consumer GPUs or cloud resources.

1.3.2 Operational Feasibility

1. Security teams can incorporate Red Sentinel into existing testing workflows without major changes.
2. The modular design supports iterative development and ease of maintenance.
3. The system reduces manual effort by automating payload creation, improving operational efficiency for developers and penetration testers.

1.3.3 Economic Feasibility

1. Costs are limited primarily to training infrastructure and optional dataset acquisition.
2. Open-source ML libraries and penetration-testing tools reduce development expense.
3. Cloud-based compute resources can be used only when necessary, minimizing expenses.

1.3.4 Sociocultural Feasibility

1. The project aligns with growing societal emphasis on cybersecurity and ethical hacking
2. The project allows for automated check of vulnerabilities by untrained personnel.

1.3.5 Legal Feasibility

1. The system must be used strictly for authorized security testing to comply with cybercrime and computer misuse laws.
2. No proprietary or personal data is required for the model, reducing legal risks.

2. LITERATURE REVIEW

The following review examines significant advancements in automated web security testing, with a particular focus on XSS payload generation and adversarial input synthesis. Existing research covers a wide spectrum of techniques, including reinforcement learning, neural machine translation, generative adversarial models, and transformer-based language approaches. By analysing these contributions, this review highlights the methodological trends, strengths, and limitations that shape for the design and development of the Red Sentinel system..

Foley and Maffeis (2022) propose HAXSS, a hierarchical reinforcement-learning framework to automatically generate XSS attack payloads. Their approach frames the payload creation as two nested RL "games." The first agent learns to escape the immediate HTML context of user output (escaping tags or attributes), while the second agent intervenes whenever the application attempts sanitization, it learns to obfuscate the payload to bypass filters. Successful obfuscations are fed back into the first agent for further refinement. Implemented as an end-to-end black-box fuzzer, HAXSS was evaluated on both synthetic benchmarks and real web applications. It identified 131 XSS vulnerabilities (20% more than state-of-the-art scanners) with zero false positives, including rediscovering known CVEs and uncovering 5 novel CVEs in production-grade sites. Thus, HAXSS demonstrates that hierarchical RL can produce diverse, context- and filter-aware payloads that significantly improve XSS discovery over traditional scanners [1].

Khan (2024) presents LL-XSS, an end-to-end deep generative model for crafting XSS payloads. Unlike hand-crafted or brute-fuzzed payloads, LL-XSS leverages a combination of auto-regressive neural networks and transformer architectures to analyze both frontend and backend web code and produce candidate attack scripts. The model is trained on example web application code to learn common injection patterns, then generates new malicious scripts aimed at identified vulnerabilities. In evaluation on the OWASP Juice Shop, the author reports that LL-XSS can automatically generate syntactically valid and exploitable XSS payloads by understanding the target's code context. This approach effectively automates the penetration-testing process: LL-XSS bypasses known filters and exposes vulnerabilities with minimal human guidance, demonstrating the promise of AI-driven payload creation for web security [2].

Frempong et al. (2021) developed HIJaX, a neural machine translation model that converts natural-language attack descriptions into working XSS payloads. The system was trained on paired examples of intent phrases and JavaScript exploits. Their experiments showed that the model could reliably generate valid payloads that triggered real XSS vulnerabilities, demonstrating that neural translation methods can automate exploit creation even for users with limited technical expertise [3].

Pala et al. (2023) examined contemporary XSS scanners and highlighted XSStrike as a tool that combines intelligent fuzzing with basic machine-learning techniques. XSStrike analyzes the structure of a web page to detect injection points and then mutates payloads based on contextual feedback. Their evaluation showed that this approach improves detection and execution of XSS payloads across different contexts, illustrating the value of context-aware fuzzing [4].

Fink (2018) introduced FOXSS, a scanner that integrates static data-flow analysis with targeted, context-sensitive fuzzing. The tool identifies potential input flows and generates tailored payloads for each sink, verifying results in a real browser. FOXSS demonstrated very high detection accuracy, outperforming conventional scanners and significantly reducing false positives, indicating that program analysis combined with adaptive fuzzing can greatly enhance XSS detection [5].

Song et al. (2023) presented a grey-box fuzzing system that uses reinforcement learning to create and refine XSS payloads. After mapping all input points through static analysis, the authors trained RL agents (DQN, DDQN, and Policy Gradient) to adjust payloads based on execution feedback. The RL-based fuzzer identified all known XSS vulnerabilities in benchmark applications with no false positives, demonstrating that RL can effectively adapt payloads to complex contexts[6].

Miczek et al. (2025) explored the use of large language models to generate obfuscated XSS attacks capable of evading machine-learning detectors. Their study showed that classifiers trained on standard payloads performed poorly when encountering obfuscated variants. By fine-tuning a transformer to generate diverse obfuscations, the authors significantly improved detector robustness after retraining. This work highlights the usefulness of LLM-generated adversarial examples for strengthening defensive models[7].

3. METHODOLOGY

3.1 Architectural Design Overview

Red Sentinel is implemented using a microservice architecture. In this design, each major functional component of the system runs as an independent service. These services communicate via well-defined APIs and are coordinated by a central orchestration core—the ”Core Module.” This microservice approach ensures that each module is isolated, independently deployable, testable, and can be scaled or replaced without impacting the rest of the system—addressing concerns of maintainability, modularity, and system complexity typical in security tools.

To connect the ML-based payload generator with the rest of the system and other modules, a data pipeline architecture is used. As described in the literature on integrating ML pipelines with microservices, this setup supports data ingestion, preprocessing, model serving, asynchronous communication, and modular isolation of ML components from other services.

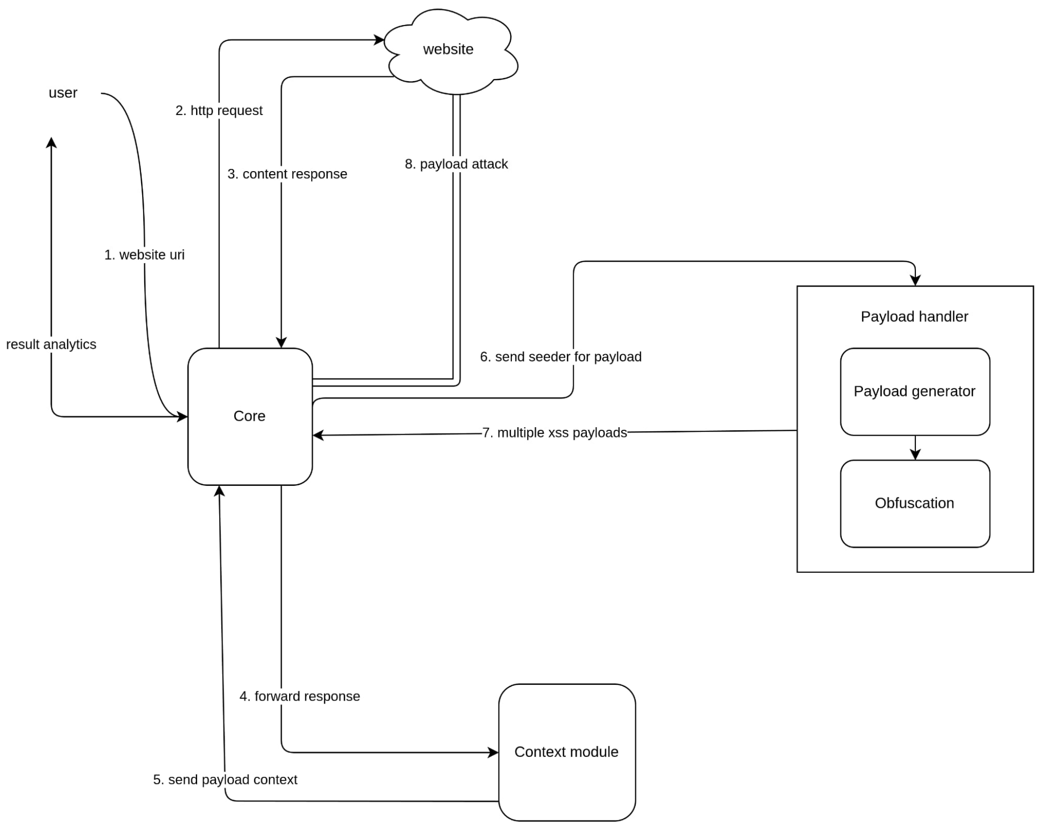


Figure 3.1.1: System Architecture Diagram

3.1.1 Core Module

The Core Module serves as the orchestration layer and primary entry point for Red Sentinel. Implemented using NestJS, a progressive Node.js framework, it provides the foundational infrastructure for coordinating distributed microservices, managing workflow execution, and ensuring system reliability. The module operates as a RESTful API gateway that bridges external security researchers and internal ML-powered services.

3.1.1.1 Architectural Role and Responsibilities

The Core Module fulfills multiple critical roles within the Red Sentinel ecosystem:

- **API Gateway and Request Routing:** Exposes RESTful endpoints that accept target URLs and scanning parameters from clients. Routes requests to appropriate downstream services based on workflow stage and service availability.
- **Input Validation and Security Enforcement:** Implements comprehensive validation logic to ensure all user-provided inputs conform to security policies. This includes URL structure validation, protocol whitelisting (HTTP/HTTPS only), and Server-Side Request Forgery (SSRF) prevention through private IP address blocking.
- **Workflow Orchestration:** Manages the multi-stage pipeline from initial target submission through context extraction, payload generation, obfuscation, and result aggregation. Coordinates asynchronous communication between services using message queues or direct HTTP invocation.
- **State Management:** Maintains scanning session state, tracks request progress, and persists intermediate results for fault tolerance and debugging. Implements distributed caching to reduce redundant operations.
- **Error Handling and Recovery:** Provides comprehensive error handling with typed exception filters, automatic retry mechanisms for transient failures, and graceful degradation when dependent services are unavailable.
- **Logging and Observability:** Generates structured logs with unique request identifiers for distributed tracing. Exposes metrics endpoints compatible with Prometheus for monitoring request rates, latency distributions, and error frequencies.

3.1.1.2 Step One: Target Input and Page Retrieval

The first operational step within the Core Module focuses on accepting target URLs, performing security validation, and retrieving raw HTML content. This foundational layer establishes the data pipeline upon which all subsequent analysis depends.

Input Validation When a client submits a target URL via the `POST /api/v1/gateway/fetch` endpoint, the system performs rigorous validation:

1. **URL Structure Validation:** Parses the URL to ensure it contains all required components (protocol, hostname) and conforms to RFC 3986 standards. Rejects malformed URLs with descriptive error messages.
2. **Protocol Enforcement:** Accepts only HTTP and HTTPS protocols. Rejects potentially dangerous schemes such as `file://`, `ftp://`, `javascript:`, and `data:` to prevent local file access and code injection attacks.
3. **Length Constraints:** Enforces a maximum URL length of 2048 characters to prevent buffer overflow vulnerabilities and resource exhaustion.
4. **DNS Resolution:** Resolves the target hostname to its IP address using standard DNS lookup mechanisms before initiating HTTP requests.

SSRF Prevention To prevent Server-Side Request Forgery attacks, the Core Module implements IP address filtering that blocks requests to private network ranges:

- **IPv4 Private Ranges:** `10.0.0.0/8`, `172.16.0.0/12`, `192.168.0.0/16` (RFC 1918)
- **Loopback Addresses:** `127.0.0.0/8` (IPv4), `::1/128` (IPv6)
- **Link-Local Addresses:** `169.254.0.0/16` (IPv4), `fe80::/10` (IPv6)
- **Reserved Ranges:** Multicast, broadcast, and experimental address spaces

Requests targeting these ranges are rejected with HTTP 403 Forbidden status, preventing attackers from scanning internal infrastructure or accessing cloud metadata endpoints.

HTTP Request Execution Upon successful validation, the Core Module configures an HTTP client with security-hardened settings:

- **Timeout Configuration:** Enforces a default timeout of 30 seconds to prevent indefinite hanging. Configurable through request parameters within the range of 1-60 seconds.
- **Redirect Handling:** Follows HTTP redirects automatically up to a maximum of 5 redirects. Prevents redirect loops and excessive chain following that could indicate malicious targets.

- **TLS/SSL Validation:** Validates SSL certificates for HTTPS requests, rejecting self-signed certificates in production mode to ensure authenticity.
- **User-Agent Identification:** Sets a custom User-Agent header (`RedSentinel/1.0 (Security Scanner)`) for ethical disclosure, allowing site administrators to identify and control scanner access.
- **Content Size Limits:** Enforces a maximum response size of 10MB to prevent memory exhaustion attacks. Aborts downloads that exceed this threshold.

Response Processing After successfully retrieving the target page, the Core Module processes the HTTP response:

1. **Status Code Capture:** Records the final HTTP status code (e.g., 200, 301, 404) for diagnostic purposes.
2. **Header Extraction:** Captures relevant response headers including `Content-Type`, `Content-Length`, `Server`, and security headers (`X-XSS-Protection`, `Content-Security-Pol`
3. **Content Validation:** Verifies the `Content-Type` header indicates HTML content (`text/html`). Non-HTML responses are logged but not rejected, as some applications serve HTML with incorrect MIME types.
4. **HTML Body Extraction:** Reads the complete response body as text, preserving all whitespace, encoding, and formatting for accurate downstream analysis.

Response Standardization The Core Module returns a standardized JSON response structure for both successful and failed operations:

```
{
  "success": true,
  "data": {
    "targetUrl": "https://example.com/search",
    "finalUrl": "https://www.example.com/search",
    "statusCode": 200,
    "contentType": "text/html; charset=UTF-8",
    "contentLength": 45678,
    "html": "<!DOCTYPE html><html>...</html>",
    "redirectCount": 1,
    "fetchDuration": 1234
  },
  "metadata": {
    "timestamp": "2025-12-10T14:32:15.789Z",
    "requestId": "req_7f8a9b1c",
    "version": "1.0.0"
  }
}
```

This consistent response format simplifies integration with downstream services and enables automated result processing.

Error Handling and Logging The Core Module implements comprehensive error handling with specific error codes for common failure scenarios:

- `INVALID_URL_FORMAT`: Malformed URL structure
- `UNSUPPORTED_PROTOCOL`: Non-HTTP/HTTPS protocol detected
- `PRIVATE_IP_BLOCKED`: SSRF prevention triggered
- `FETCH_TIMEOUT`: Request exceeded timeout duration
- `CONTENT_TOO_LARGE`: Response size exceeded 10MB limit
- `TOO_MANY_REDIRECTS`: Redirect count exceeded maximum

All requests are logged with structured JSON formatting, including request IDs for distributed tracing, target URLs (sanitized to remove credentials), execution duration, and error details. Logs are categorized by severity (INFO, WARN, ERROR) and exported to centralized logging infrastructure for monitoring and auditing.

3.1.1.3 Technology Stack and Implementation

The Core Module leverages modern TypeScript-based technologies for reliability and maintainability:

- **Framework:** NestJS 10.x with TypeScript 5.x for strong typing and compile-time safety
- **HTTP Client:** Axios with configurable timeout, redirect, and proxy support
- **Validation:** class-validator and class-transformer for declarative DTO validation
- **Logging:** Winston with JSON formatting for structured logging
- **Testing:** Jest for unit tests, Supertest for integration tests
- **Documentation:** Swagger/OpenAPI for automated API documentation

The modular architecture enables independent testing, deployment, and scaling of the Core Module, supporting Red Sentinel's microservice design philosophy.

3.1.2 Context-Aware Analysis Module

The Context-Aware Module is responsible for examining how user-controlled input appears inside a webpage and determining whether that location is exploitable. Red Sentinel performs this using a hybrid approach that combines static HTML parsing, dynamic browser execution tracing, rule-based reasoning, and machine learning models. The output of this module is a normalized and labeled structure, known as a C-Script, which the payload generator later uses to craft attack strings.

3.1.2.1 Static Context Extraction

This stage performs offline HTML parsing using **BeautifulSoup4 (BS4)** and custom parsers. The system inspects the DOM to identify injection surfaces such as attributes, text nodes, script bodies, URL parameters, and form fields.

- Extracts tag names, attributes, raw values, depth, parent, and sibling structure.
- Detects static flags (HTML-entity usage, URL encoding, JavaScript escaping).
- Produces a structured static context object for every potential injection point.

3.1.2.2 Dynamic Context Extraction

Static content alone fails to capture runtime behavior. Red Sentinel launches a headless browser using **Playwright** and records dynamic modifications triggered by JavaScript execution.

- Detects `innerHTML` / `outerHTML` sinks.
- Logs event listeners (`onclick`, `onload`, custom JS handlers).
- Captures nodes created or modified at runtime.
- Records whether the context becomes dynamic and vulnerable after execution.

The static and dynamic information is then merged into a unified structure.

3.1.2.3 Rule-Based Classification

A custom rule engine evaluates structural and behavioral patterns to infer an initial attack class.

- Attributes starting with `on*` are labeled as event-handler contexts.
- Any element inserted through `innerHTML` is marked as DOM-XSS.

- URL-based attributes may produce JavaScript protocol execution.

These deterministic rules form the foundation for supervised ML labels and validation.

3.1.2.4 ML-Based Attack and Payload Classification

To enhance generalization, Red Sentinel trains two **Random Forest** classifiers using the unified context features:

1. Attack Class Model (e.g., event-handler, DOM-based, attribute-breakout)
2. Payload Type Model (e.g., js-exec, event-transition, html-breakout)

Contexts are encoded using one-hot vectors for tags and attributes, together with dynamic boolean features. The ML output refines the rule-based inference and improves robustness across diverse HTML structures.

3.1.2.5 C-Script Construction

The final stage produces a C-Script, a compact representation that describes the vulnerability surface.

```
{
  "attackClass": "dynamic-event",
  "payloadType": "js-exec",
  "riskScore": 0.92,
  "sink": "innerHTML",
  "allowedChars": "<>'\"/`",
  "isDynamic": true
}
```

This unified structure guides the Payload Generator by specifying contextual restrictions, browser behavior, and exploitability.

3.1.2.6 Context Dataset Construction

The module automatically generates training data by storing each context and its inferred labels in **JSONL** format. This dataset combines:

- BS4 static extraction output

- Playwright dynamic logs
- Rule-engine classifications
- Cleaned ML-ready feature vectors

The result is a scalable dataset used to train and evaluate the Random Forest classifiers.

Summary The Context-Aware Module forms the analytical backbone of Red Sentinel. By combining static DOM parsing, dynamic browser execution tracing, rule-based inference, and Random Forest classification, it produces a precise understanding of every injection point. This information is distilled into the C-Script structure, enabling the payload generator to craft highly accurate, context-specific XSS payloads. The module's hybrid design ensures reliability, extensibility, and compatibility with ML-driven offensive security workflows.

3.1.3 Payload Handler

The Payload Handler consists of two primary models working in tandem: the Payload Generator and the Obfuscation Model.

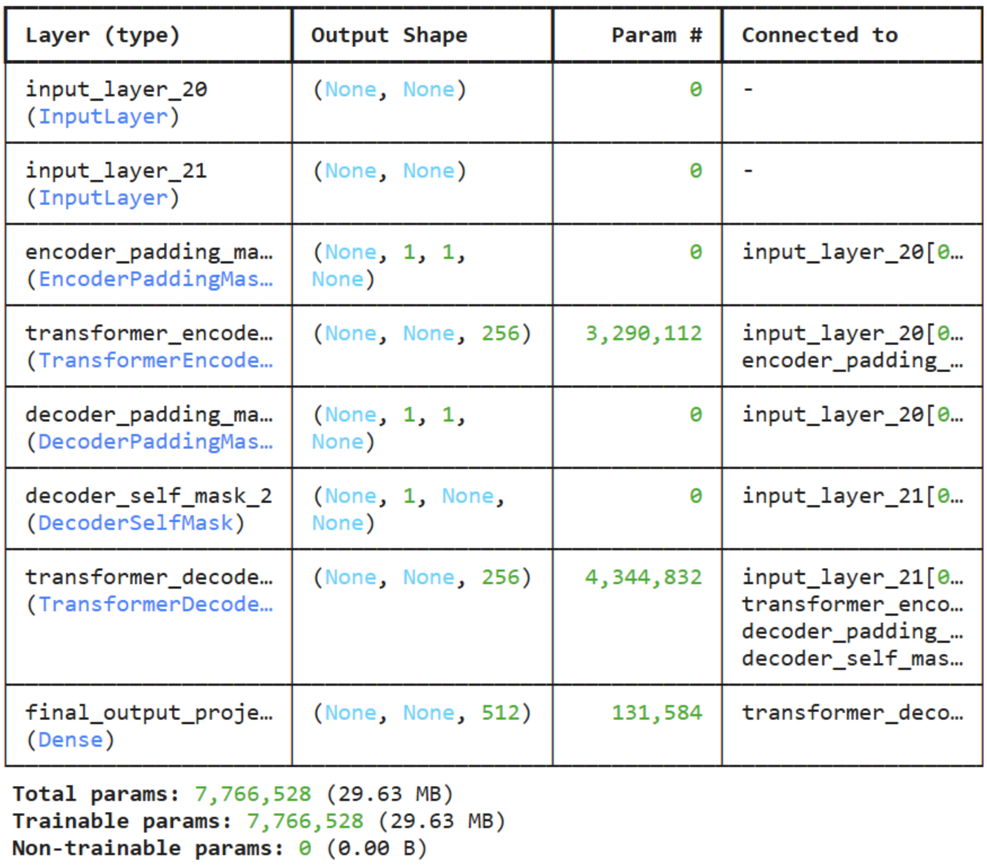
3.1.3.1 Payload Generator

The Payload Generator is responsible for producing syntactically valid, context-adapted, and execution-ready XSS attack strings. Red Sentinel employs a transformer-based encoder-decoder architecture trained specifically for cross-site scripting contexts and adversarial behavior.

The transformer model is trained on a dataset formed by pairs of sanitized script structures provided by the Core Module and the corresponding XSS payloads. The generator is built on an encoder-decoder transformer network, chosen because of its exceptional ability to model long-range dependencies and handle complex code sequences. The model comprises:

- **Byte-Level Tokenizer**
  Instead of word- or character-level tokenization, Red Sentinel uses a byte-level tokenizer (similar to Byte-Pair Encoding) to ensure that all characters—including <, >, `'`, `"`, `(`, `)`, \, and Unicode variants—are preserved without normalization. This is crucial because minor character transformations can change the exploitability of an XSS payload.

- **Encoder**
  The encoder receives the attack type, payload type, and contextual information extracted by the Context Module. The encoder produces a contextual embedding that expresses the syntactic and semantic constraints of the injection point.
- **Decoder**
  The decoder autoregressively generates an attack string conditioned on the encoder output. It learns patterns for escaping contexts, invoking JavaScript execution, nesting HTML/JS structures, and exploiting browser quirks. It is designed to avoid generating malformed payloads by learning valid grammar structures from curated training data.
- **Attention Mechanisms**
  Attention heads enable the model to correlate specific positions in the context (e.g., inside quotes, inside script tags) with correct exploit strategies. This facilitates generation of highly specific payloads such as:
  - Attribute breakouts: `"><svg/onload=alert(1)>`
  - Script-block injections: `';alert(1);//`
  - URL-based injections: `javascript:alert(1)`



Layer (type)	Output Shape	Param #	Connected to
input_layer_20 (InputLayer)	(None, None)	0	-
input_layer_21 (InputLayer)	(None, None)	0	-
encoder_padding_ma… (EncoderPaddingMas…	(None, 1, 1, None)	0	input_layer_20[0…
transformer_encode… (TransformerEncode…	(None, None, 256)	3,290,112	input_layer_20[0… encoder_padding_…
decoder_padding_ma… (DecoderPaddingMas…	(None, 1, 1, None)	0	input_layer_20[0…
decoder_self_mask_2 (DecoderSelfMask)	(None, 1, None, None)	0	input_layer_21[0…
transformer_decode… (TransformerDecode…	(None, None, 256)	4,344,832	input_layer_21[0… transformer_enco… decoder_padding_… decoder_self_mas…
final_output_proje… (Dense)	(None, None, 512)	131,584	transformer_deco…

```
Total params: 7,766,528 (29.63 MB)
Trainable params: 7,766,528 (29.63 MB)
Non-trainable params: 0 (0.00 B)
```

Figure 3.1.2: Transformer Model Structure

3.1.3.2 Obfuscation Model

Modern defensive systems often rely on pattern matching or signature detection, which is particularly vulnerable to obfuscation. Therefore, incorporating systematic obfuscation increases the likelihood of discovering hidden vulnerabilities and evaluating the true resilience of a target.

Encoding-Based Obfuscation This class manipulates the representation of characters while preserving their semantics at runtime:

- URL encoding (percent-encoding): `%3Cscript%3E`
- HTML entity encoding: `&#x3C;script&#x3E;`
- Unicode homoglyphs: Alternative representations of common symbols
- Base64 wrapper techniques: e.g., `eval(atob("YWxlcnQoMSk="))`

These methods exploit weaknesses in sanitization routines that decode values inconsistently.

Structural Obfuscation Structural modification alters the payload's syntax without changing its effect:

- String splitting: `a = "al" + "ert"; window[a](1)`
- Wrapped event handlers: `<img src=x onerror=%61%6c%65%72%74(1)>`
- Nonstandard tag nesting
- Junk insertion (harmless characters or comments)

This category is particularly effective against filter engines that scan for simple signatures (e.g., `alert`).

JavaScript-Based Dynamic Obfuscation A more advanced transformation relies on runtime reconstruction:

- Using constructor functions: `Function("al"+"ert(1)")()`
- Indirect invocation using event stacks
- Using proxies or dynamically generated DOM nodes to execute embedded code

These methods exploit JavaScript's dynamic nature to evade static analysis.

Obfuscation Module Overview The Obfuscation Module integrates into the system workflow as follows:

1. The Payload Generator produces a set of base payloads
2. Payloads are sent to the Obfuscation Service when enabled
3. The transformed payloads are injected into the target applications
4. All variants and their execution results are logged

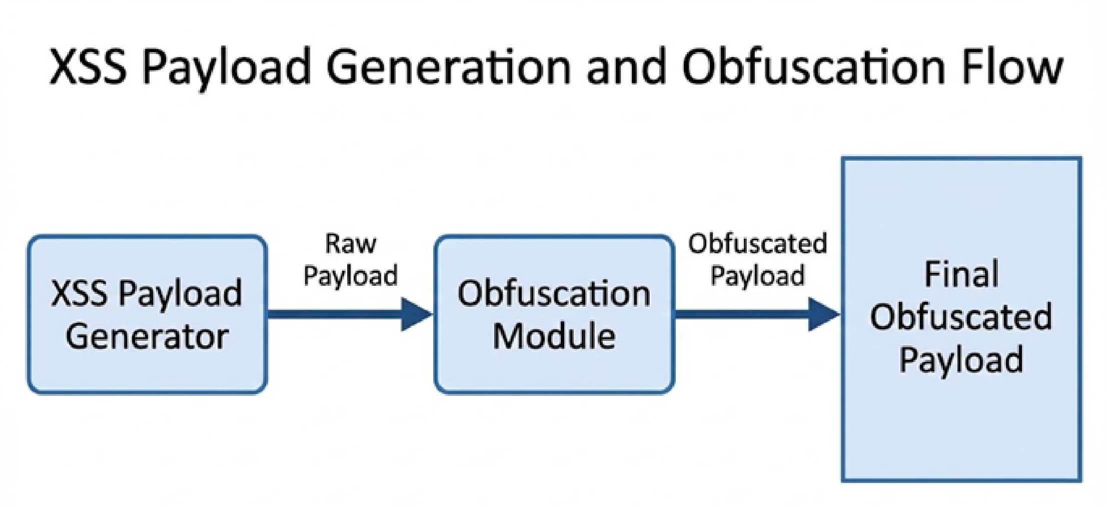


Figure 3.1.3: Payload Handler Flow Structure

Together, the Payload Generator and Obfuscation Module form the intelligent core of Red Sentinel. The generator creates contextually accurate, execution-ready XSS payloads, while the obfuscation system transforms them to evade filters and explore deeper vulnerabilities. Their microservice design ensures modularity, scalability, and extensibility, supporting Red Sentinel's mission of providing advanced, ML-driven offensive security capabilities.

3.2 Dataset Preparation and Preprocessing

A high-quality dataset is essential for training the transformer-based payload generator. The dataset construction process involved several stages:

3.2.1 Data Collection

Payload data was collected from multiple sources:

1. **Open-Source Repositories:** XSS payload collections from GitHub repositories such as PayloadsAllTheThings, XSS Hunter, and OWASP's XSS Filter Evasion Cheat Sheet
2. **Academic Publications:** Payloads extracted from research papers on XSS vulnerability detection
3. **Vulnerability Databases:** Real-world exploit examples from CVE databases and security advisories
4. **Synthetic Generation:** Rule-based generation of context-specific payloads for underrepresented categories

3.2.2 Context Labeling

Each payload was manually or semi-automatically labeled with:

- **Attack Class:** Reflected, Stored, DOM-based
- **Payload Type:** Event handler, script injection, attribute breakout, etc.
- **Context Type:** HTML attribute, JavaScript string, URL parameter, etc.
- **Risk Score:** Estimated severity and exploitability (0.0 to 1.0)

3.2.3 Preprocessing Pipeline

The preprocessing pipeline included:

1. **Deduplication:** Removal of exact and near-duplicate payloads using hash-based and fuzzy matching
2. **Normalization:** Standardization of whitespace, encoding formats, and character representations
3. **Validation:** Syntactic validation to ensure payloads are well-formed
4. **Tokenization:** Application of byte-level SentencePiece tokenization with byte fallback
5. **Sequence Formatting:** Construction of input-output pairs with special tokens for context metadata

Example formatted training instance:

```
Input: <ATTACK_CLASS>event-handler</ATTACK_CLASS>
       <PAYLOAD_TYPE>event-mouse</PAYLOAD_TYPE>
       <RISK>0.97</RISK>
```

```
Output: "><img src=1 onerror=prompt(document.domain)>
```

3.3 Activity Diagram

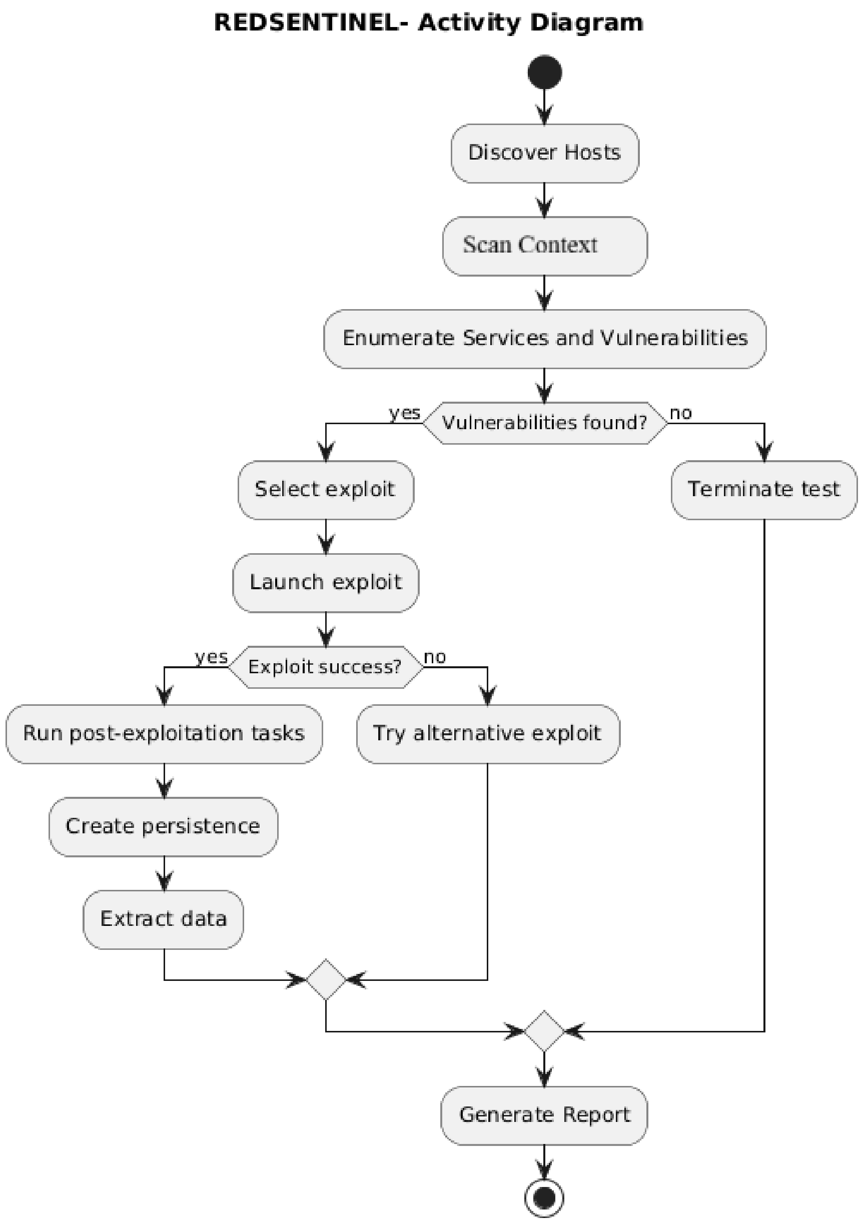


Figure 3.3.1: System Activity Diagram

4. WORK COMPLETED AND PROGRESS REPORT

4.1 Work Completed

4.1.1 Research

Extensive research was conducted on cross-site scripting vulnerabilities, attack vectors, and modern web security challenges. This included studying the OWASP Top Ten, existing XSS scanners such as XSStrike and DalFox, and academic literature on ML-based exploit generation. Transformer architectures, byte-level tokenization methods, and adversarial obfuscation techniques were analyzed to determine their suitability for generating context-aware payloads. A detailed survey of microservice architectures and ML-serving pipelines was also completed to guide the system's design.

4.1.2 Familiarization with Tools and Frameworks

The team became proficient with relevant frameworks including TensorFlow for model development, FastAPI for microservice integration, Docker for containerization, and GitHub for version control and CI/CD workflows. Tools commonly used in penetration testing, such as Burp Suite, OWASP ZAP, and browser, based developer consoles, were familiarized to support payload testing and context extraction. Additional effort was dedicated to understanding deployment tools required for scalable ML microservices.

4.1.3 Dataset Preparation and Preprocessing

A dataset of XSS payloads was collected and curated from open-source repositories, academic publications, and synthetic generation procedures. Payloads were categorized by injection context (HTML attributes, script blocks, URL parameters, etc.) and normalized into a format compatible with byte-level tokenization. Preprocessing steps included context-labeling, deduplication, noise removal, encoding normalization, and construction of input-output pairs for supervised transformer training.

4.1.4 Model Development and Analysis

Initially multiple models were developed to analyze the efficacy of different architectures for XSS payload generation.

4.1.4.1 3-Layer GRU Decoder Model & 3-Layer LSTM Decoder Model

In addition to the transformer-based architecture, a recurrent neural network variant was developed to evaluate lightweight sequence-generation approaches for XSS payload synthesis. The implemented model is a three-layer unidirectional GRU decoder, designed to process byte-tokenized input sequences of fixed length (150 tokens).

The architecture begins with an embedding layer that maps discrete byte indices into a 256-dimensional continuous vector space, enabling the model to capture syntactic and semantic relationships between characters commonly used in XSS payloads. Each GRU block contains 256 hidden units and is followed by layer normalization to stabilize training and mitigate exploding gradients. Skip-connections and logical operations are incorporated between recurrent layers to enhance information flow and to allow the model to combine contextual signals derived from both the embedding space and the hidden states.

A final TimeDistributed dense layer projects each timestep output into the vocabulary space, enabling autoregressive token prediction for payload generation. Despite its relatively small size (1.34 million parameters), this model is capable of learning structural patterns such as attribute breakouts, event-handler injections, and common JavaScript invocation sequences. Its efficiency and reduced computational footprint make it suitable for rapid experimentation, ablation studies, and low-latency microservice deployment where a full transformer model may be unnecessary or too resource-intensive.

The same architecture was implemented using LSTM layers for comparison.

Example Results This model was capable of generating working XSS payloads from a starting payload seed:

```
Seed:    "<script"
Payload: "<script>alert(1)</script>"
```

4.1.4.2 Byte-Level Transformer Payload Generator

Following the initial RNN experiments, a more advanced transformer-based sequence-to-sequence model was developed to improve generative fidelity and contextual awareness. This model used a byte-level SentencePiece tokenizer with byte fallback enabled, ensuring full coverage of printable and non-printable characters,a critical requirement for XSS payloads, which often include symbols outside typical word/token vocabularies.

The preprocessing pipeline encoded both structured metadata (attack class, payload type, risk score) and target payloads into padded integer sequences. Custom encoder-decoder padding masks, autoregressive self-attention masks, and explicit positional encodings were implemented to maintain compatibility with TensorFlow's serialization system.

The transformer architecture consisted of:

- 4-layer encoder with multi-head attention (8 heads)
- 4-layer decoder with masked multi-head autoregressive attention
- $d_{model} = 256$, $d_{ff} = 1024$
- Final dense projection over the full byte vocabulary

The model was trained using a masked cross-entropy loss function that ignored padding tokens and optimized with the Adam optimizer. Training was stabilized with learning-rate scheduling, ReduceLROnPlateau, and early stopping. A custom inference engine was built, including a specialized decoder-step model for stepwise token generation, enabling greedy, sampling-based, and beam-search decoding strategies.

Example Results In practice, the byte-level transformer significantly outperformed the GRU model. It was able to generate longer, structurally complex payloads with embedded JavaScript calls, event handlers, HTML attribute breakouts, and encoded characters. The model could take structured context such as:

```
Input:
<ATTACK_CLASS>event-handler</ATTACK_CLASS>
<PAYLOAD_TYPE>event-mouse</PAYLOAD_TYPE>
<RISK>0.97</RISK>

Output:
"><img src=1 onerror=prompt(document.domain)>
```

4.1.4.3 T5-Based Large Language Model Fine-Tuning

To benchmark the transformer against a pre-trained language model, a third model was developed by fine-tuning the T5-base architecture using the same structured dataset.

HuggingFace's `AutoModelForSeq2SeqLM`, `DataCollatorForSeq2Seq`, and Adafactor optimizer were used to perform supervised fine-tuning across five epochs with gradient accumulation.

T5's pre-training on large-scale text corpora provided strong generative priors, and early experimentation revealed significantly faster convergence compared to the GRU and custom transformer models. T5 was capable of producing syntactically rich payloads and often generated multi-stage injection sequences (e.g., event-triggered JavaScript execution combined with HTML entity encoding) without explicitly being instructed to do so.

This model served two purposes:

1. As a baseline metric to evaluate the performance of the custom byte-level transformer
2. As an alternative model candidate for potential integration into Red Sentinel's payload-generation engine

While T5 exhibited high generative quality, it lacked fine-grained control over byte-level precision, which is essential for payloads requiring arbitrarily encoded characters. Therefore, T5's role remains supplementary, while the byte-level transformer continues as the main candidate for integration.

4.2 Challenges Encountered

1. **Dataset Quality and Context Ambiguity**
   Obtaining high-quality, context-labeled XSS payload datasets was difficult. Many publicly available samples lacked structured metadata, requiring extensive manual curation and synthetic augmentation.
2. **Byte-Level Tokenization Complexity**
   Designing a tokenizer capable of faithfully representing special characters, escape sequences, and Unicode variants introduced challenges in maintaining consistency between training and inference.
3. **Model Stability During Training**
   Early versions of the transformer exhibited unstable loss curves due to highly variable sequence lengths and the presence of rare byte patterns. This required specialized padding masks, learning-rate scheduling, and careful regularization.
4. **Context-to-Payload Alignment**
   Ensuring the model correctly interpreted structured metadata (such as `<ATTACK_CLASS>` labels) required additional preprocessing logic and multiple ablation studies to

verify attention alignment.

5. **Microservice Integration Overhead**
   Integrating the model into a containerized microservice pipeline introduced latency, serialization constraints, and cross-module communication issues, particularly during high-volume inference.
6. **Sandboxed Evaluation Environment**
   Building a controlled, safe execution environment for evaluating generated payloads was non-trivial, as it required strict isolation to prevent unintended script execution or security risks.
7. **Obfuscation Module Early-Stage Limitations**
   Although the initial obfuscation module worked for basic encoding transformations, more advanced dynamic or multi-stage obfuscation strategies remain challenging and require further model guidance.

4.3 Work in Progress

The project is ongoing with several components under active development. The transformer payload generator has reached a functional stage, but optimization, integration, and extended evaluation remain areas of focus. Improvements to the context extraction module, obfuscation mechanisms, and data pipeline orchestration are currently underway. Additional evaluation experiments and adversarial robustness testing are also planned to ensure practical usability.

4.3.1 Remaining Tasks

The remaining tasks for the project include integrating advanced obfuscation techniques such as dynamic JavaScript-based transformations, multi-stage encoding, and adversarial mutation strategies. The context extraction module will be enhanced to better handle nested HTML structures, script-block boundaries, and complex dynamic DOM behaviors. Further model retraining and hyperparameter tuning are planned, involving extended training cycles, refined datasets, larger batch sizes, learning-rate sweeps, and experiments with deeper model architectures. The system will also be benchmarked against established tools including XSStrike, DalFox, and commercial vulnerability scanners. Additional work includes developing a web-based dashboard for visualizing discovered vulnerabilities, payload performance, and scan metrics; strengthening microservice security with API gateways, rate limiting, mTLS, and container isolation; and establishing a WAF adversarial testing loop using ML-based detectors to create a feedback-driven defensive–offensive training environment. Finally, full end-to-end pipeline optimization will be performed to enhance orchestration, reduce inference latency, and ensure stable, high-throughput performance across all modules.

4.4 Project Scheduling

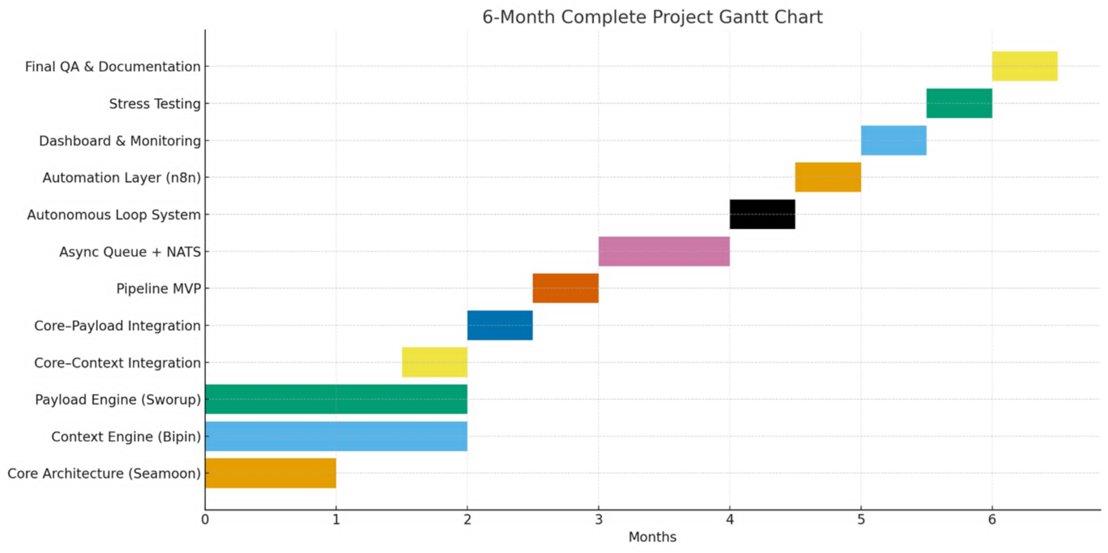


Figure 4.4.1: Gantt Chart Showing Work Schedule

5. CONCLUSION AND FUTURE WORK

This mid-term report has detailed the design, development, and initial evaluation of Red Sentinel, a machine learning–driven system for generating context-aware XSS payloads. By leveraging transformer-based neural architectures, the project overcomes limitations of traditional signature-based scanners, enabling the creation of syntactically valid, context-adapted payloads capable of bypassing modern filtering mechanisms. The system is built on a modular microservice architecture consisting of a Context Extraction Module, a Payload Handler, and an Orchestration Core, ensuring scalability, maintainability, and flexibility in development. Experiments with GRU, LSTM, transformer, and T5-based models show that the byte-level transformer significantly outperforms recurrent models, producing structurally complex and execution-ready payloads tailored to HTML attributes, JavaScript contexts, event handlers, and URL parameters.

Dataset preparation involved assembling diverse payload sources, applying byte-level tokenization to preserve special characters, and constructing context-labeled training pairs. The obfuscation module further enhances evasion capabilities through encoding-based, structural, and dynamic transformations aimed at bypassing web application firewalls and pattern-matching defenses. These combined innovations demonstrate the system's technical feasibility and its potential impact on automated vulnerability discovery.

Future development will focus on expanding system integration through plugins for tools such as Burp Suite, OWASP ZAP, and Metasploit, along with establishing a continuous learning pipeline and enabling distributed scanning via containerized microservices. Evaluation and validation efforts will include comprehensive benchmarking against open-source and commercial scanners using standardized test beds like WebGoat and DVWA, systematic WAF evasion testing against major platforms, and user studies with security professionals to measure usability, effectiveness, and workflow integration.

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