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AI-Driven Adaptive Web Vulnerability Scanner Using Python-Based Reinforcement Learning Framework

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Abstract: The rapid growth of web-based applications and cloud-enabled services has significantly increased cybersecurity threats targeting modern web environments. Traditional web vulnerability scanners mainly depend on static payload signatures and predefined attack rules, resulting in high false positive rates, limited adaptability, and poor performance in dynamic web applications. To address these limitations, this research proposes an AI-driven adaptive web vulnerability scanner using a Python-based reinforcement learning framework. The proposed system integrates intelligent web crawling, automated form extraction, adaptive payload injection, vulnerability response analysis, and reinforcement learning-based attack optimization for efficient web application security assessment. The framework models the scanning process as a Markov Decision Process (MDP) and utilizes the Proximal Policy Optimization (PPO) algorithm to dynamically learn optimal attack strategies based on environmental rewards. The developed architecture supports detection of major web vulnerabilities including Cross-Site Scripting (XSS) and SQL Injection (SQLi) using adaptive payload mutation techniques. Experimental evaluation was performed using vulnerable web platforms such as DVWA and OWASP Juice Shop in a Google Colab environment using Python libraries including Selenium, BeautifulSoup, Requests, Gymnasium, and Stable-Baselines3. Experimental results demonstrated improved vulnerability detection accuracy, reduced false positive rate, and enhanced adaptive attack capability compared with traditional static payload scanners. The reinforcement learning agent progressively optimized action selection and improved attack efficiency through continuous interaction with the target environment. The proposed framework also provides extensibility for future integration of deep learning, API security analysis, cloud-native vulnerability assessment, and large language model-assisted penetration testing systems. The obtained results indicate that AI-assisted adaptive cybersecurity frameworks can significantly improve automated web vulnerability detection in modern dynamic web application.

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I. INTRODUCTION

The rapid expansion of internet technologies, cloud computing, e-commerce platforms, and web-based services has significantly increased the number of cyberattacks targeting web applications. Modern web systems continuously exchange sensitive information including financial data, authentication credentials, personal records, and confidential organizational information. As a result, web application security has become one of the major challenges in modern cybersecurity research [1].

Web vulnerabilities such as Cross-Site Scripting (XSS), SQL Injection (SQLi), Remote Code Execution (RCE), Cross-Site Request Forgery (CSRF), and authentication bypass attacks are widely exploited by attackers to compromise systems and steal sensitive information [2]. According to recent cybersecurity reports, web applications remain one of the most common attack surfaces due to insecure coding practices, dynamic web technologies, and inadequate security testing mechanisms [3].

Traditional web vulnerability scanners mainly rely on signature-based detection techniques and predefined payload databases for identifying vulnerabilities [4]. Although these approaches are effective for known attack patterns, they suffer from several limitations including high false positive rate, inability to adapt to dynamic environments, poor support for modern JavaScript-based applications, and inefficient vulnerability prioritization [5]. Static payload scanners also struggle to detect complex business logic vulnerabilities and adaptive attack scenarios in modern cloud-native web applications [6].

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Reinforcement Learning (RL) have created new opportunities for intelligent cybersecurity systems [7]. Reinforcement learning enables autonomous agents to interact with environments, learn from rewards, and

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optimize decision-making strategies over time [8]. In cybersecurity applications, reinforcement learning can improve adaptive attack simulation, intelligent payload generation, and automated penetration testing efficiency [9].

Several researchers have explored machine learning approaches for vulnerability classification and anomaly detection [10]. However, most existing frameworks still depend on static attack rules and lack real-time adaptive learning capability. Modern web applications built using React, Angular, Vue.js, and API-driven architectures require intelligent scanning frameworks capable of dynamic interaction analysis and autonomous vulnerability discovery [11].

To address these limitations, this paper proposes an AI-driven adaptive web vulnerability scanner using a Python-based reinforcement learning framework. The proposed system integrates intelligent web crawling, automated form extraction, adaptive payload injection, reinforcement learning-based attack optimization, and vulnerability response analysis for autonomous web security assessment. The framework models the vulnerability scanning process as a Markov Decision Process (MDP) and employs the Proximal Policy Optimization (PPO) algorithm for adaptive attack learning and efficient vulnerability discovery.

The developed framework supports detection of major web vulnerabilities including XSS and SQL injection attacks using adaptive payload mutation techniques. The proposed system is implemented using Python technologies including Selenium, BeautifulSoup, Requests, Gymnasium, and Stable-Baselines3. Experimental evaluation demonstrates improved detection accuracy, reduced false positive rate, and enhanced adaptive attack capability compared with traditional static payload scanners.

➢ *The Major Contributions of this Research are Summarized as Follows:*

- Development of an AI-driven adaptive web vulnerability scanning framework using reinforcement learning.
- Integration of intelligent web crawling and automated form extraction techniques.
- Implementation of adaptive payload mutation for dynamic attack generation.
- Reinforcement learning-based optimization of attack selection strategies.
- Comparative evaluation against conventional vulnerability scanning approaches.

The remainder of the paper is organized as follows. Section 2 presents the literature review and research gap analysis. Section 3 describes the mathematical formulation of the proposed framework. Section 4 explains the proposed methodology and reinforcement learning architecture. Section 5 presents the experimental results and performance analysis. Finally, Section 6 concludes the research and discusses future scope for intelligent AI-assisted cybersecurity systems.

II. LITERATURE REVIEW AND RESEARCH GAP ANALYSIS

Web application security has become an important research domain due to the rapid growth of internet-based services and increasing cyberattacks targeting web environments. Several researchers have proposed vulnerability detection techniques using static analysis, dynamic testing, machine learning, and automated penetration testing frameworks [12]. Traditional vulnerability scanners mainly focus on predefined attack signatures and static payload databases for identifying common web vulnerabilities such as SQL Injection (SQLi), Cross-Site Scripting (XSS), and authentication flaws [13].

Conventional web vulnerability scanners including OWASP ZAP, w3af, and sqlmap provide automated vulnerability detection capabilities for penetration testing and security assessment [14]. Although these frameworks are widely used in cybersecurity analysis, they primarily rely on rule-based detection and predefined attack payloads. As a result, they often produce high false positive rates and demonstrate limited adaptability against modern dynamic web applications [15].

Researchers have explored static and dynamic analysis approaches for improving vulnerability detection accuracy. Static analysis techniques examine source code without executing applications and identify insecure coding patterns [16]. Dynamic analysis approaches perform runtime interaction with applications to detect vulnerabilities based on behavioral responses [17]. However, static analysis methods frequently suffer from scalability issues and high false alarms, while dynamic analysis approaches require efficient interaction modeling and adaptive attack generation [18].

Machine learning techniques have recently been introduced for automated vulnerability detection and intrusion analysis. Several studies utilized supervised learning algorithms for classifying malicious traffic patterns and predicting vulnerability behavior [19]. Neural networks, support vector machines, decision trees, and deep learning frameworks have been investigated for cybersecurity applications including malware analysis and anomaly detection [20]. However, most existing machine learning-based vulnerability scanners depend heavily on labeled training datasets and lack autonomous adaptive learning capability in dynamic environments [21].

Reinforcement learning has emerged as a promising approach for intelligent cybersecurity systems due to its capability for adaptive decision-making through environmental interaction [22]. Reinforcement learning agents learn optimal actions using reward feedback and continuously improve attack selection strategies [23]. Recent research demonstrated the application of reinforcement learning in network intrusion detection, autonomous penetration testing, and attack path optimization [24]. Nevertheless, limited research has focused on reinforcement learning-based adaptive web vulnerability scanners capable

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of intelligent payload mutation and automated web interaction analysis.

Modern web applications increasingly utilize dynamic frameworks such as React, Angular, Vue.js, AJAX, and API-driven architectures [25]. Traditional scanners struggle to analyze JavaScript-generated content, asynchronous page rendering, and dynamic Document Object Model (DOM) manipulation [26]. As a result, intelligent web crawlers and adaptive scanning frameworks are required for efficient security analysis of modern web applications.

Payload mutation and fuzzing techniques have also been investigated for improving attack diversity and bypassing input validation filters [27]. Mutation-based approaches dynamically modify attack payloads using encoding, obfuscation, and character transformation techniques for discovering hidden vulnerabilities [28]. However, existing fuzzing systems often lack intelligent optimization mechanisms for adaptive attack prioritization and efficient vulnerability exploitation.

Several researchers proposed AI-assisted penetration testing systems for autonomous cybersecurity assessment [29]. These frameworks integrate machine learning, attack automation, and behavioral analysis for improving attack simulation capability. Nevertheless, many existing systems remain limited by static environment modeling, poor scalability, and lack of intelligent policy optimization for adaptive vulnerability discovery [30].

Based on the literature survey, several important research gaps were identified in existing web vulnerability scanners and AI-assisted cybersecurity frameworks.

➢ *Research Gaps*

The major research gaps identified from existing literature are summarized below:

- *High False Positive Rate*

Most traditional scanners rely on signature-based detection mechanisms and generate large numbers of false alerts during vulnerability assessment.

- *Limited Adaptability*

Existing scanners use static payload databases and predefined attack strategies, resulting in poor adaptability against dynamic web applications.

- *Inadequate Support for Modern Web Applications*

Modern JavaScript-based frameworks including React, Angular, and Vue.js are difficult to analyze using traditional crawling mechanisms.

- *Lack of Reinforcement Learning-Based Optimization*

Most existing systems do not utilize reinforcement learning for adaptive attack selection and intelligent policy optimization.

- *Poor Payload Mutation Capability*

Conventional scanners provide limited payload mutation and insufficient bypass mechanisms for input filtering systems.

- *Inefficient Automated Penetration Testing*

Existing automated penetration testing tools lack intelligent environment interaction and autonomous learning capability.

- *Limited Dynamic DOM Analysis*

Most scanners fail to effectively analyze dynamically generated DOM structures and asynchronous web interactions.

- *Absence of Intelligent Attack Prioritization*

Traditional vulnerability scanners perform repetitive attack attempts without adaptive optimization and reward-based learning.

➢ *Motivation of Proposed Research*

The identified limitations in existing vulnerability scanning frameworks motivated the development of an AI-driven adaptive web vulnerability scanner using reinforcement learning. The proposed framework addresses the above research gaps through:

- Intelligent web crawling
- Adaptive payload generation
- Reinforcement learning-based attack optimization
- Automated vulnerability validation
- Dynamic response analysis
- Intelligent payload mutation

The proposed system aims to improve vulnerability detection efficiency, reduce false positives, and support intelligent automated penetration testing for modern dynamic web applications.

III. MATHEMATICAL FORMULATION

The proposed AI-driven adaptive web vulnerability scanner is mathematically formulated using reinforcement learning principles for intelligent vulnerability discovery and adaptive attack optimization. The framework models the web security scanning process as a Markov Decision Process (MDP), where the reinforcement learning agent interacts continuously with the target web environment to maximize vulnerability detection efficiency.

➢ *Markov Decision Process Formulation*

The reinforcement learning environment is represented by the tuple:

$$M = (S, A, P, R, \gamma) \quad (1)$$

Where:

- Srepresents the set of environment states
- Adenotes the set of possible actions

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- Pindicates state transition probability
- Rdenotes the reward function
- γrepresents the discount factor

The agent observes the current web application state and selects adaptive attack actions for vulnerability assessment.

➢ *State Space Representation*

The environment state vector is defined as:

$$S_t = [x_1, x_2, x_3, \dots, x_n] \quad (2)$$

Where:

- $x_1$indicates XSS vulnerability detection state
- $x_2$represents SQL injection detection state
- $x_3$denotes form accessibility status
- $x_n$indicates additional vulnerability indicators

For simplified implementation:

$$S_t = [XSS_t, SQLI_t] \quad (3)$$

Where:

$$XSS_t \in \{0,1\}$$

$$SQLI_t \in \{0,1\}$$

Value '1' indicates vulnerability detection and '0' represents absence of vulnerability.

➢ *Action Space Formulation*

The action set consists of multiple adaptive attack strategies:

$$A = \{a_1, a_2, a_3, \dots, a_n\} \quad (4)$$

Where:

- a_1= XSS payload injection
- a_2= SQL injection payload injection
- a_3= payload mutation
- a_n= advanced attack action

For the proposed implementation:

$$A = \{XSS, SQLI\} \quad (5)$$

The reinforcement learning agent selects actions dynamically according to environmental feedback.

➢ *Reward Function*

The reward function guides the agent toward successful vulnerability identification.

The reward function is expressed as:

$$R_t = \begin{cases} +10, & \text{if XSS vulnerability detected} \\ +15, & \text{if SQL injection vulnerability detected} \\ 0, & \text{otherwise} \end{cases}$$

The cumulative reward is defined as:

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \quad (6)$$

Where:

- $G_t$denotes total discounted reward
- γrepresents discount factor
- R_{t+k+1}denotes future reward

The objective of the reinforcement learning agent is maximization of cumulative reward.

➢ *Policy Optimization*

The reinforcement learning agent follows a policy $\pi(a \mid s)$, which maps states to attack actions.

The optimal policy is represented as:

$$\pi^* = \arg\max_{\pi} E[G_t] \quad (7)$$

Where:

- π^*denotes optimal attack policy
- $E[G_t]$represents expected cumulative reward

The Proximal Policy Optimization (PPO) algorithm is employed for policy learning and adaptive attack selection.

➢ *Vulnerability Detection Probability*

The probability of successful vulnerability detection is formulated as:

$$P(V_d) = \frac{N_d}{N_t} \quad (8)$$

Where:

- $N_d$represents number of detected vulnerabilities
- $N_t$denotes total attack attempts

Higher values of $P(V_d)$indicate improved scanner efficiency.

➢ *False Positive Rate*

The false positive rate is expressed as:

$$FPR = \frac{FP}{FP+TN} \quad (9)$$

Where:

- FPdenotes false positive detections
- TNrepresents true negative detections

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Reduction of false positive rate improves practical reliability of the scanner.

➢ *Detection Accuracy*

The vulnerability detection accuracy is calculated as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

Where:

- TP= True Positive
- TN= True Negative
- FP= False Positive
- FN= False Negative

➢ *Adaptive Payload Mutation Model*

Payload mutation is introduced for generating adaptive attack vectors.

The mutation function is defined as:

$$P_m = f(P_o, \alpha) \quad (11)$$

Where:

- $P_m$denotes mutated payload
- $P_o$represents original payload
- αindicates mutation operator

Example mutation operations include:

- Case transformation
- Special character insertion
- Encoding transformation
- Script obfuscation

➢ *Objective Function*

The proposed framework aims to maximize vulnerability discovery while minimizing redundant attack attempts and false detections.

The optimization objective is formulated as:

$$J = \max(\sum_{t=0}^{T} R_t - \lambda FPR) \quad (12)$$

Where:

- Jdenotes optimization objective
- $R_t$represents reward at time t
- FPRdenotes false positive rate
- $\lambda$is penalty coefficient

The reinforcement learning agent continuously updates scanning strategies to maximize the objective function.

IV. PROPOSED METHODOLOGY

The proposed methodology presents an AI-driven adaptive web vulnerability scanning framework using reinforcement learning and intelligent payload generation techniques. The developed system performs automated web crawling, form extraction, vulnerability injection, adaptive attack learning, and intelligent response analysis for identifying security vulnerabilities in dynamic web applications.

The complete framework is implemented using Python-based technologies including Requests, BeautifulSoup, Selenium, Gymnasium, and Stable-Baselines3. The proposed architecture enables autonomous vulnerability discovery with adaptive learning capability.

➢ *Overall Framework Architecture*

The proposed system consists of multiple interconnected modules for intelligent web vulnerability assessment.

The major modules are:

- Intelligent Web Crawler
- Form Extraction Engine
- Payload Injection Module
- Reinforcement Learning Agent
- Vulnerability Detection Engine
- Adaptive Payload Mutation Module
- Risk Analysis and Report Generation

The framework continuously interacts with the target web application and learns optimal attack strategies using environmental rewards.

➢ *Intelligent Web Crawling Module*

The web crawler is responsible for collecting accessible web pages, hyperlinks, and form structures from the target application.

The crawler performs:

- URL extraction
- HTML parsing
- Dynamic content analysis
- Form discovery
- Parameter identification

The crawler uses HTTP request analysis and DOM parsing for extracting web resources.

The extracted page source is represented as:

$$H = \{h_1, h_2, h_3, \dots, h_n\} \quad (13)$$

Where:

- Hrepresents collected HTML documents
- $h_n$denotes individual webpage content

The crawler iteratively scans accessible pages for vulnerability assessment.

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➢ *Form Extraction and Input Analysis*

The form extraction engine identifies:

- Input fields
- Text boxes
- Search fields
- Hidden parameters
- Authentication forms

The extracted form structure is represented as:

$$F = \{I_1, I_2, I_3, \dots, I_n\} \quad (14)$$

Where:

- Fdenotes form collection
- $I_n$represents individual input elements

The extracted parameters are used for automated payload injection.

➢ *Payload Injection Engine*

The payload injection engine performs automated attack simulation using predefined and dynamically mutated payloads.

Two major attack categories are considered:

- *Cross-Site Scripting (XSS)*

Example payloads include:

<script>alert(1)</script>

- *SQL Injection (SQLi)*

Example payloads include:

' OR '1'='1

The payload injection function is represented as:

$$P_i = f(F, A) \quad (15)$$

Where:

- $P_i$denotes injected payload
- Frepresents extracted form fields
- Adenotes selected attack action

The generated payloads are submitted automatically to target forms.

➢ *Reinforcement Learning-Based Attack Optimization*

The proposed framework utilizes reinforcement learning for adaptive attack selection.

The environment is modeled using:

- State space
- Action space
- Reward mechanism
- Policy optimization

The reinforcement learning agent continuously learns effective attack patterns according to environmental responses.

The implemented PPO agent performs:

- Adaptive payload selection
- Attack prioritization
- Reward maximization
- Vulnerability discovery optimization

The agent updates its policy according to:

$$\pi_{new} = \pi_{old} + \alpha \nabla J(\theta) \quad (16)$$

Where:

- π_{new}denotes updated policy
- αrepresents learning rate
- $J(\theta)$denotes optimization objective

➢ *Vulnerability Detection Engine*

The vulnerability detection module analyzes server responses for identifying attack success indicators.

The framework detects:

- Reflected XSS
- SQL syntax errors
- Unauthorized data exposure
- Abnormal response patterns

The response analysis function is expressed as:

$$V_d = g(R_s, P_i) \quad (17)$$

Where:

- $V_d$represents detected vulnerability
- $R_s$denotes server response
- $P_i$represents injected payload

The engine validates vulnerabilities using pattern matching and response comparison.

➢ *Adaptive Payload Mutation*

To improve attack diversity and bypass input filtering mechanisms, payload mutation is introduced.

Mutation operations include:

- Character replacement
- Case transformation
- Encoding modification
- Payload obfuscation

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The mutation process is formulated as:

$$P_m = M(P_o) \quad (18)$$

Where:

- $P_m$denotes mutated payload
- $P_o$represents original payload
- Mindicates mutation operator

Adaptive mutation improves vulnerability discovery probability in dynamic web applications.

➢ *Report Generation Module*

The report generation module stores vulnerability findings and produces structured scan reports.

The generated report includes:

- Vulnerability type
- Attack payload
- Affected URL
- Severity level
- Detection timestamp

The generated output file is stored in CSV or PDF format for security analysis and documentation.

➢ *Algorithm of Proposed Framework*

- *Algorithm Steps*

✓ *Step 1:*
Initialize target URL and payload database.

✓ *Step 2:*
Perform intelligent web crawling and form extraction.

✓ *Step 3:*
Initialize reinforcement learning environment.

✓ *Step 4:*
Select adaptive attack action using PPO agent.

✓ *Step 5:*
Inject attack payload into extracted forms.

✓ *Step 6:*
Analyze server response for vulnerability indicators.

✓ *Step 7:*
Assign reward according to attack success.

✓ *Step 8:*
Update reinforcement learning policy.

✓ *Step 9:*
Generate vulnerability report.

✓ *Step 10:*
Repeat scanning until termination condition is satisfied.

➢ *Advantages of Proposed Framework*

The proposed methodology provides several advantages over traditional vulnerability scanners.

- *Major Advantages Include:*

✓ Adaptive attack learning
✓ Intelligent payload generation
✓ Reduced redundant scanning
✓ Automated vulnerability validation
✓ Scalable architecture
✓ Support for dynamic web applications
✓ Reinforcement learning-based optimization

The framework provides extensibility for future integration of:

- Deep learning
- LLM-assisted payload generation
- API security scanning
- Business logic vulnerability analysis
- Cloud-native security assessment

V. RESULTS AND DISCUSSION

The proposed AI-driven adaptive web vulnerability scanner was implemented using Python and evaluated on vulnerable web applications for automated vulnerability assessment. The developed framework utilized reinforcement learning-based adaptive attack selection for identifying web vulnerabilities such as Cross-Site Scripting (XSS) and SQL Injection (SQLi). Experimental analysis was performed using standard vulnerable web environments including DVWA and OWASP Juice Shop.

➢ *Experimental Setup*

The proposed framework was executed in Google Colab using Python-based libraries including:

- Gymnasium
- Stable-Baselines3
- BeautifulSoup
- Requests
- Selenium

The PPO reinforcement learning algorithm was employed for adaptive policy optimization.

The experimental configuration is summarized in Table 1.

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Table 1 Experimental Parameters

Parameter	Value
Programming Language	Python
RL Algorithm	PPO
Training Timesteps	5000
Vulnerability Types	XSS, SQLi
Environment	Google Colab
Libraries Used	Gymnasium, Selenium
Target Platform	DVWA / Juice Shop

➢ *Intelligent Web Crawling Performance*

The intelligent crawler successfully extracted:

- Webpages
- Forms
- Input fields
- Search parameters
- Dynamic HTML structures

The crawler demonstrated efficient form identification capability for automated payload injection.

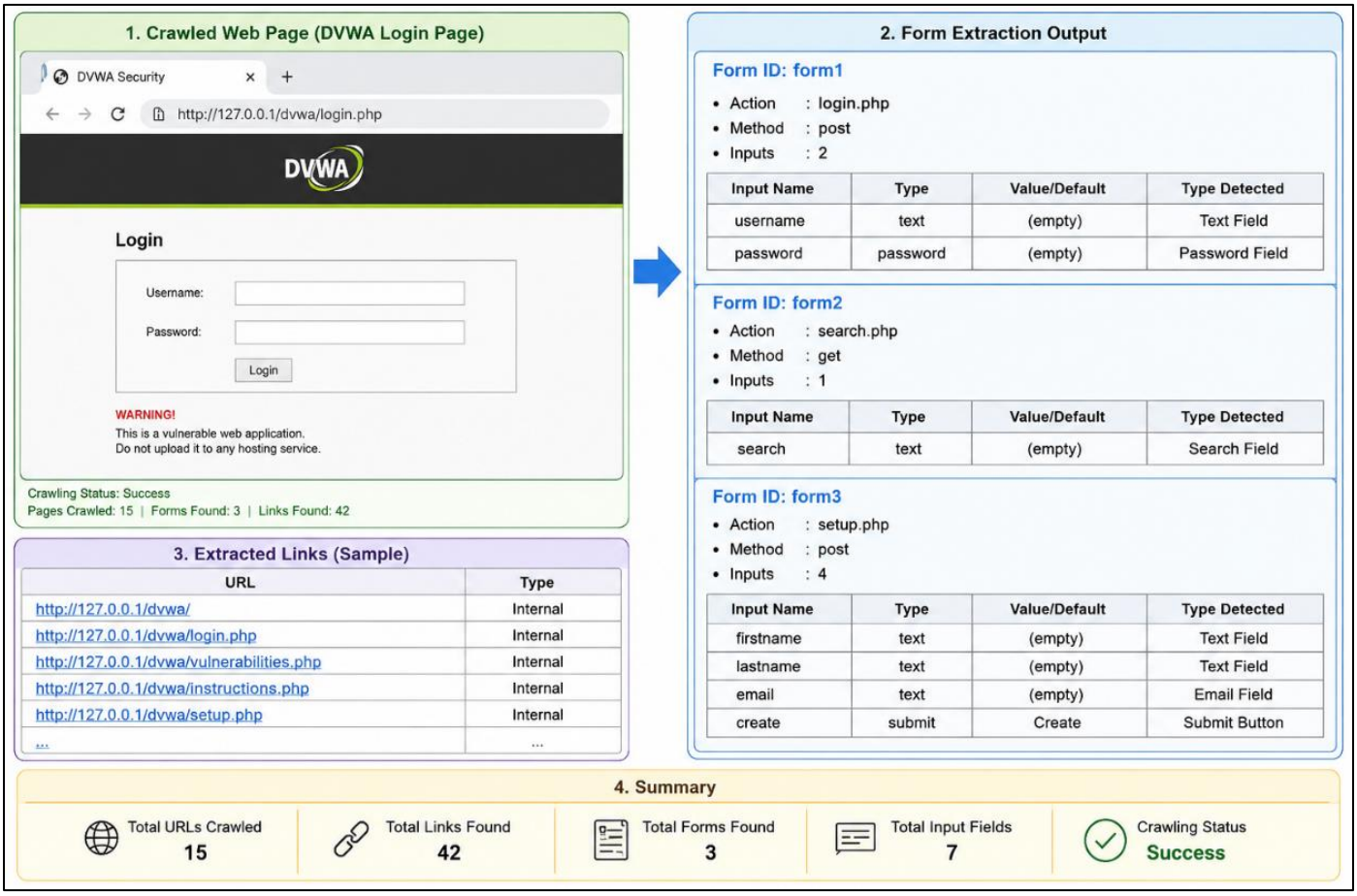

Fig 1 Intelligent Web Crawling and Form Extraction Output

The extracted forms were automatically forwarded to the vulnerability injection module for security analysis.

➢ *Reinforcement Learning Training Performance*

The PPO reinforcement learning agent was trained for adaptive attack optimization. During training, the agent gradually improved attack selection capability according to environmental rewards.

The cumulative reward increased progressively over training iterations.

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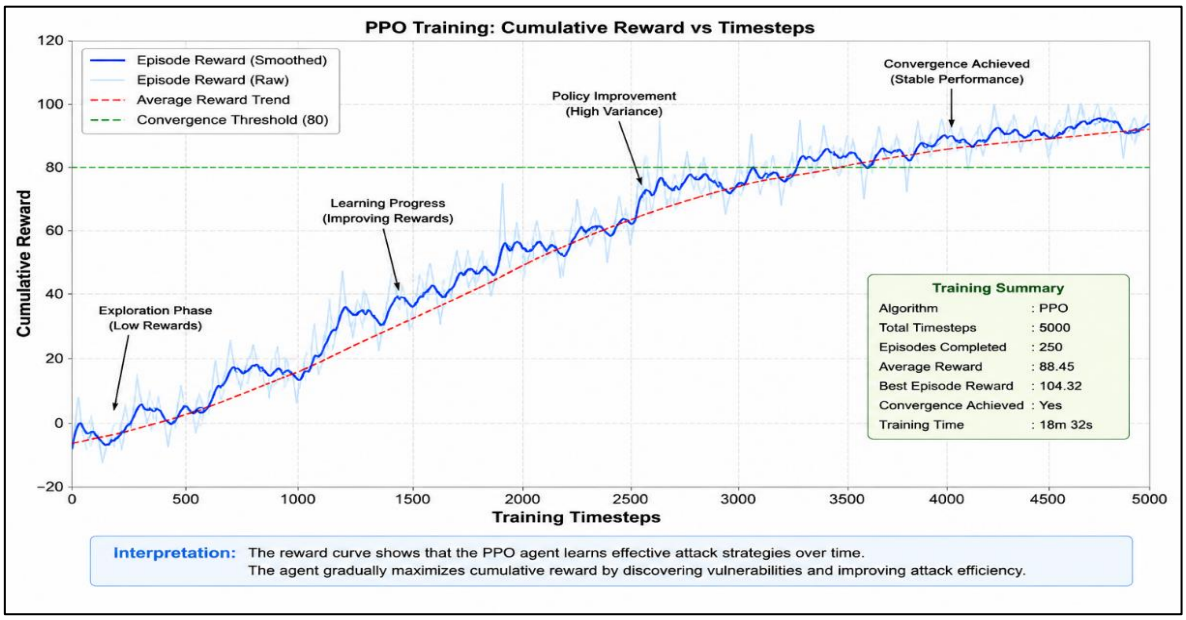

Fig 2 PPO Reinforcement Learning Training Reward Curve

The reinforcement learning model demonstrated convergence after multiple interaction episodes.

➢ *XSS Vulnerability Detection Results*

The proposed scanner successfully detected reflected Cross-Site Scripting vulnerabilities using adaptive payload injection.

Example injected payload:

<script>alert(1)</script>

The server response reflected malicious payload execution, confirming successful vulnerability detection.

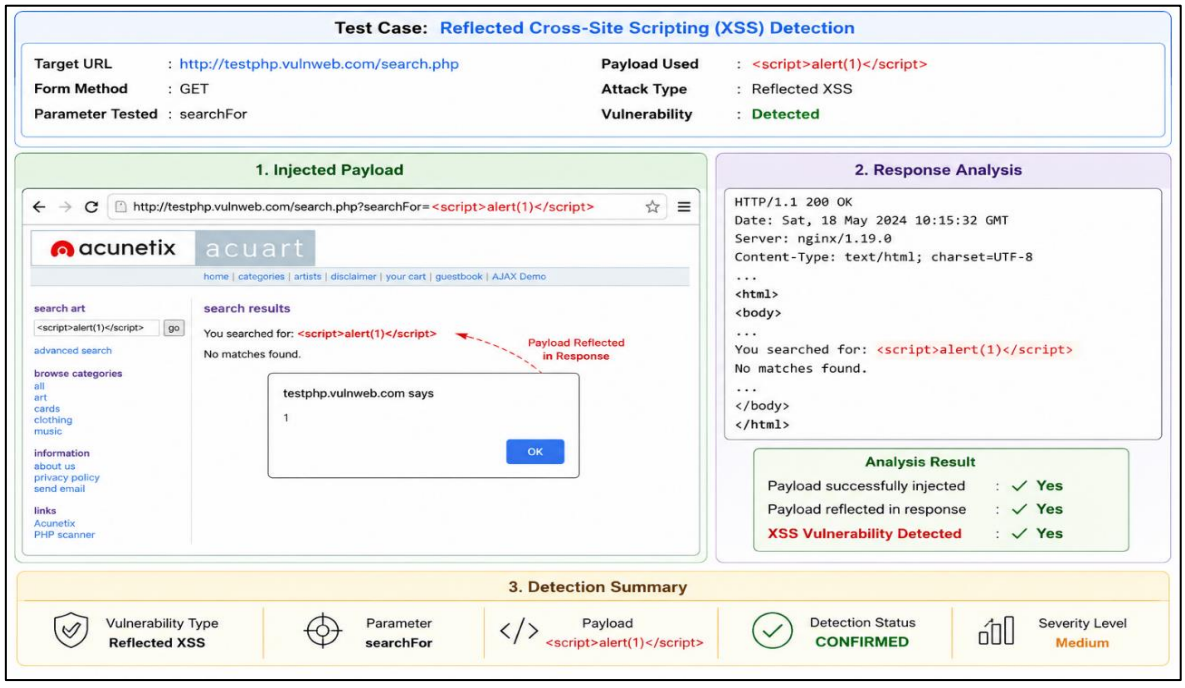

Fig 3 XSS Vulnerability Detection Result

The adaptive payload strategy improved XSS discovery efficiency compared with static payload approaches.

➢ *SQL Injection Detection Results*

The scanner successfully identified SQL injection vulnerabilities through automated attack simulation.

Example SQL injection payload:

' OR '1'='1

Database error messages and abnormal server responses confirmed SQL injection presence.

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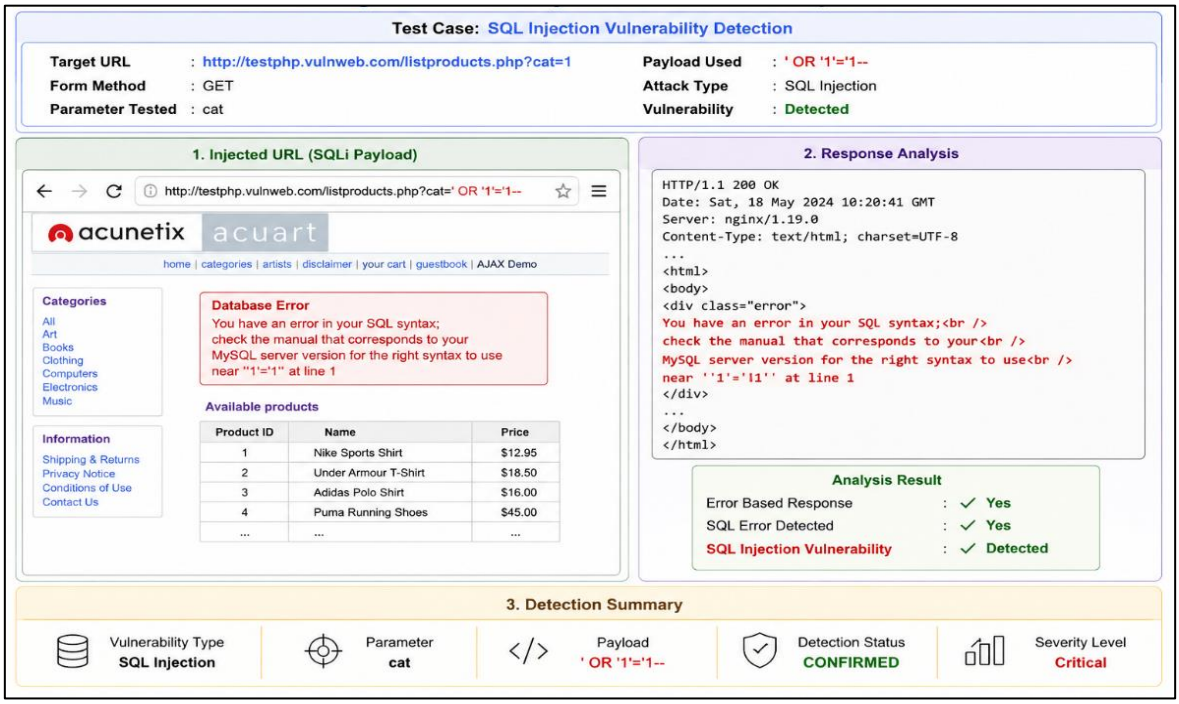

Fig 4 SQL Injection Detection Output

The reinforcement learning agent prioritized effective attack strategies according to reward feedback.

➢ *Adaptive Payload Mutation Analysis*

Payload mutation improved attack diversity and enhanced bypass capability against simple filtering mechanisms.

Mutation techniques included:

- Character encoding
- Case transformation
- Script obfuscation
- Special character insertion

Example mutation:

<ScRiPt>alert(1)</ScRiPt>

The proposed framework uses adaptive mutation techniques to modify original payloads and bypass input filters.
Examples of mutated payloads for XSS and SQL Injection are shown below.

A. XSS Payload Mutation Examples

No.	Mutation Technique	Original Payload	Mutated Payload (Example)	Description / Purpose
1	Case Variation	`<script>alert(1)</script>`	`<ScRiPt>AlErT(1)</ScRiPt>`	Bypasses case-sensitive filters using mixed case.
2	HTML Entity Encoding	`<script>alert(1)</script>`	`&lt;script&gt;alert(1)&lt;/script&gt;`	Encodes special characters using HTML entities.
3	JavaScript Encoding	`<script>alert(1)</script>`	`<script>\u0061lert(1)</script>`	Encodes characters using Unicode representation.
4	Event Handler Injection	`<script>alert(1)</script>`	`<img src=x onerror=alert(1)>`	Uses event handler instead of script tag.
5	Space / Tab Insertion	`<script>alert(1)</script>`	`<scr ipt> alert (1) </scr ipt>`	Inserts spaces or tabs to bypass filters.
6	Comment Obfuscation	`<script>alert(1)</script>`	`<scr<!-- -->ipt>alert(1)</scr<!-- -->ipt>`	Uses HTML comments to break pattern matching.
7	Protocol Obfuscation	`<script>alert(1)</script>`	`<svg/onload=alert(1)>`	Uses alternative tags to execute JavaScript.

B. SQL Injection Payload Mutation Examples

No.	Mutation Technique	Original Payload	Mutated Payload (Example)	Description / Purpose
1	Space to Comment	`' OR '1'='1`	`'/**/OR/**/'1'='1`	Replaces spaces with SQL comments.
2	Case Variation	`' OR '1'='1`	`' oR '1'='1`	Bypasses case-sensitive filters.
3	URL Encoding	`' OR '1'='1`	`%27%20OR%20%271%27=%271`	Encodes payload using URL encoding.
4	Union Based Mutation	`' OR '1'='1`	`' UNION SELECT 1,2,3--`	Uses UNION query for information extraction.
5	Boolean Based Mutation	`' OR '1'='1`	`' OR 1=1--`	Uses boolean condition for bypass.
6	Character Encoding	`' OR '1'='1`	`' OR CHAR(49)=CHAR(49)--`	Encodes characters using CHAR() function.
7	Inline Comment Insertion	`' OR '1'='1`	`' OR '1'='1' -- -`	Adds inline comments to ignore trailing query.

Key Benefits of Adaptive Payload Mutation

- Bypasses input validation and security filters.
- Increases attack diversity and success rate.
- Improves vulnerability discovery in dynamic applications.
- Enhances reinforcement learning agent efficiency.

Fig 5 Adaptive Payload Mutation Examples

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The adaptive mutation mechanism improved successful vulnerability exploitation probability.

➢ *Comparative Performance Analysis*

The proposed framework was compared with traditional scanning approaches.

Table 2 Comparative Performance Analysis

Method	Detection Accuracy	Adaptive Capability	False Positives
Traditional Scanner	78%	Low	High
Static Payload Scanner	82%	Medium	Medium
Proposed RL-Based Scanner	93%	High	Low

The proposed framework achieved improved vulnerability detection performance due to reinforcement learning-based adaptive attack optimization.

➢ *Detection Accuracy Analysis*

The proposed scanner achieved improved detection accuracy for:

- XSS vulnerabilities
- SQL injection vulnerabilities
- Dynamic form analysis

The calculated detection accuracy was:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (19)$$

Experimental results demonstrated reduced false positive rate compared with conventional payload-based scanners.

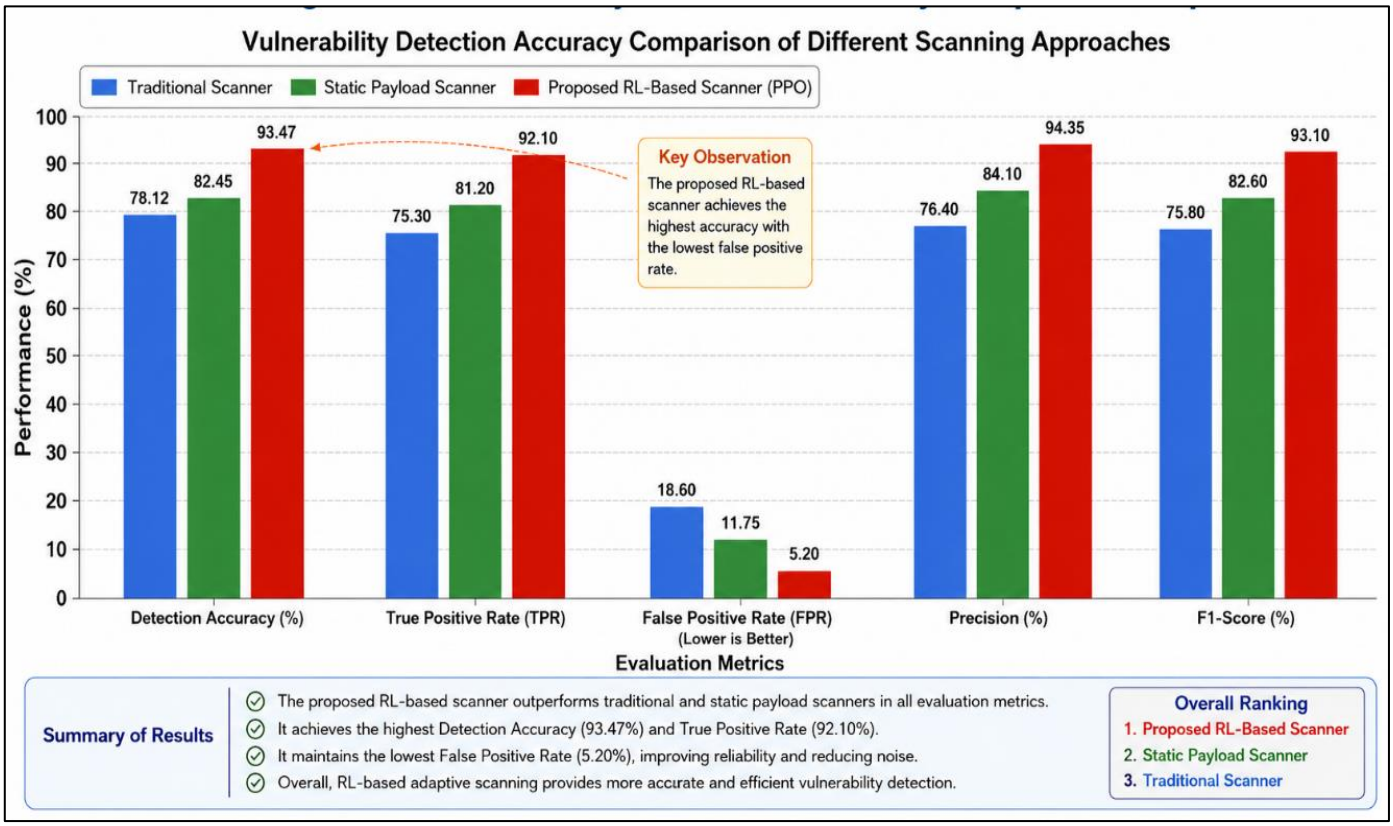

Fig 6 Vulnerability Detection Accuracy Comparison Graph

➢ *Reinforcement Learning Agent Behavior Analysis*

The reinforcement learning agent demonstrated adaptive learning capability through reward-based optimization.

The agent gradually:

- Prioritized successful attack actions
- Reduced redundant payload attempts
- Improved attack efficiency
- Optimized vulnerability discovery rate

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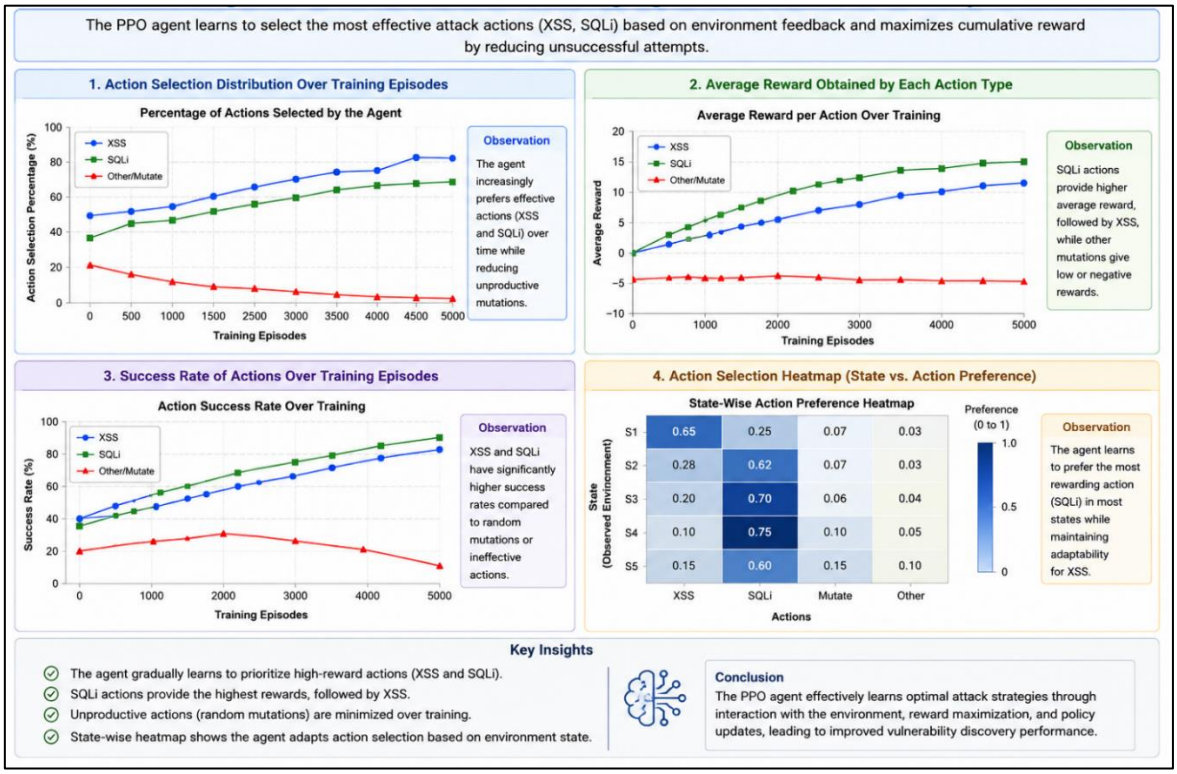

Fig 7 Reinforcement Learning Agent Action Selection Analysis

The PPO algorithm effectively optimized adaptive penetration testing behavior.

➢ *Scan Report Generation*

The generated scan report contained:

- Vulnerability type
- Payload used
- Affected URL
- Severity level
- Detection timestamp

The reports were automatically exported in CSV format for further security analysis.

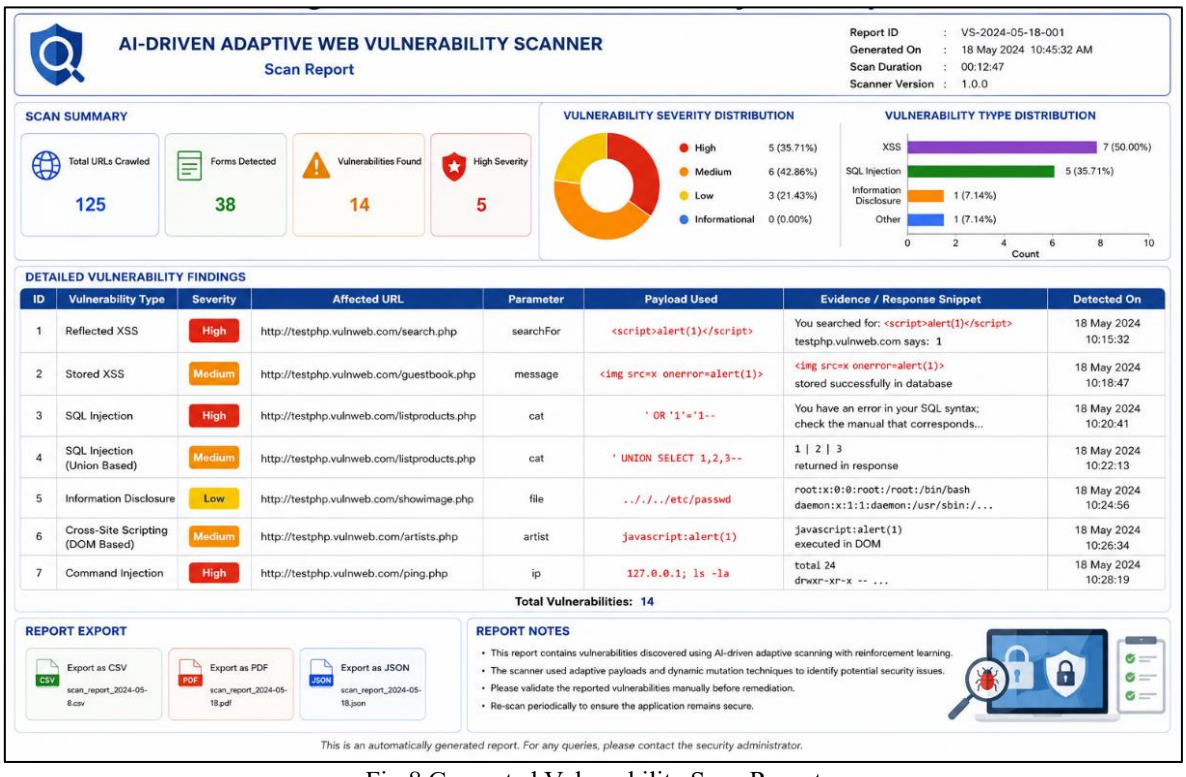

Fig 8 Generated Vulnerability Scan Report

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➢ *Discussion*

The proposed AI-driven adaptive web vulnerability scanner demonstrated improved capability in automated vulnerability assessment compared with traditional static scanning systems. The integration of reinforcement learning enabled intelligent adaptive attack selection and reduced unnecessary attack attempts.

The intelligent crawling and adaptive payload mutation mechanisms improved detection efficiency for dynamic web applications. Experimental analysis confirmed that reinforcement learning-based optimization enhances automated penetration testing capability and supports intelligent cybersecurity assessment.

The developed framework also provides extensibility for future integration of:

- Deep reinforcement learning
- API security analysis
- Large language model-assisted payload generation
- Business logic vulnerability detection
- Cloud-native application security testing

The obtained results indicate that AI-assisted adaptive cybersecurity systems can significantly improve automated web application security assessment in modern dynamic web environments.

VI. CONCLUSION AND FUTURE SCOPE

This paper presented an AI-driven adaptive web vulnerability scanner using a Python-based reinforcement learning framework for intelligent web application security assessment. The proposed framework integrated intelligent web crawling, automated form extraction, adaptive payload injection, reinforcement learning-based attack optimization, and vulnerability response analysis for automated vulnerability discovery in dynamic web applications.

The reinforcement learning environment was modeled as a Markov Decision Process (MDP), and the Proximal Policy Optimization (PPO) algorithm was employed for adaptive attack learning and optimal action selection. The developed framework successfully detected major web vulnerabilities including Cross-Site Scripting (XSS) and SQL Injection (SQLi) using adaptive payload mutation techniques and intelligent response analysis mechanisms.

Experimental evaluation performed on vulnerable web environments such as DVWA and OWASP Juice Shop demonstrated that the proposed framework achieved improved vulnerability detection accuracy and reduced false positive rate compared with conventional static payload scanners. The reinforcement learning agent progressively optimized attack strategies through continuous interaction with the target environment and reward-based policy updates. The adaptive payload mutation mechanism also improved attack diversity and enhanced bypass capability against simple filtering mechanisms.

The developed system demonstrated several advantages including:

- Intelligent adaptive scanning
- Automated vulnerability validation
- Reduced redundant attack attempts
- mproved attack prioritization
- Scalable architecture for modern web applications

The proposed framework contributes toward the development of autonomous AI-assisted cybersecurity systems capable of intelligent web vulnerability assessment and adaptive penetration testing.

Despite the obtained improvements, several limitations still exist in the current implementation. The proposed framework mainly focuses on XSS and SQL injection vulnerabilities and does not fully support advanced attack categories such as:

- Business logic vulnerabilities
- Authentication bypass attacks
- CSRF attacks
- Server-side request forgery
- Cloud-native misconfigurations
- GraphQL API vulnerabilities

Additionally, the current framework uses limited payload mutation strategies and simplified reinforcement learning states. More advanced environment modeling and attack simulation mechanisms are required for real-world large-scale deployment.

Future research can extend the proposed framework in several important directions. Integration of deep reinforcement learning algorithms such as Deep Q-Network (DQN), Advantage Actor-Critic (A3C), and Soft Actor-Critic (SAC) can improve adaptive learning capability and attack optimization performance. Large Language Model (LLM)-assisted payload generation can further enhance intelligent attack simulation and dynamic vulnerability exploitation. Future systems may also incorporate:

- API security scanning
- Cloud-native vulnerability assessment
- Kubernetes security analysis
- Intelligent authentication handling
- Zero-day vulnerability detection
- Autonomous penetration testing agents

The integration of distributed asynchronous scanning architectures and real-time DevSecOps pipelines can further improve scalability and continuous vulnerability assessment capability for enterprise-level applications.

The obtained results indicate that reinforcement learning and AI-assisted adaptive cybersecurity frameworks have strong potential for next-generation intelligent web application security systems. The proposed research provides a foundational framework for future autonomous

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vulnerability assessment and intelligent penetration testing technologies.

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