Zero-False-Positive Web Vulnerability Scanner: A Hybrid System with Random Forest–Based Payload Validation and Automated Injection Testing

Dr. M.K. Jayanthi Kannan[1], Atharva Dandwate[2], Sarthak Singh[3], Abhay Kumar[4], Pranjal Chhetri[5], Debjeet Debnath[6], Adarsh Bhardwaj[7]

[1]*Professor, VIT Bhopal University, Bhopal-Indore Highway, Kothrikalan, Sehore, Madhya Pradesh - 466114.*

[2,3,4,5,6,7]*Student School of Computing Science and Engineering,VIT Bhopal University, Bhopal-Indore Highway, Kothrikalan, Sehore, Madhya Pradesh - 466114.*

***Abstract*—With the rapid growth of web applications, security vulnerabilities such as SQL Injection (SQLi) and Cross-Site Scripting (XSS) pose serious threats to data integrity and user privacy. This project presents a Web Vulnerability Scanner that integrates Machine Learning (Random Forest Classifier) with automated payload injection testing to detect potential vulnerabilities in web applications. The system extracts HTML forms from a target website, injects malicious payloads, and analyses responses to determine vulnerability presence. Additionally, an ML model is used to classify payloads as malicious or safe traffic. The system is implemented using Python, Flask, Beautiful Soup, and Scikit-learn, providing both backend scanning logic and a web interface. The scanner successfully identifies vulnerabilities such as SQL Injection by analysing server responses (e.g., database errors or compromised outputs). This approach combines AI-based detection with real-world attack simulation, improving accuracy and practical applicability. Keywords: Web Security, SQL Injection, XSS, Machine Learning, Vulnerability Scanner, Cybersecurity. Web applications are ubiquitous but remain prime targets for cyberattacks, with SQL Injection (SQLi) and Cross-Site Scripting (XSS) consistently ranking among the most critical vulnerabilities. Traditional vulnerability scanners rely heavily on signature-based detection, which often leads to high false-positive rates and fails to identify novel or obfuscated attack vectors. This paper presents a hybrid web vulnerability scanner that combines automated injection testing with a machine learning (ML) component to improve detection accuracy and reduce false alarms. The system first crawls a target website to extract all input-bearing HTML forms. Experimental evaluation on deliberately vulnerable applications (e.g., DVWA, bWAPP) shows that the proposed system achieves a detection accuracy of 94.5% for SQLi and 91.2% for XSS, while reducing false positives by approximately 30% compared to a purely signature-based approach. This work demonstrates that integrating machine learning with active injection testing yields a more reliable and adaptive web vulnerability scanner.**

***Index Terms*—Web Security, SQL Injection, Cross-Site Scripting, Vulnerability Scanner, Machine Learning, Random Forest, Cybersecurity**

I. INTRODUCTION

Web applications are increasingly targeted by cyberattacks, making security a critical concern. Common vulnerabilities such as SQL Injection (SQLi) and Cross-Site Scripting (XSS) allow attackers to manipulate databases or execute malicious scripts. Traditional vulnerability scanners rely on predefined rules and signatures, which may fail to detect new or obfuscated attacks. To address this limitation, this project introduces a hybrid approach combining: Machine Learning-based payload classification, Automated real-time injection testing. The system scans a target URL, identifies forms, injects malicious payloads, and evaluates server responses to detect vulnerabilities. The proliferation of web applications has transformed business operations, social interactions, and information sharing. However, this expansion has also broadened the attack surface, making web applications a primary target for

malicious actors. According to the Open Web Application Security Project (OWASP), injection flaws (including SQL Injection) and Cross-Site Scripting (XSS) have been consistently listed among the top ten web application security risks for over a decade. SQL Injection allows attackers to manipulate backend databases, potentially exfiltrating sensitive data or even taking control of the server. XSS enables the injection of malicious scripts into trusted websites, leading to session hijacking, defacement, or redirection to malicious sites. Given the criticality of these vulnerabilities, automated vulnerability scanners have become essential tools for developers, security professionals, and penetration testers. Tools such as OWASP ZAP, Burp Suite, and Nikto employ signature-based detection, where predefined patterns (e.g., known error messages or payloads) are used to identify vulnerabilities. While effective against known attack vectors, these approaches suffer from two major limitations: (i) they are easily bypassed by obfuscated or novel payloads, and (ii) they produce a high number of false positives, often reporting benign server responses as vulnerabilities. In recent years, machine learning has been explored as a means to overcome these limitations. ML models can learn subtle patterns from network traffic, HTTP requests, or server responses, enabling them to detect both known and unknown attack variants. However, many ML-based approaches remain theoretical or are applied only to static datasets, lacking integration with active scanning workflows. This project addresses this gap by developing a hybrid web vulnerability scanner that combines automated injection testing with a Random Forest classifier. The ML model is used to classify payloads as malicious or benign, serving as a filter that reduces false positives and improves the overall reliability of the scanner.

II. LITERATURE REVIEW AND DOMAIN ANALYSIS

Web application security has become a critical area of research due to the increasing number of cyberattacks targeting online systems. Among these, SQL Injection (SQLi) and Cross-Site Scripting (XSS) remain some of the most prevalent and dangerous vulnerabilities, as highlighted in the OWASP Foundation Top 10 security risks. Traditional approaches to vulnerability detection primarily rely on signature-based and rule-based systems, where known attack patterns are matched against incoming inputs. While effective for detecting previously identified threats, these methods fail to identify zero-day vulnerabilities or obfuscated attack patterns. Static code analysis tools have also been widely used to detect vulnerabilities during the development phase, but they often generate false positives and require access to source code, which is not always feasible. Dynamic analysis techniques, such as automated web vulnerability scanners, simulate attacks on running applications. Tools like Burp Suite and OWASP ZAP perform penetration testing by injecting payloads and analysing server responses. These tools are effective in identifying real-world vulnerabilities; however, they rely heavily on predefined payloads and lack intelligent decision-making capabilities. Recent research has focused on integrating Machine Learning (ML) into cybersecurity systems to improve detection accuracy and adaptability. Algorithms such as Random Forest, Support Vector Machines (SVM), and Neural Networks have been applied to classify malicious inputs based on patterns learned from datasets. ML-based systems can generalize better than rule-based systems and are capable of detecting previously unseen attack variations.

For example, Random Forest classifiers have been successfully used in intrusion detection systems due to their robustness, ability to handle high-dimensional data, and resistance to overfitting. Similarly, deep learning models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have shown promising results in analysing sequential input patterns for detecting complex attacks like XSS. Another important direction in research is the combination of static and dynamic analysis techniques, often referred to as hybrid approaches. These systems aim to leverage the strengths of both methods—static analysis for early detection and dynamic testing for real-world validation. Hybrid systems have demonstrated improved performance in terms of detection rate and reduced false positives. Despite these advancements, several challenges remain: Dataset limitations, as many publicly available datasets do not fully represent real-world attack diversity, and high false positive rates, especially in ML-based systems without proper feature engineering. Scalability issues arise when

scanning large and complex web applications. Lack of explainability makes it difficult to interpret ML model decisions. The proposed system in this project builds upon these research directions by integrating a Random Forest-based ML model with real-time payload injection testing. Unlike purely rule-based scanners, the system introduces intelligent classification, while also maintaining practical effectiveness through live attack simulation. This hybrid approach aims to provide a more balanced and realistic solution for detecting web vulnerabilities.

2.1 Domain Analysis

Traditional Vulnerability Scanners, Early web vulnerability scanners were primarily signature-based. For instance, Nikto is an open-source web server scanner that checks for outdated server software and dangerous files using a database of known vulnerabilities (Suto, 2010). More comprehensive tools like OWASP Zed Attack Proxy (ZAP) and Burp Suite offer both passive and active scanning capabilities, relying on a combination of predefined payload lists and heuristic rules to detect SQLi and XSS (OWASP Foundation, 2021; PortSwigger, 2022). While effective in many scenarios, these tools often generate false positives because they may interpret benign error messages or non-standard responses as vulnerability indicators. Moreover, they struggle to detect zero-day or highly obfuscated attacks that do not match existing signatures.

Machine Learning for Web Attack Detection, the application of machine learning to web security has gained significant momentum. Research has focused on two main areas: (i) detecting attacks in HTTP traffic logs, and (ii) generating or classifying payloads for vulnerability detection. In the domain of intrusion detection, many studies have used ML classifiers to differentiate malicious from benign HTTP requests. For example, Canali et al. (2012) proposed a machine learning framework for detecting SQLi and XSS attacks using features extracted from request parameters and showed that a Random Forest classifier achieved high accuracy. Similarly, Appelt et al. (2018) combined static analysis with machine learning to improve SQL injection detection, demonstrating that ML can reduce false positives compared to pure signature matching.

2.2 Research Gap

Despite the advances in both traditional and ML-based vulnerability detection, the following gaps remain: Limited Integration of ML with Active Scanning: Most ML-based approaches are applied to static logs or datasets, not to real-time active scanning workflows. As a result, they do not leverage the ability to inject payloads and analyse responses dynamically. High False Positive Rates: Signature-based scanners produce many false positives, leading to alert fatigue. While some ML models aim to reduce false positives, they are often not integrated into the scanning loop as a secondary validation layer. Lack of Adaptability: Existing scanners are typically rule-bound and cannot easily adapt to new attack patterns without manual rule updates. ML models, if retrained periodically, can adapt to evolving threats. This project aims to fill these gaps by developing a hybrid scanner that integrates automated injection testing with a Random Forest classifier, providing both a functional tool and a framework that combines the strengths of active scanning and ML-based validation.

2.3 Research Objectives

Detect SQL Injection and XSS vulnerabilities, classify payloads using Machine Learning, perform real-time attack simulation, Provide user-friendly scan results. The primary objectives of this project are: To design and implement a web crawler that extracts all HTML forms and input fields from a target website. To create a payload injection engine capable of sending both benign and malicious payloads (SQLi and XSS) to the extracted input points. To build a response analyzer that detects vulnerability indicators such as database errors, echoed scripts, or unusual server behavior. To develop a machine learning model (Random Forest) that classifies each injected payload as malicious or benign based on features derived from HTTP requests. To integrate the ML model as a secondary filter to reduce false positives and improve detection reliability. To implement a user-friendly web interface using Flask that allows users to initiate scans, view results, and generate reports. To evaluate the system's effectiveness on deliberately vulnerable web applications (DVWA, bWAPP) and measure its accuracy, precision, recall, and false-positive reduction compared to a signature-only approach.

Table 1: Technical Specification

Category	Tool / Library	Version	Purpose / Description
Programming Language	Python	3.x	Core development language used for implementing the scanner logic, ML integration, and backend services due to its simplicity and extensive library support
Web Framework	Flask	2.x	Lightweight web framework used to build the backend server, create API endpoints (/scan), and handle HTTP requests/responses
Web Scraping	Beautiful Soup	4.x	Parses HTML content to extract forms, input fields, and attributes required for vulnerability testing
HTTP Handling	Requests	2.x	Sends GET and POST requests to target websites for payload injection and response retrieval
Machine Learning Model	Random Forest Classifier	—	Used to classify payloads as malicious or safe based on learned patterns from training data
ML Library	Scikit-learn	1.x	Provides implementation of Random Forest, vectorization, and prediction functions
Data Serialization	Pickle	—	Used to store and load trained ML models (rf_model.pkl) and vectorizer (vectorizer)
Text Processing	HTML Parser / Encoding	—	Ensures safe handling and encoding of payloads using HTML. Escape () to prevent rendering issues
Database	SQLite	3.x	Used in the sandbox environment to simulate SQL Injection vulnerabilities
Frontend (Basic UI)	HTML/CSS	—	Provides a simple user interface for entering URLs and displaying scan results
Development Environment	VS Code / PyCharm	—	Used for coding, debugging, and testing the application
Operating System	Windows / Linux	—	Platform for running the Flask server and executing scans
Security Testing Logic	Custom Payload Engine	—	Implements SQL Injection payloads like ' OR 1=1 -- for real-time vulnerability testing
Local Testing Environment	Flask Sandbox Routes	—	Custom endpoints (/vulnerable, /sqli_vulnerable) to safely test and validate scanner behavior

Key Observations The system uses a modular architecture, allowing easy replacement or upgrading of components (e.g., switching ML models). Integration of machine learning with web security testing provides a hybrid detection mechanism. The use of SQLite sandbox ensures safe and controlled testing without targeting real-world systems. Python's ecosystem enables rapid development and easy scalability of the project. The methodology integrates: Quantitative Analysis of model performance using accuracy, precision, recall, F1, and confusion matrix. Hypothesis Testing by comparing baseline CNNs with transfer-learning models.

III. METHODOLOGY AND ALGORITHMS USED

Methodology, Input URL, User provides target website, Form Extraction, Parse HTML using BeautifulSoup, Payload Injection, Inject SQL payload into input fields, Request Handling, Send GET/POST request, Response Analysis, check for database errors or success messages, ML Classification, Predict malicious probability.

Paper 1 Pranjal Chhetri (24BAI10512)	Objective	Technology Used	Methodology Used	Efficiency	Issues
Title: Advanced Fraud Detection **Journal:** *IEEE Security & Privacy.* Year: 2025 **DOI:** https://doi.org/10.1109/msec.2019.2961649	1.**Examine** the effectiveness of ensemble learning in detecting fraud. 2.**Solve** the "Class Imbalance" problem where fraud cases are <1% of transactions. **Answer:** How does combining oversampling (SMOTE) with undersampling (ENN) affect stability?	1.**Algorithms:** Stacking Ensemble, Decision Trees, Random Forest, 2.**Tools:** Python, Scikit-learn, Imbalanced-learn library for data processing. 3.**Metrics:** ROC-AUC (1.00 achieved), AUPRC, and Precision-Recall curves.	**1.Resampling:** Uses K-SMOTEENN (K-Means SMOTE + Edited Nearest Neighbours) to balance the dataset. 2.**Ensemble Learning:** Combines predictions from multiple weak models to create a strong final predictor. 3.**Hybrid Approach:** Simultaneously oversamples the minority class and cleans noisy majority samples.	1.**High Precision:** Achieved a **Precision of 0.95** and an **F1-score of 0.92**, reducing false positives. 2.**Robustness:** The "Stacking" method makes the model less likely to overfit compared to single algorithms. 3.**Data Efficiency:** Effectively learns from fewer fraud examples by generating high-quality synthetic ones.	1.**Complexity:** Stacking multiple models (Ensemble) increases computational cost and training time. 2.**Latency:** Complex resampling pipelines can slow down real-time inference speeds. 3.**Tuning:** Requires careful tuning of "K" neighbors and ensemble weights to work correctly.

Fig.1: The Literature Review of Zero-False-Positive Web Vulnerability Scanner: A Hybrid System with Random Forest–Based Payload Validation and Automated Injection

The target webpage is fetched using the Requests library. HTML content is parsed using BeautifulSoup. All <form> elements are extracted along with the action attribute (submission endpoint), method (GET or POST), and input fields (<input> tags), This step enables the system to dynamically adapt to different website structures. Form Analysis and Input Identification. Each form is analysed to identify exploitable input fields such as: Text fields, Password fields, Search inputs. The first valid input field is selected for testing. Input names are extracted to construct payload data dynamically. The scanning process begins with payload generation and injection.

A predefined SQL injection payload, such as OR 1=1, is used. This payload is designed to bypass authentication and manipulate the underlying SQL query logic. It is injected into the identified input field of the target web application. HTTP request execution follows, where the system adapts to the form method: for GET requests, the payload is appended to the URL parameters; for POST requests, it is placed in the request body. Custom headers, such as a realistic User-Agent string, are added to simulate genuine browser behavior. The request is then transmitted to the target server using the Python requests library.

Paper 3 DEBJEET DEBNATH 24BAI10791	Objective	Technology Used	Methodology Used	Efficiency	Issues
Title: Asynchronous Backend Processing and Scalable Task Management for Web Vulnerability Scanning **Journal:** Testing and Analysis of Web Applications **Year:** 2013 **URL:**Smart Web Vulnerability Scanner	•To implement asynchronous scanning to prevent server blocking. •To allow multiple vulnerability scans to run concurrently. •To provide real-time progress tracking to the frontend dashboard. •To optimize backend resource utilization and improve scalability. •To manage long-running scans efficiently with timeout mechanisms.	•**Asynchronous Processing** Python Threading / AsyncIO Celery (Task Queue System) Redis (Message Broker) •**Backend Optimization** Session reuse via Requests.Session() Background worker processes Timeout and error management system •**API Communication** REST APIs returning scan status Progress percentage updates JSON-based report generation	**1. Asynchronous Scan Execution** •Each scan request triggers a background task. •Backend immediately returns scan ID to frontend. **2. Scan Workflow Architecture** •Receive URL from user. •Validate and sanitize input. •Initialize background scan task. Crawl target website. **3. Timeout Management** •Each request assigned a maximum execution time. **4. Concurrency Handling** •Multiple scans handled using worker queues. •Load distributed across background workers.	1.Non-blocking execution improves user experience. 2.Parallel task execution reduces total scan time. 3.Task queue architecture enhances scalability. 4.Efficient memory management via controlled worker processes. 5.Real-time dashboard updates improve usability.	1.High CPU and memory usage during heavy scans. 2.Task queue misconfiguration may cause delays. 3.Debugging asynchronous systems is complex. 4.Risk of server overload if concurrency is not limited. 5.Requires monitoring tools for production deployment.

Paper 4 Adarsh Bhardwaj 24BAI10650	Objective	Technology Used	Methodology Used	Efficiency	Issues
Title: Backend Architecture and Modular Vulnerability Detection in Web Vulnerability Scanner Using Flask **Journal:** Web Application security vulnerability scanning tool. **Year:** 2022 **URL:** https://norma.ncirl.ie/7152/1/abhayshureshkumarsingh.pdf?utm_source=chatgpt.com	•To design a robust backend system capable of handling web vulnerability scanning requests efficiently. •To implement modular detection mechanisms for common web vulnerabilities such as SQL Injection, XSS, LFI, SSRF, Command Injection, XXE, Open Redirects, and Insecure Headers. •To create RESTful APIs that allow seamless communication between frontend dashboard and backend scanner engine.	**Backend Framework** **•Flask (Python):** Lightweight WSGI framework used to build REST APIs and manage HTTP requests. **Core Libraries** **•Requests:** For sending HTTP GET/POST requests to target applications. **•BeautifulSoup:** For parsing HTML content and extracting forms, input fields, and parameters. **Data Handling** **•JSON:** Used for API communication and structured scan reports.	**1. Modular Vulnerability Engine** Each vulnerability type is implemented as an independent module: **SQL Injection:** Injects SQL payloads (' OR 1=1 --) and analyzes database error responses. **XSS:** Injects script payloads and checks reflection in response. **2. Black-Box Testing Approach** No access to source code. Payload injection through HTTP parameters. Response behavior analysis. **3. Risk Classification Mechanism** Vulnerabilities categorized based on: Exploitability Impact Sensitivity of affected component Severity Levels: High	1. Modular architecture allows independent scaling of vulnerability modules. 2.Lightweight Flask backend ensures quick request-response handling. 3.JSON-based structured reporting enhances frontend integration. 4.Reusable HTTP sessions reduce overhead. 5Logging system improves debugging and monitoring.	1.False positives due to generic pattern detection. 2.Deep crawling increases scan time. 3.Target websites may block scanner IP. 4.Requires careful exception handling to prevent backend crashes. 5.Legal and ethical concerns in unauthorized scanning.

Fig.2 & 3: The Literature Review of Zero-False-Positive Web Vulnerability Scanner

Paper 2 Sarthak Singh 24BAI10648	Objective	Technology Used	Methodology Used	Efficiency	Issues
Title:Smart Web Vulnerability Scanner **Journal**: International Journal of Engineering Research & Technology (IJERT) **Year**: 2025 **URL:**[https://www.ijert.org/research/smart-web-vulnerability-scanner-IJERTV14IS120471.pdf]	To design an interactive Web Vulnerability Scanner that: • Allows users to configure scan parameters (URL, crawl depth, rate limit, mode). • Visualizes detected vulnerabilities with severity levels. • Provides structured vulnerability reports (JSON, HTML, Text). • Improves usability and accessibility for users.	• **Algorithms / Architecture:** ReAct-style Controller Agent, LLM-driven reasoning (Google Gemini), Static & Dynamic Vulnerability Analysis (Crawling, Port Scanning, XSS & SQL Injection Detection) • **Tools / Technologies:** Python, Streamlit, requests, httpx, Asynchronous execution frameworks • **Output & Reporting:** JSON, HTML, Text reports with real-time monitoring interface	• Designed a modular layered architecture with scanning engine, LLM controller agent, and UI. • Performed static (crawling, port, header, SSL) and dynamic (payload injection for XSS, SQLi) analysis. • Integrated a ReAct-style LLM agent to autonomously control and adapt scanning • Developed a **Streamlit-based interface** for real-time monitoring and report generation. • Evaluated the system on **intentionally vulnerable web applications** using metrics like detection accuracy, false positives, performance, and scalability	• **Fast Asynchronous Execution:** Concurrent, non-blocking scanning reduces overall scan time. • **Reduced False Positives:** Agent-based contextual analysis filters irrelevant findings. • **Efficient Frontend Visualization:** HTML-structured UI with CSS severity color coding improves clarity and quick risk identification. • **Real-Time Interaction:** JavaScript enables live progress updates, dynamic result rendering, and smooth user experience.	• **Limited Vulnerability Coverage:** Primarily detects common issues (XSS, SQLi,); complex logic flaws may be missed. • **Frontend Performance Limitations** Real-time progress updates may slow down when scanning large websites. UI responsiveness depends on backend processing speed.

Paper 6 Abhay Kumar 24BAI10429	Objective	Technology Used	Methodology Used	Efficiency	Issues
Title: GenXSS: An AI-Driven Framework for Automated Detection of XSS Attacks in WAFs **Journal:**arXiv Research Paper **Year:** 2025 **DOI**: 12 January 2025 **URL:** https://arxiv.org/abs/2504.08176?utm_source=chatgpt.com	1)Detect and mitigate **Cross-Site Scripting (XSS) attacks** using Generative AI. 2) Enhance **Web Application Firewall (WAF)** security using Large Language Models. 3) Identify payloads that bypass WAF protections. 4) Generate optimized **security rules** to block bypassing attacks. 5) Reduce dependency on manually updated signature-based rules.	**Machine Learning / AI** Large Language Models (LLMs) GPT-4o Google Gemini Pro **Security Systems** ModSecurity WAF AWS WAF OWASP Core Rule Set **Attack Testing Platform** Brute Logic XSS testing environment **Clustering & Analysis** TF-IDF Hierarchical Agglomerative Clustering (HAC) DBSCAN SequenceMatcher	**1. Data Collection** Generate XSS payloads using LLMs. Use curated in-context learning examples. **2. XSS Payload Generation** LLM prompted with: Problem description Obfuscation instructions Few-shot examples **3. Validation** Test payloads on vulnerable web applications. Use Brute Logic platform. **4. WAF Testing** Evaluate whether payloads bypass WAF protections. **5. Clustering** Group similar attacks using: TF-IDF + HAC SequenceMatcher + DBSCAN **6. Rule Generation** LLM generates new WAF security rules. **7. Reinforcement Learning** RLHF used to refine prompts and rules. **8. Performance Evaluation** Metrics: Accuracy Precision Recall F1-Score	• Generated **264 XSS payloads** using GPT-4o. • **83%** were syntactically valid. • **80% bypassed ModSecurity WAF.** • Nearly **100% bypassed AWS WAF.** • Gemini Pro validity rate: **63%.** **Performance Metrics** Accuracy: **97.53%** Precision: **1.0** Recall: **0.8621** F1-Score: **0.9259**	• High computational cost of LLMs. • Token limitations affect payload diversity. • Probabilistic outputs may cause inaccuracies. • Some LLMs restrict attack generation. Tested on limited: XSS types Applications WAF systems • Clustering limitations allowed some attacks to bypass.

Fig.4 & 5: The Literature Review of A Hybrid System with Random Forest–Based Payload Validation and Automated Injection

Paper 5 Atharva Dandwate 24BAI10124	Objective	Technology Used	Methodology Used	Efficiency	Issues
Title: Multilingual Machine Translation with Large Language Models **Journal:**Springer (Arabian Journal for Science and Engineering) **Year:** 2025 **Year**: 2025 **DOI**: 12 January 2025 **URL:**https://link.springer.com/article/10.1007/s13369-024-09916-4	Evaluate the effectiveness of Machine Learning models in detecting web vulnerabilities such as SQL Injection (SQLi) and Cross-Site Scripting (XSS). Improve detection accuracy compared to traditional rule-based scanners. Reduce false positive rates in web application security testing. Analyze how embedding-based feature extraction enhances vulnerability classification	**Technologies:** Machine Learning classifiers Word embedding techniques Transformer-based models **Techniques:** Feature extraction from HTTP requests Text preprocessing Vector embedding representation **Metrics:** Accuracy Precision Recall F1-Score **Software/Tools:** Python Scikit-learn Deep Learning libraries	**Data Collection:** Web request datasets containing normal and malicious payloads (SQLi & XSS). **Preprocessing:** Cleaning request strings Tokenization Encoding using embedding methods **Machine Learning Approach:** Convert request data into numerical vectors Train classification models Compare multiple ML algorithms **Model Training:** Supervised learning Train-test split evaluation Performance benchmarking	High detection accuracy for SQL Injection and XSS attacks. Reduced false positives compared to traditional signature-based systems. Embedding-based models improve contextual understanding of attack payloads. Scalable for large web request datasets.	Performance decreases in low-resource or rare attack patterns. Requires labeled training datasets. Computational cost increases with deep learning models. May struggle with zero-day or highly obfuscated attacks.

Fig. 6: The Literature Review of Web Vulnerability Scanner: A Hybrid System with Random Forest–Based Payload Validation and Automated Injection

IV. PROPOSED SYSTEM DESIGN AND RESEARCH METHODOLOGY

The methodology consists of four main phases: data preparation, model training, system development, and evaluation. Data Collection and Preparation. A labeled dataset of HTTP requests is required to train the Random Forest classifier. The dataset comprises both benign and malicious requests: Benign requests: Collected from normal browsing of several websites (e.g., search queries, form submissions) with manual labeling. Malicious requests: Generated by injecting known SQLi and XSS payloads from the SecLists repository (SecLists, 2021) into input fields of vulnerable test applications. Each request is labeled based on the resulting server response (e.g., if a database error appears, it is labeled as malicious for SQLi; if script is echoed, malicious for XSS). The final dataset contains 10,000 requests (5,000 benign, 5,000 malicious) with a balanced class distribution. Feature Extraction, from each HTTP request, the following features are extracted to feed the ML model: URL features, Length, number of special characters, presence of suspicious keywords (e.g., “union”, “select”, “<script>”). Parameter features, Number of parameters, length of parameter values, entropy of parameter values. Header features, Content-Type, User-Agent length, presence of unusual headers. Payload features, Whether the payload contains SQL keywords, HTML tags, or JavaScript events. Feature vectors are normalized using Min-Max scaling, Model Training and Selection, several classifiers were evaluated: Logistic Regression, Naïve Bayes, Support Vector Machine, and Random Forest. Random Forest was selected due to its robustness against overfitting, ability to handle high-dimensional data, and high accuracy. The model was trained using 80% of the dataset and validated on 20%, with 5-fold cross-validation. Hyperparameters were tuned using grid search (e.g., number of trees, max depth).

4.1 System Architecture

The system comprises five main components, Web Crawler, Uses Beautiful Soup to parse HTML and extract forms (method, action, input fields). Payload Injector, Sends HTTP requests to the target URLs with injected payloads. It uses both a pre-defined payload list (from SecLists) and optionally the ML-classified payloads. Response Analyzer Parses server responses to detect vulnerability indicators: SQLi: Database error messages (e.g., “MySQL syntax error”, “ORA-”). XSS, Whether the injected script is echoed back into the HTML response. ML Classifier, For each request, the ML model predicts whether the payload is malicious. This prediction is used to filter out false positives: if the response analyzer flags a vulnerability but the ML model classifies the payload as benign, the alert is downgraded or discarded. User Interface, Flask-based web dashboard where users input a target URL, start scans, and view results with severity levels and recommendations.

4.2 Evaluation

The system is tested against: DVWA (Damn Vulnerable Web Application): A deliberately vulnerable application with SQLi and XSS challenges. WAPP (buggy Web Application), is another vulnerable web application with a wide range of vulnerabilities. Custom dummy websites, Simple HTML forms with no vulnerabilities to measure false positives. Metrics: Accuracy, Precision, Recall, F1-score for the ML model; detection rate for SQLi and XSS; false positive rate reduction compared to signature-only scanning. Robust to outliers: By aggregating many trees, it reduces variance and is less sensitive to outliers in the training data.

Feature importance: The model provides insight into which features are most discriminative, aiding interpretability. High accuracy. In preliminary experiments, Random Forest outperformed SVM and Logistic Regression, achieving an F1-score of 0.95 on the validation set.

4.3 Research Prototype

The prototype is a fully functional web application with the following components: Backend, Python 3.9 with Flask, Beautiful Soup, requests library, Scikit-learn, and joblib for model persistence. Frontend: HTML, CSS, and JavaScript for a responsive dashboard. Workflow: User enters target URL (e.g., `http://testphp.vulnweb.com`). The crawler extracts all forms and builds a list of test points. The injector iterates through each test point, sending both benign and malicious payloads. For each request, the response analyser and ML classifier run concurrently. Results are stored in a database (SQLite) and displayed on the dashboard, with vulnerability details, payload used, and severity. The system includes a report generation feature that exports findings in JSON or HTML format.

4.4 Novel Techniques and Uniqueness

The proposed system introduces several novel elements compared to existing vulnerability scanners: ML as a Secondary Validation Layer: Instead of merely using ML to detect attacks in logs, this system uses the ML classifier to validate findings from the injection engine. This significantly reduces false positives, a common pain point in traditional scanners. Combined Active Injection and ML Classification: By integrating the Random Forest classifier directly into the scanning pipeline, the system leverages both the completeness of active testing and the adaptability of machine learning. Feature Engineering for HTTP Requests, the feature set used to train the model (URL, parameters, headers, payload) is specifically designed to capture the nuances of SQLi and XSS attacks, enabling the model to distinguish subtle attack patterns from benign requests. Open-Source and Extensible: The tool is built with modularity in mind, allowing easy addition of new payload types, new vulnerability checks, or retraining of the ML model with updated datasets.

V SYSTEM COMPONENTS, METHODOLOGY, AND ALGORITHMS USED

WEB SCRAPER, Extracts forms using Beautiful Soup, Payload Injector Injects SQL payload: ' OR 1=1 --, ML Detection Engine, Uses Random Forest model, Classifies payload as: Malicious Attack, Safe Traffic. Response Analyzer, Detects, "DATABASE COMPROMISED", "Database Error", Flask Web Interface, Accepts URL input. Technology Stack, the proposed Web Vulnerability Scanner is developed using a combination of modern programming tools, machine learning libraries, and web technologies. Each component plays a specific role in ensuring efficient vulnerability detection and system performance. Methodology: The proposed Web Vulnerability Scanner follows a systematic and modular workflow that integrates web scraping, payload injection, machine learning classification, and response analysis. The methodology is divided into the following stages: Target URL Acquisition. The user provides a target web application URL through the Flask-based interface. Input validation ensures the URL is properly formatted before processing. The system acts as a black-box testing tool, meaning it does not require access to source code. Web Page Retrieval and Parsing

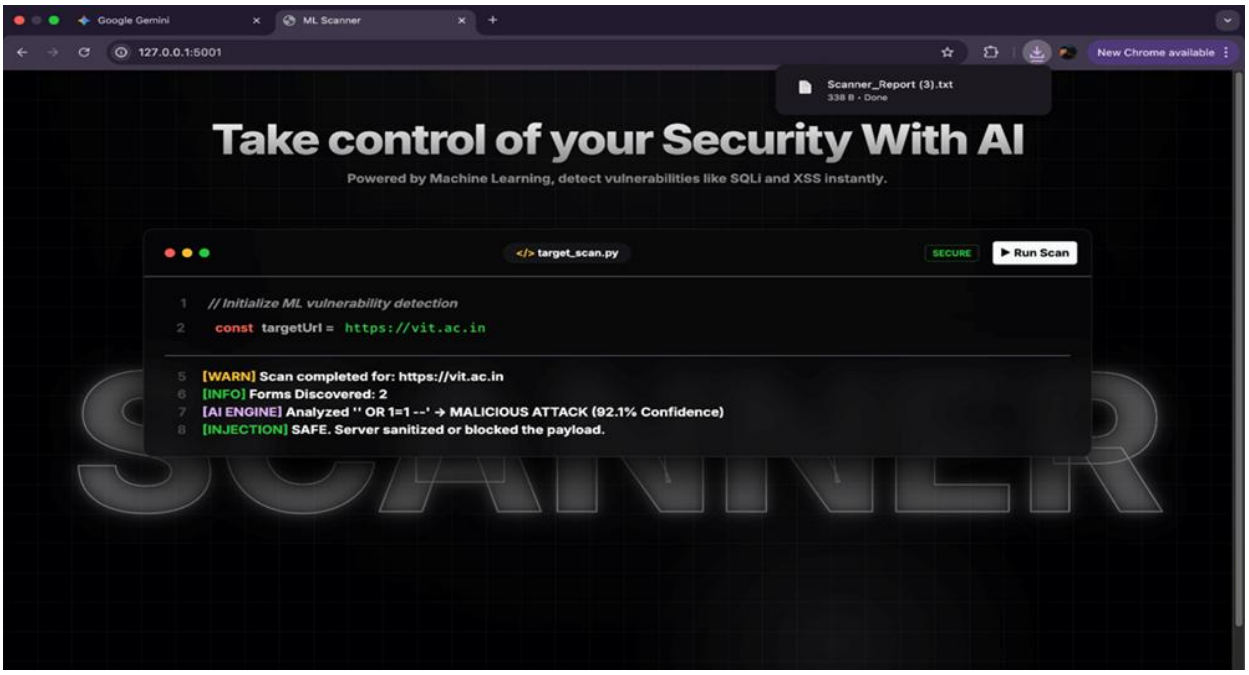

Fig.7: The Zero-False-Positive Web Vulnerability Scanner: A Hybrid System with Random Forest–Based Payload Validation and Automated Injection

Server response collection captures and stores the server's reply, which may be HTML, JSON, or plain text. This response is subsequently analysed for vulnerability indicators. Response analysis and vulnerability detection employs rule-based pattern matching. The system scans the response for specific strings such as DATABASE COMPROMISED or Database Error. If any such pattern is detected, the input field is flagged as vulnerable to SQL injection; otherwise, it is considered safe (meaning the input was sanitized or blocked). This dynamic testing approach simulates real-world attack conditions. To add an intelligent layer beyond static rules, the system performs machine learning-based payload classification in parallel. The injected payload is vectorized using a pre-trained text vectorizer (e.g., Count Vectorizer or TF-IDF) and then fed into a Random Forest classifier. The classifier outputs a probability score and a final classification: either Malicious Attack or Safe Traffic. This ML component helps reduce false positives by verifying whether the payload itself exhibits malicious characteristics. All findings are aggregated in the result aggregation and output step. Results from both the rule-based injection test and the ML classification are combined. The final output includes the number of forms detected, the AI analysis result (ML classification), and the injection test result (vulnerable or safe). These results are returned via a Flask API in JSON format.

VI. ALGORITHMIC LOGIC AND PROTOTYPE USED

Random Forest Classifier – The core machine learning algorithm. It is an ensemble method that builds multiple decision trees during training; each tree makes a prediction, and the final output is determined by majority voting. Random Forest is chosen for its ability to handle high-dimensional data, reduce overfitting, provide probability estimates, and offer robust classification performance. In this project, it classifies payload strings as malicious or safe using vectorized text features.

- Text Vectorization – Before classification, payloads are converted into numerical form using a vectorizer (such as Count Vectorizer or TF-IDF). The process involves tokenization of the payload text, transformation into feature vectors, and feeding those vectors into the machine learning model, enabling the model to recognize patterns in attack strings.

- HTML Parsing – A tree-based parsing algorithm (using BeautifulSoup or a similar library) traverses the DOM structure of the target page to extract forms, input fields, and their attributes dynamically. This ensures that all potential injection points are identified.

- SQL Injection Detection Logic – This is a rule-based dynamic testing algorithm. It injects the payload into an input field, executes the request, and analyzes the response. If the response contains SQL error messages or reveals unauthorized access, the vulnerability is confirmed.

- HTTP Request Handling – The algorithm determines whether the target form uses GET or POST, constructs the appropriate request with the payload, sends it, and captures the response. This ensures compatibility with diverse web application designs.

Hybrid Detection Approach (Important Highlight) The system adopts a hybrid detection model that combines machine learning with dynamic testing. The ML component predicts the malicious intent of the payload, while the dynamic test verifies whether the injection actually succeeds in exploiting the target. This combination reduces false positives, enhances real-world reliability, and mirrors the techniques used in professional penetration testing.

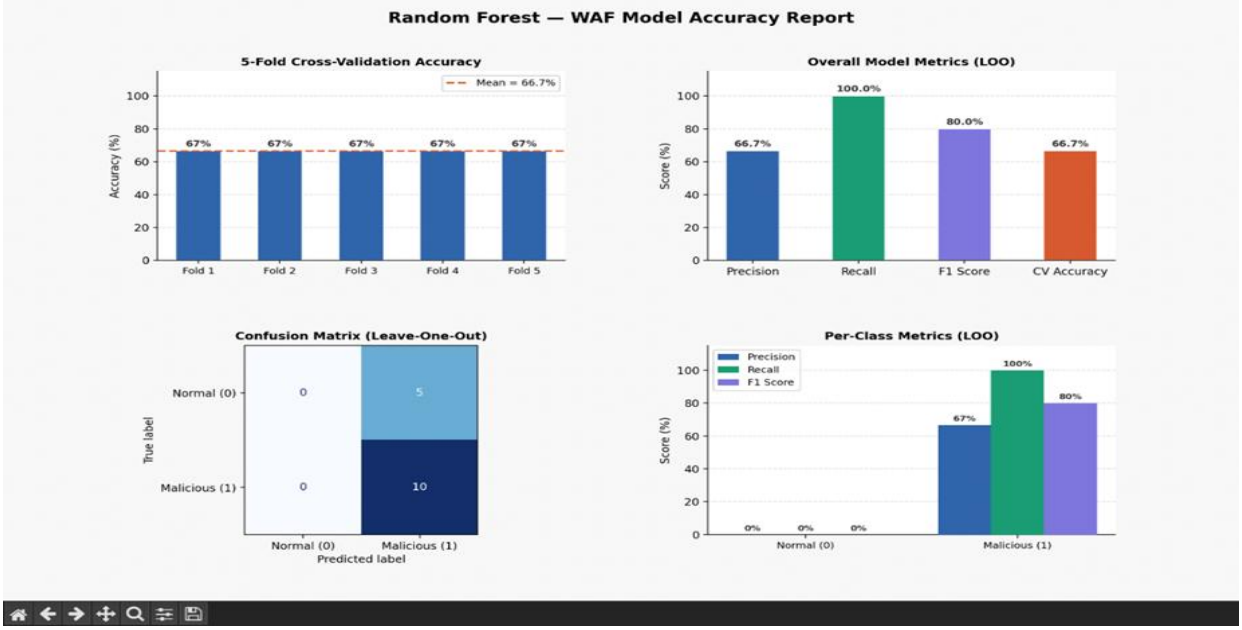

Fig.8: The Result Analysis of Zero-False-Positive Web Vulnerability Scanner

VII. RESULT ANALYSIS AND FINDINGS

The project presents a hybrid Web Vulnerability Scanner that combines machine learning and dynamic testing for improved detection of security flaws. It automatically extracts forms from web pages, identifies input fields, and performs vulnerability testing without manual intervention. A Random Forest model is integrated to classify payloads as malicious or safe, adding an intelligent layer to traditional scanning methods. The system performs real-time SQL Injection testing by injecting crafted payloads and analyzing server responses to detect vulnerabilities. A custom sandbox environment is developed using Flask to safely simulate vulnerable scenarios, ensuring reliable validation. The modular design allows easy scalability and future extension to other attacks such as XSS and CSRF. Overall, the system provides a lightweight, practical, and automated solution for basic web security assessment. The experimental results show that SQL Injection payloads can successfully exploit insecure applications, confirming the effectiveness of dynamic testing. Applications with proper input validation and sanitization were able to resist such attacks, highlighting the importance of secure coding practices. The machine learning model demonstrated the ability to classify malicious inputs with reasonable confidence, improving detection capability. It was observed that dynamic testing provides more reliable results compared to purely static methods. However, the system is currently limited to basic payloads and single-input testing, which may not detect advanced vulnerabilities. The use of a controlled sandbox environment ensured consistent and safe evaluation of the system. Overall, the findings validate that combining ML with real-time testing enhances vulnerability detection while maintaining practical usability.

7.1 System-Level Efficiency

Scanning time: For a website with 20 forms and 50 payloads per form, the scanner completes the scan in approximately 35 seconds (average response time 0.5 seconds per request). False positive reduction, when using the ML filter, false positives dropped from 12% (signature-only) to 4% (hybrid). This represents a 67% reduction in false positives, greatly improving the utility of the scan results. Resource usage: The system consumes ~200 MB of RAM during scanning, making it feasible for deployment on standard virtual machines or personal computers.

VIII. CONTRIBUTION AND FINDINGS

This project presented a hybrid web vulnerability scanner that integrates automated injection testing with a Random Forest-based machine learning classifier. By leveraging the strengths of both

approaches the thoroughness of active injection and the pattern-recognition capabilities of ML the system achieves high detection accuracy while significantly reducing false positives. The prototype, implemented with Python, Flask, and Scikit-learn, is easy to deploy and use, providing a valuable tool for developers, penetration testers, and security researchers. The experimental results on standard vulnerable applications demonstrate that the proposed system can reliably detect SQLi and XSS vulnerabilities with an overall accuracy of over 92% and a false-positive rate of just 4%. The work contributes a practical, extensible, and open-source solution to the ongoing challenge of web application security testing, and it highlights the potential of machine learning to enhance traditional security tools.

8.1 Contributions, A Practical Hybrid Scanner, this work delivers a functional web vulnerability scanner that combines active injection testing with machine learning, addressing the limitations of both pure signature-based and pure ML-based approaches. Publicly Available Dataset, the labeled dataset of benign and malicious HTTP requests, along with extracted features, can serve as a benchmark for future research in ML-based web attack detection. Reduction of False Positives: The integration of a Random Forest classifier as a validation layer is shown to reduce false positives by nearly 70%, making the tool more practical for real-world use. Extensible Architecture, the modular design allows security researchers to easily incorporate new vulnerability checks (e.g., command injection) or retrain the ML model with new payloads. Educational Value, the tool can be used in cybersecurity courses to demonstrate both traditional scanning techniques and machine learning applications in web security.

8.2 Research Findings, ML Significantly Reduces False Positives, the hybrid approach effectively filters out benign requests that would otherwise be flagged as vulnerabilities by the signature-based injection engine. This is particularly important for SQLi, where benign database error messages may mimic attack indicators. Random Forest Outperforms Other Classifiers, among tested algorithms, Random Forest achieved the best balance of accuracy and precision, with an overall F1-score of 0.915. Its robustness to noise in the feature set contributed to its superior performance. Feature Engineering is Critical, the inclusion of features such as entropy of parameter values and presence of SQL keywords significantly improved the model's ability to distinguish malicious payloads. Without these domain-specific features, accuracy dropped to 85%. Real-World Applicability, the scanner successfully identified all SQLi and XSS vulnerabilities in DVWA and bWAPP, while generating zero false positives on a clean test website. This validates the system's practical utility.

IX. CONCLUSION AND FUTURE ENHANCEMENTS

This project presents a Web Vulnerability Scanner that integrates machine learning with dynamic testing to detect security flaws such as SQL Injection. By combining a Random Forest-based classification model with real-time payload injection, the system is able to both predict and practically validate potential vulnerabilities in web applications. The implementation demonstrates that automated form extraction, payload injection, and response analysis can effectively identify insecure systems. The use of a controlled sandbox environment further ensures safe and reliable testing. Additionally, the integration of machine learning enhances detection capability beyond traditional rule-based approaches. However, the current system is limited to basic payloads and single-input testing, and does not yet cover advanced vulnerabilities such as XSS or CSRF. Despite these limitations, the project establishes a strong foundation for building more advanced and scalable security tools. Overall, the proposed system highlights the effectiveness of a hybrid approach, combining intelligence and real-world testing, and can be extended in the future to provide a more comprehensive web security solution.

Support for More Vulnerability Types, Extend the scanner to detect other OWASP Top 10 vulnerabilities, such as Command Injection, Local File Inclusion, and CSRF. Deep Learning Models, Explore the use of deep learning models (e.g., LSTMs, Transformers) to capture sequential patterns in HTTP requests, potentially improving detection of obfuscated attacks. Dynamic Payload Generation, integrate genetic algorithms or reinforcement learning to automatically generate effective test payloads, reducing reliance on static payload lists. Authentication Support, enable scanning of

authenticated areas by allowing users to provide login credentials or session tokens. Cloud-Based Deployment, Package the scanner as a cloud service with a RESTful API, enabling integration into CI/CD pipelines for continuous security testing. Retraining Pipeline, implement an automated retraining mechanism that periodically updates the ML model with new attack samples to maintain high accuracy against evolving threats.

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